INTEGRATION OF SEASONAL FORECAST INFORMATION AND CROP MODELS TO ENHANCE DECISION MAKING IN SMALL-SCALE FARMING SYSTEMS OF SOUTH AFRICA

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DECLARATION I

DECLARATION II

I declare that this thesis is my own work and has not been submitted in any form for another degree or diploma at any university or other institute of tertiary education. Information derived from the published and unpublished work of others has been acknowledged in the text and a list of references is given.

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ABSTRACT

Climate variability threatens agricultural productivity and household food security, amongst small-scale farmers of South Africa. Managing climate variability is challenging due to the variation of climate parameters and the difficulty in making decisions under such conditions. Integrated seasonal forecast information and crop models have been used as a tool that enhances decision making in some countries. Utilization of such an approach in South Africa can enhance decision making in climate variability management. The study therefore sought to formulate a decision-making approach to enhance climate variability management in small-scale farming systems of South Africa through integrating seasonal forecast information and crop models. Current practices, challenges and opportunities for climate variability management by different small-scale farmer types were identified using focus group discussions and local agricultural extension officers. The Climate Forecast System version 2 (CFSv2) model-based forecasts were integrated with the Decision Support System for Agrotechnology Transfer (DSSAT) v4.7, a mechanistic crop model based on the Global Climate Model (GCM) approach. The GCM approach was the most appropriate technique for integrating seasonal forecast information and the crop model due to the compatibility in the forecast and crop model format. The decision-making process was formulated through assessing the simulation yield patterns under a range of farm management practices and seasonal forecasts for different cropping seasons, crops and farmer types for Limpopo and Eastern Cape, South Africa for 2017/18 season. The study assessed 48 different potential combinations of farm management practices: organic amendments, varieties, fertilizers and irrigation. Benefits of the decision formulation process and specific seasonal forecast-based recommendations were then assessed in the context of the performance of the practices under historical measured data for the conditions; 2011-2017, using percentile ranking. Assessing the yield response patterns under different farm management practices and seasonal forecasts (2017/2018), the study realized a range of decision scenarios. These are (1) *low decision capacity and low climate sensitivity* where there is low value for decision due to the homogeneous performance of the different management practices given climate forecasts. (2) *high decision capacity and low climate sensitivity*, where there is higher potential value for decision making as the different practices have uniform performance across climate forecasts. (3) *High decision capacity and high climate sensitivity,* where the good response to change in practices under changing climate forecasts. Confidence in the decision formulation process

was re-enforced as some of the decision scenarios were also realized under different conditions in the period; 2011-17. The scenario (2): *High decision capacity and low climate sensitivity* was predominant in locations with low forecast skill. In contrast the scenario (3): *High decision capacity and high climate sensitivity* was predominant in locations with high forecast skill. The decision formulation process allows for assessment of farm management practices in the seasonal forecast decision space. Although the case study realized some scenarios ahead of others, the process is robust and repeatable under any conditions. Although the process does not always offer recommendation with improved value for decision making, the value of recommendations is greater under decision scenarios with greater decision capacity. Such benefits are crop and location dependent. Improved seasonal forecasting skill increases reliability of the decision-making process, decision scenarios and associated recommendations. Such assertions need to be tested on the field scale to assess their practical feasibility.

SUPERVISOR

Dr. Olivier Crespo

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DEDICATION

To my late father.

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Chapter 1

1.1 Introduction

This chapter provides information on the background, rational, motivation and expectations from the study. This includes the problem statement, problem context, justification and overall aim of the study. Specifically, the chapter includes information on current state of small-scale farming in South Africa in the context of Africa at large. There is also information on current challenges facing farmers under current and projected climate variability as well as the potential impact on crop productivity. It highlights their efforts and challenges in managing climate variability, exposing the need for further research in developing approaches to enhance climate variability management. The section further highlights the potential value of using seasonal forecasts and the additional value of 'integrating seasonal forecast information and crop models' as an approach to inform decision making in small-scale farming. The section then highlights the specific objectives addressed in the study.

1.2 Small-scale farming in South Africa

At least 60% of the population in Africa lives in the rural areas and small-scale farming is their main source of livelihood in the form of food and income (Pienaar and Traub, 2015; Wiggins, 2009). They are supported by at least 30 million small-scale farmers, which translates to 75% of all the farmers in Africa (Altieri, 2009). At least 4 million people in South Africa, are involved in small-scale farming in the former homelands, which are marginalized areas with poor soils (Baiphethi and Jacobs, 2009). There are about 2.6 million small-scale farming households in South Africa which support at least 10 million individuals constituting about 20 % of the population. In South Africa, small-scale farming is undertaken on about 10 % of the 13 million hectares of South Africa's arable land (Pienaar and Traub, 2015). About 50 % of the arable land under small-scale farming is situated in mostly semi-arid to arid agro-ecologies. Small-scale farming is mainly undertaken on small-land holdings of less than 1.6 ha by at least 60 % of the farmers. About 20 % of these farmers have 1.6-10 ha of land and 10 % have at least 10 ha of land (Fanadzo and Ncube, 2018). Small land sizes limit the potential food production. Small-scale farmers associated with livestock ownership have relatively large land holdings areas exceeding 10 ha (Mutero et al., 2016; Pienaar and Traub, 2015). Not all land is however, cultivated due to various challenges associated with small-scale farming. The sector is of utmost importance to the continent. Any challenges to the small-scale agricultural farming has a potential negative impact on food security, livelihood and livelihood sustainability of the continent (Altieri, 2009).

Small-scale farming is plagued by multiple challenges. Such challenges include shortage of improved cereal and legume seed, poor soil fertility, land degradation, ever-dwindling grazing land, poor livestock breeds, limited access to fertilizers, insect pests, crop diseases and climate variability (Aliber and Hall, 2012; Mpandeli and Maponya, 2014; Musa and Phillip, 2016). As a result, farmers face recurrent crop yield losses, food shortages and ultimately severe food insecurity. Average maize yields in Malawi in small-scale farming systems range around 0.8 tha^{-1} (Altieri, 2009) which is insufficient for feeding a normal household (Mango et al., 2018). This is in comparison to 3.9 tha^{-1} attained under optimal rainfed conditions (Nyagumbo et al., 2015). In South Africa, maize crop yields can be as low as 0.5 tha^{-1} in small-scale farming (Kgonyane et al., 2013). Such a pattern is common across all crops cultivated by small-scale farmers in Africa. In most cases such yield sizes are insufficient to feed an average family (Baiphethi and Jacobs, 2009). Extensive research has been undertaken on most of the challenges affecting the small-scale farmers (Cairns et al., 2013; Chikowo and Zingore, 2014; Samaké et al., 2006). Farmers have evolved to manage some of the challenges through indigenous knowledge and extension services, but such evolution is hampered by climate variability. Small-scale agriculture is mostly rainfed dependent, hence it is very sensitive to rainfall variability (Sibhatu and Qaim, 2017). Climate variability decimates the benefits from improved management of other challenges. Advances have been made in climate variability adaptation, but farmers still experience the negative impacts of climate variability such as increased frequency of dry spells. Small-scale farmers in South Africa have highlighted increased climate unpredictability as one of their major challenges (Thomas et al., 2007).

1.3 Climate variability in South Africa

Recent climate research has been mainly biased towards long term climate change (Graham et al., 2011; Zinyengere et al., 2014; Ncube et al., 2015). Future projections show a range of contrasting changes in climate and corresponding impacts on agriculture (Zinyengere et al., 2013). Future climate change research has evolved from emission based to the current Representative Concentration Pathway scenarios (IPCC, 2014). Formulation of different climate change projections has considerably advanced climate science but their accuracy is limited (Fallis, 2013; IPCC, 2014). This shows the dynamism and potential unreliability of long term climate change research (Mearns et al., 2001). Long term climate change research does not sufficiently address the immediate preparedness to climate variability (Sivakumar et al., 2002). Worsening climate variability as evidenced by the increased frequency of *El Niño*s, dry spells and extreme rainfall and temperature events highlights the need to focus on seasonal weather variability research (Akpalu et al., 2009; Bouba et al., 2013).

Climate variability is manifested through increased unpredictable temporal and spatial variation over a relatively shorter time period, in the mean and other statistical aspects defining climate (IPCC, 2014). In southern Africa during austral summer, rainfall varies over a range of temporal scales such as synoptic (3-7 days), inter-seasonal (2-10 years), quasi-decadal (10-15 years) and inter-decadal (15-30 years) variability (Pohl et al., 2018). All these, except synoptic variability and to a lesser extent inter-seasonal variability, exhibit significant forms of cyclicity (Fauchereau et al., 2003). Climate variability, particularly rainfall variability is directly correlated to the ENSO phases. The difference in phases is associated with different degrees of variability, with the *El Niño* being associated with low rainfall of higher variability, neutral with average rainfall and *La Nina* being associated with above average rainfall of low variability (Pomposi et al., 2018). Most of the rainfall variability experienced within the southern African regions, specifically South Africa is attributed to varying ENSO phases (Yuan and Tozuka, 2014).

Assessment of historical climate variability shows a gradual increase in the manifestation of climate variability in Southern Africa. There has been an increase in the manifestation of the *El Niño* related events and are projected to increase in the future (Ray et al., 2015). Most of the inter-seasonal and quasi-decadal variability has been associated with the ENSO phenomenon. Specifically the droughts in 1991/2, 1994/5, 1997/8 and 2015/16 (Pomposi et al., 2018). Inter-seasonal variability has gradually increased up to 20% in the northern parts of Africa over the period; 1965-2005 (Bouba et al., 2013). The frequency of extreme temperature events has also increased as manifested as an increase in the frequency of heat waves in the sub-Saharan African region for the period: 1900-2000 (Niang et al., 2014). Specifically, North Africa has experienced an average of 40-50 heat waves a year during the period; 1989-2009 (Vizy and Cook, 2012). On the other hand, the southern African region has also experienced increased frequency of occurrence of droughts (IPCC, 2014). Climate variability has also been associated with increased variability in the commencement and cessation of the rainfall season as well as the increase in frequency and duration of mid-season dry spells. The frequency of rainy days which has been characterized with high rainfall intensity per rainfall event has also decreased (Tadross et al., 2005).

Projections show increased temporal and spatial climate variability in Southern Africa (Niang et al., 2014). CMIP3 and CMIP5 global climate models (GCM) based projections show increase in precipitation in the East and West African regions with insignificant delays in the commencement of the rainy season and decrease in dry spells (Shongwe et al., 2011). On the contrary, CMIP3 and CMIP5 projections show decrease in precipitation characterised with delays in rainfall commencement and decrease in dry spells in parts of Southern Africa such as Botswana and Namibia (Roehrig et al., 2013; Washington et al., 2013). The same model predicts increased precipitation over south East-South Africa as well as over the Drakensberg mountain range. Decreases in rainfall will be characterized by greater variability in the onset of rainfall which is also gradually tilting towards delayed onset (Engelbrecht et al., 2011). Some GCMs predict increase in extreme rainfall events over west Africa. East Africa has experienced increase in droughts over the past 50 years, but projections show increase in precipitation but with high variability. GCMs also predict extreme warm and cold indices as hot days, hot nights and warmer winters in Southern Africa (Vizy and Cook, 2012). Intra-seasonal climate changes have a significant impact on crop yields compared to long term climate change. Specifically, the number of dry days is the most critical yield determining factor (Bouba et al., 2013).

Rainfall and temperature are key parameters that have a direct impact on crop growth and development. There is a direct correlation between rainfall and crop growth and development (Ray et al., 2015). In some parts of North Africa, inter-seasonal variability has led to a coefficient of variation of 25, 40 and 45 % for cotton, groundnut and sorghum yields respectively (Bouba et al., 2013). Inter-seasonal rainfall variability has also resulted in large maize yield losses as high as 60 %. This was the case in Malawi in the 1991/92 season (Clay et al., 2003). Climate variability therefore causes notable yield variation, with consequences to household and national food security. Climate variability has led to recurrent partial to total crop yield losses in Southern Africa (Mkuhlani et al., 2019b). Variability in the commencement of the rainy season has a greater impact on productivity compared to the end of the rainy season (Bouba et al., 2013). In eastern Southern Africa a projected 20 % increase in intra-seasonal temperatures will potentially reduce crop yields by about 4.2 %, 7.2 % and 7.6 % for maize, sorghum and rice respectively (Rowhani et al., 2011). This highlights the need for improved decision making capacity to enhance preparedness of the current farming systems to climate variability using seasonal forecast information (Johnston et al., 2004).

South Africa has a unimodal rainfall pattern. The country has noticeable spatial-temporal rainfall variability (Roffe et al., 2019). Most of the country is relatively arid and receives rainfall of less than 500 mm per season (Botai et al., 2018). The country, especially the western Cape province undergoes notable fluctuations of wet and dry seasons in almost every 20 years. About 5 of the 9 provinces of South Africa face frequent seasonal droughts. The western Cape province has been receiving gradually lower seasonal rainfall every season for the past 20 years. In-season variability has also been gradually increasing with fluctuations in the commencement and cessation of rainfall becoming more notable (Du Plessis and Schloms, 2017).

1.4 Value of integrating seasonal forecast information and crop models

Use of seasonal forecast information has the potential to improve the capacity of small-scale farmers to manage seasonal weather variability. Forecasts provide information on the magnitude and direction of weather parameters at a given location in time (Klopper et al., 2006), with rainfall and temperature being the key parameters. Forecasts can be very short (few hours), short (6 hours to a few days), short to medium (3 to 7 days), medium to long term (beyond 7 days to 3 months) and up to 24 months (Zhang, 2014; Luo et al., 2016). Accuracy however differs with the Forecast horizon with short and long term being the most and least accurate respectively (Zhang, 2014). Accuracy also varies with forecast skill for specific locations (Landman et al., 2012).

Seasonal forecast information has a wide range of potential applications which include agricultural policy, insurance, crop and climate risk management (Nelson et al., 2002; Hansen, 2005). It can be used for crop and cultivar selection, soil water conservation and determine planting time among other options. Despite this potential, the uptake of seasonal forecast information remains minimal amongst small-scale farmers (Taylor et al., 2015). Limited uptake is attributed to the limited skill (Martin et al., 2000), incompatibility of the forecast format with end user's needs and the untimely dissemination of forecast information

(Taylor et al., 2015). The limited financial resource base also limits uptake of seasonal forecast information where response mechanisms such as irrigation may need financial input (Johnston et al., 2004). Improved dissemination and understanding of potential benefits increase the chances of uptake of seasonal forecast information. Incompatibility between the information format and user's needs also leads to poor interpretation and understanding of the seasonal forecast information. There is therefore need for improved dissemination of seasonal forecast information to ensure relevance and usability of seasonal forecast information (Taylor et al., 2015) .

Linking of seasonal forecast information to crop models presents a potential for increasing the value of forecasts through assessing the corresponding crop yield response at a seasonal scale (Hansen, 2005). Crop models have been integrated with seasonal forecast information for purposes such as decision making in the USA (Shafiee-Jood et al., 2014); Europe (Cantelaube and Terres, 2005), Australia (Nelson et al., 2002) and East Africa (Hansen and Indeje, 2004). Specifically, integrated seasonal forecasts and crop models, have been utilized in assessing productivity of different crops under different cropping systems such as those with irrigation, rain-fed and varying fertility in the USA (Jones et al., 2000). The approach has been utilized to enable decision making and policy formulation given projected wheat harvesting in Europe (Cantelaube and Terres, 2005). In West Africa the approach has been utilized to assess potential crop type of choice under predicted drought conditions (Paeth et al., 2016). In west Africa such an approach has also been used to evaluate productivity of indigenous and hybrid sorghum crop varieties (Mishra et al., 2008). Similar research could be of importance to the Southern African regions but there has been limited research on the application of integrated crop models and seasonal forecast information (Hansen et al., 2006). Research has been limited to determination of skill (Landman, 2014), acknowledging the potential use (Johnston et al., 2004), association of historical climate forecast information and historical yield patterns (Vogel, 1995). These and other research outputs have significantly improved farm management in other countries (Hansen and Sivakumar, 2006).

Most studies have assessed farm management practices under seasonal forecasts individually or based on a few practices (Mishra et al., 2008). Small-scale farmers, however use a combination of farm management practices to improve effectiveness of the practices, reduce risk and minimize costs (Nazir et al., 2019). No dedicated research could be however identified on the productivity and decision assessment of the combinations of management practices given seasonal forecast information. This research would provide a more pragmatic illustration of small-scale farms by accounting for the combined effect of practices.

1.5 Dynamics in adopting research outputs

Increased weather variability coupled with the gradual disappearance and weak manifestation of indigenous climate indicators (behavior of animal and plant species, springs and culturally revered forests, mountains and water bodies) which have traditionally been used by small holder farmers (Mapfumo et al., 2016) has increased the need to integrate indigenous knowledge and seasonal forecast information to improve farmers' preparedness to seasonal weather variability. Farmers can therefore potentially use seasonal forecast information to determine practices they can utilize such as planting time, choice of crop and variety to cultivate. In-depth research on such practices has been undertaken within the Southern African region. These practices can also be utilized for climate variability management (Thierfelder et al., 2014; Nyagumbo et al., 2015). Despite this value, there has been limited adoption of such practices amongst small-scale farmers. Farmers are however making marginal changes to farming systems in response to climate variability, but the changes are however not transformational because of the lack of appropriate context. Use of seasonal forecasts and long-term climate change projections can be used to inform incremental changes that can lead to ultimate transformation. Even the least food secure households are not making changes to their farming systems for adaptation (Kristjanson et al., 2012). This is mostly attributed to high risk aversion (Knowler and Bradshaw, 2007), relatively high initial costs of changing cropping systems (FAO, 2001), system and agro-ecology incompatibility (Mazvimavi and Twomlow, 2009), limited institutional support (Ngwira et al., 2014). Twomlow et al., (2008) highlights use of blanket recommendations ignoring a range of underlying socio-economic and cultural aspects as the leading cause of poor adoption. The limited adoption of these research outputs (Grabowski, 2011) and the ineffectiveness of the 'top down approach' (Gumbs, 1994) warrants assessment of the farmer's bio-physical and socio-economic characteristics to provide inroads on improving adoption of research outputs. Such assessment can be undertaken using the farm typology approach, participatory approaches and 'bottom-up' approach. The farm typology approach enables use of practices corresponding to farmer's corresponding socio-economic characteristics (Ajani et al., 2013; Mapfumo et al., 2016).

1.6 Research question

Can farm decision making be improved to enhance climate variability management in small-scale farming systems?

Aim

This thesis aims at formulating an approach that can be utilized to make recommendations under potential climate variability conditions. It seeks to couple seasonal forecast information with crop models. The decision-making process was formulated by assessing the pattern of crop yield outputs from the interaction effects between farm management decisions and seasonal forecast information. The study then assesses the effectiveness of the decision-making process, decision capacity scenarios and the corresponding specific farm management recommendation. The study also explores the effectiveness of the specific seasonal forecast-based recommendations under a range of agro-ecological conditions and farmer types in South Africa.

This was achieved through the following specific objectives:

1. Assessment of the perceptions, practices and challenges in climate variability management under different small-scale farmer types of South Africa.
2. Assessment of techniques for linking seasonal forecast information to crop models under South African conditions.
3. Formulation of potential decision-making process based on integrating seasonal forecast information and crop models in South Africa.
4. Assessment of the effectiveness of the decision-making process and specific seasonal forecast information-based recommended farm management practices in small-scale farming systems of South Africa.

Structure of the thesis

The thesis comprised of 6 Chapters. Chapter 1 and 6 are introductory and conclusion chapters, respectively. Chapter 2 provides a theoretical literature review of the study. Each of chapters 3, 4 and 5 is comprised of an abstract, introduction, methodology, result, discussion and conclusion section specific to the subject of each of those chapters. Each of the Chapters 3, 4 and 5 has information on the materials and methodology which forms the materials and methodology for the whole study. Chapter 3 provides information about the study setting. This includes information about the study location. This includes details about farmers soring in on farmer diversity in the study area. Chapter 4 provides information on the key results of the study. Chapter 5 provides additional information on the results as well as discussion of the study. Each of the chapters 2 to 5, fulfilled the specific objectives of the study respectively.

Chapter 1 introduces background, scope, aim and objectives of the study as well as the structure of the thesis. Specifically, it provides general information on the impact of climate variability, seasonal forecasts, 'integrated use of forecasts and crop models' in decision making as well as the use of farm classification to enhance adoption of research outputs.

Chapter 2 reviews literature on the various aspects related to the subject of the study. This therefore provides the foundation and rationale of the study. It highlights the advances made in integrating seasonal forecast information and crop models. It identifies, techniques for 'integrating seasonal forecast information and crop models' that are applicable in Southern African conditions. The section shows the potential application of the 'integrated seasonal forecast information and crop model approach to inform farm management decision making in climate variability management amongst small-scale farming systems of South Africa.

Chapter 3 provides information on the study setting through describing the state of small-scale farming in South Africa where the study is based on. This was done by assessment of the diversity of small-scale farmers in Limpopo and Eastern Cape provinces of South Africa. Diversity has an impact on the uptake of climate variability management practices as well as the potential use of forecasts. The section assesses the various practices and challenges faced by different farmer classes in managing climate variability.

Chapter 4 highlights formulation of the decision-making process and the decision scenarios using simulation outputs from different combination of management practices and seasonal forecasts. The decision scenarios were developed based on the 2017/18 season conditions, through integration of seasonal forecasts and the DSSAT crop model using the GCM approach. The chapter also assesses the variation in the seasonal forecast information in relation to the corresponding variation in crop yield forecasts.

Chapter 5 assesses the value of the decision-making process, decision scenarios and recommendations, through the comparison of the recommended practices in the context of the performance of similar practices under measured weather data in different cropping seasons, crops, farmer types and locations. Specifically, it assesses the conditions under which the seasonal forecast-based recommendations are effective.

Chapter 6 provides information summarizing the study. Specifically, this is the conclusion which includes information on the main study findings and implications of the findings. The section terminates by highlighting the contribution of the research to the overall body of knowledge, study limitations and potential recommendations.

Chapter 3 is presented in this thesis as a paper that has been published in an internationally peer reviewed scientific journal.

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Chapters 2, 4, and 5 are at various stages for preparation for publication.

Chapter 2

2.0 Linking seasonal forecast information to crop models under South African conditions

2.1 Chapter summary

Rain-fed agricultural systems are common in at least 80 % of small-scale farmers in Southern Africa and are vulnerable to climate variability (Biazin et al., 2012). Seasonal forecast information has the potential to improve farmers' preparedness to climate variability. The value of seasonal forecasts can be increased through recommendation of corresponding climate variability management strategies and prediction of the corresponding crop yields. This literature review assessed the current state and potential application of integrating seasonal forecast information with crop models for potential application in climate variability management in small-scale farming systems of southern Africa. Compared to empirical models, process-based crop models are potentially more effective for assessment of climate variability management. This is attributed to their ability to account for plant physical and physiological processes and farm management practices related to climate variability management such as irrigation, mulching and variety selection. Seasonal forecasts are usually issued as temporal and spatial summaries which are however not directly compatible with mechanistic crop models, that require input weather data at a daily time step. A range of approaches have been assessed to improve connection between seasonal forecast information and mechanistic crop models which include Global Climate Models (GCM), analogue, stochastic disaggregation and statistical prediction through converting seasonal weather summaries into the daily weather. Compared to other approaches GCM outputs are produced in a format technically compatible with mechanistic crop models. GCM outputs can be further conditioned to improve their accuracy but the conditioned outputs can at times lead to overprediction of rainfall. From the review mechanistic crop models are more suited in simulating climate variability management compared to empirical models. Research on the integration of seasonal forecast and crop models in Southern Africa, potentially allows for preliminary assessment of the effectiveness of a range of farm management practices. This therefore equips farmers with tailored information on the upcoming season and the corresponding climate variability management strategies. Despite the potential benefits of integrating seasonal forecasts and crop models, there may be challenges in dissemination the outputs to small-scale farming communities. Extension officers can therefore be a bridge between researchers and small-scale farmers.

2.2 Introduction

Small-scale farming is undertaken on at least 70 % of arable land in Southern Africa (SAT, 2011). It is characterized by low capital investment and input usage, limited farming knowledge, higher transport costs, poor market access and poor crop and livestock productivity. As a result, small-scale farmers in the region experience recurrent food insecurity (Baloyi, 2010). Most small-scale farmers practice rain-fed farming and have highlighted seasonal weather variability as the greatest threat to livelihood (Thomas et al., 2007).

Southern Africa experiences high seasonal rainfall variability. The coefficient of variation of rainfall ranges from 20 to 45 % across sub-humid to semi-arid agro-ecologies (Batisani and Yarnal, 2010; Oguntunde et al., 2011). As a consequence, rain-fed crop yields vary from 15 % to 60 % relative to mean yield (Lumsden and Schulze, 2007). Crop yield variability affects food security, with severe impacts being experienced amongst resource constrained, rain-fed dependant, small-scale farming households (Sivakumar et al., 2002). Seasonal forecast information has the potential to improve farmers' preparedness to seasonal weather variability through use of low cost input strategies such as mulch, intercropping before or during the cropping season (Johnston et al., 2004). Seasonal forecasts provide information on the magnitude and direction of weather parameters at specific temporal and spatial scales (Klopper et al., 2006), with rainfall and temperature being the defining key parameters. Forecasts can be very short (few hours), short (6 hours to a few days), medium (3 to 9 days) and long term (beyond 9 days). Short term forecasts have greater accuracy compared to long term forecasts (Zhang, 2014). Dynamic and statistical forecasting are the most commonly used methods to produce seasonal forecasts. Statistical forecasts mathematically relate large scale meteorological climate features to local conditions (Tumbo et al., 2010). Dynamic forecasting predicts climate based on a set of computer based mathematical equations that integrates factors that define climate (Doblas-Reyes et al., 2006).

Seasonal forecasts have a wide range of potential applications which include agricultural policy formulation, insurance, crop and climate risk management (Nelson et al., 2002;

Hansen, 2005). Farmers can make farm management decisions on crop and cultivar selection or soil water conservation based on the seasonal forecast. Use of seasonal forecast information in agriculture has led to improved disease prediction, assessment of grazing and pasture productivity and timing of fishery and forestry operations (WAMIS, 2003). Despite such potential, the uptake of seasonal forecast information is lower among small-scale compared to commercial farmers (Vogel, 2000). The limited uptake is attributed to lack of awareness, reluctance to change existing farming practices, limited financial resources (Bruno-Soares and Dessai, 2015), complexity in format and untimely dissemination of seasonal forecast information (Vogel, 2000). Limited financial resources also limit uptake of seasonal forecast information where response mechanisms such as irrigation or purchase of drought tolerant seed need financing (Bruno-Soares and Dessai, 2015). The value of seasonal forecast information to small-scale farmers can be increased through implementing farm management decisions corresponding to the predicted weather. Farm management decisions can be in the form of climate variability adaption strategies (Stone and Meinke, 2005).

Coping mechanisms are short term techniques utilized in response to sudden changes in weather. In contrast, adaptation involves long term adjustments in response to expected long term climatic conditions (Nelson et al., 2008). Both mechanisms offer a range of options in preparation for the oncoming season which can be better informed through use of seasonal forecast information. Extensive field and modelling research has been undertaken to evaluate such coping and adaptation options as climate risk adaptation management strategies based on historical weather and future long term climate projections within southern Africa (Nyagumbo et al., 2015; Mupangwa et al., 2016; Thierfelder et al., 2017; Steward et al., 2018). Limited research has however been undertaken to evaluate the suitability of these practices as preparedness strategies given seasonal forecast information (Hansen et al., 2006). Such research would involve use of crop models (Holzworth et al., 2014).

Crop models provide the means of conducting prior ex-ante assessment of the response benefits of these practices to given seasonal information (Hansen, 2005). Crop models are utilised in simulating cropping and farming system dynamics. They mimic the cropping and farming system of interest. Specifically, mechanistic crop models predict crop growth and development of several field crops, vegetables, fruit trees on a daily or seasonal time scale (Holzworth et al., 2014). They provide alternate off-field cost effective, less complex and less risky means of assessing crop yields in response to climate information (Jones et al., 2003).

Crop models are increasingly being used in yield prediction using seasonal forecast information in the United States of America (USA) (Shafiee-Jood et al., 2014); Europe (Cantelaube and Terres, 2005), Australia (Nelson et al., 2002) and East Africa (Hansen and Indeje, 2004). There is however limited research on the use of crop models with seasonal forecasts to enhance climate variability management within southern Africa (Hansen et al., 2006). Research to date has been limited to association of historical forecasts and measured weather patterns to historical agricultural productivity (Vogel, 1995; 2000, Johnston et al., 2004; Vogel and O'Brien, 2006). Seasonal forecasts are issued as spatial and temporal summaries. The information is also usually reported in probabilistic terms (Johnston et al., 2004). Most mechanistic crop models, however require weather data in a daily step format rather than as seasonal weather summaries (Jones et al., 2003; Holzworth et al., 2014). This therefore reduces the compatibility between seasonal forecast and crop models for use in climate variability research (Hansen et al., 2006).

The chapter aimed to assess the state of research on integrating seasonal forecast information with crop models in Southern Africa for potential use in climate variability management. Specifically, this chapter provided an assessment of a range of tools that can be utilised to integrate seasonal forecast information with crop models for potential use under Southern African conditions. The literature review assessed crop models and sources of seasonal forecast information suitable for undertaking climate variability research in Southern Africa. The chapter also assessed the potential application of 'integrated seasonal forecast and crop models' in evaluating the effectiveness of alternate farm management practices in small-scale farming with the aim of improving climate variability management.

2.3 Results

2.3.1 Seasonal forecasts information

Climate forecasts predict the long-term state of the atmosphere at a broader, temporal and spatial scales. Seasonal forecasts are an estimation of the state of the atmosphere from a few hours to a year (Palmer, 2014). Key variables in seasonal forecast information are rainfall and temperature but occasionally include variables of interest at specific temporal and spatial scales such as hail storms and hurricanes (Klopper et al., 2006). Improved understanding of the interactions between the atmosphere and related systems coupled with corresponding advancements in modelling climate systems have increased the ability to predict weather (Goddard et al., 2001). Seasonal forecasts are broadly categorised into deterministic and probabilistic. Deterministic forecasts are expressed as a best guess value for a specific location or region in time such as frequency of- or onset of- rain. Probabilistic forecasts are commonly expressed as the probability of the occurrence of specific climatic events using a set of pre-defined categories as reference (Mason, 2012). There are 2 main approaches widely used in developing seasonal forecasts: (1) statistical and (2) dynamical. These are based on assessment of historical climate and current weather as a basis for future weather and climate prediction. Weather data is collected from a network of land, sea, mobile and satellite weather collection devices. The data is utilised for development and validation of statistical and dynamic models (Goddard et al., 2001).

Statistical forecasting hinges on the mathematical relationship between historical, current or expected values of predictors and predictands. Regression models are the most common statistical forecasting technique. Other statistical forecasting approaches are multiple regression (Kouadio et al., 2014), analogue, single spectrum analysis (Schoellhamer, 2001), auto-regressive, probabilistic and discriminant analysis (Goddard et al., 2001). In southern Africa, the skill of statistical seasonal forecasts is relatively higher for *El Niño*–Southern Oscillation (ENSO) seasons compared to non-ENSO seasons. Non-ENSO seasons are characterised by non-significant increase in Sea Surface Temperatures (SST) which are not easily detected compared to usually more extreme warming and cooling characterising *El Niño* and *La Niña* seasons respectively (Holbrook et al., 2009). This can be improved through addition of atmospheric predictors in the statistical model. Statistical models can account for many climate determinants, but they however require rigorous testing to ensure operational reliability (Goddard et al., 2001).

Dynamical forecasting utilises models that mimic the land-ocean-atmosphere systems to predict weather. The most commonly used models are hybrid models which comprise of an atmospheric model coupled to ocean general circulation models (GCM) or an intermediate ocean model. The most used GCMs include HadGEM (Collins et al., 2008), ECHAM (Roeckner et al., 2003) and GFDL (Anderson et al., 2004). Dynamical forecasting accounts for a wide range of land, sea and atmospheric variables. There is therefore greater confidence in the predictions compared to statistical forecasting. Parameterisation of ocean and atmospheric thermodynamics is however complex since it demands more computational resources as it accounts for numerous parameters such as temperature, pressure (Doblas-Reyes et al., 2006).

Statistical and dynamical forecasts were evaluated for their reliability compared to observed meteorological data using the root mean square error (RMSE) during the cold season in the United States of America (USA). Low RMSE corresponded to an increase in skill. There was a minute difference in RMSE between statistical and dynamic downscaling but that was dependent with the parameters being evaluated. The RMSE for temperature ranges from 0.9-1.3 whereas rainfall is 1.7 to 2.7 %. Forecasting skill is relatively higher in temperature compared to rainfall prediction. For both rainfall and temperature, statistical downscaling increases skill especially when combined with RCMs (Yoon et al., 2012).

Seasonal forecasts are normally issued as temporal summaries of at least multi-monthly time scale. The chaotic nature of the atmosphere leads to uncertainty in forecasting hence forecasts are normally issued out in probabilistic terms. Regional and national meteorological agencies such as South African Weather Service in South Africa have a mandate for generating, issuing and regulating local forecasts. Seasonal forecast information is usually communicated via government extension workers, radio, internet and television (Ziervogel, 2004).

Forecast quality

Use of seasonal forecast information is highly dependent on the quality of the forecast. The quality of forecast is determined by a combination of factors which are reliability, resolution, sharpness, robustness, uncertainty and skill. Reliability is the extent of over and under-estimation of the forecast compared to the later observed value. Magnitude of the parameters of good quality forecasts should be similar to those produced from standard forecasting. Forecasts should have a high temporal and spatial resolution. Some models have high resolutions of $0.28125^{\circ} \times 0.1875^{\circ}$ (Nozawa et al., 2007). Forecasts should have greater sharpness, which is the ability be able to categorically predict ‘all or nothing’ events such as hail storms. Forecasts should be robust despite relying on a few assumptions (Mailier et al., 2006). Forecasts should also have reduced uncertainty (Johnston et al., 2004).

Forecast skill is affected by a range of aspects such as lead time, model accuracy, parameters being forecasted and time of the season (Johnston et al., 2004). The skill of statistical seasonal forecast is low for non-ENSO seasons but can be improved through addition of atmospheric predictors in the statistical model (Holbrook et al., 2009). There is greater skill from one-tiered models that are based on ocean-atmosphere interactions compared to two-tiered models based on sea surface temperature (SST) anomalies force general circulation models (Landman et al., 2012). Skill can be improved through use of hybrid forecast systems that can combine dynamical and statistical downscaling (Yoon et al., 2012). Skill also varies with geographical location within the globe with tropical regions having greater prediction skill than higher altitudes (Harrison et al., 2007). There is greater prediction skill in the north-western and central parts of southern Africa compared to north eastern South Africa (Yuan and Tozuka, 2014).

The format in which seasonal forecasts are issued differs with the intended target audience and method of forecasting. To increase uptake, forecasts should be communicated in user tailored formats. Farmers for instance prefer them in 'categorical and definitive' qualitative formats such as 'no, normal or high' rainfall as opposed to probabilities and complex numerical expressions which may not auger well with literacy levels (Patt and Gwata, 2002; Vogel and O'Brien, 2006). Forecasts should also be communicated with sufficient lead time enabling change in management conditions (Stone and Meinke, 2006). Farmers have highlighted that 'good' forecasts should be availed to them with corresponding management information and expected crop yields (Johnston et al., 2004).

2.3.2 Crop models

Within climate research, crop modelling tools have been mainly used in southern African for projection of yields under climate change (Akumaga et al., 2018; Corbeels et al., 2018; van Oort and Zwart, 2018; Zinyengere et al., 2014) and to a limited extend under climate variability (Ambrosino et al., 2011). Crop models are broadly categorised into empirical and mechanistic crop models. Mechanistic models determine crop productivity through dynamic relationships between plant physiological processes and environmental conditions. Most mechanistic models utilise meteorological data in a daily time step format with outputs similarly being produced at a daily time step (Jones et al., 2003; Holzworth et al., 2014). Empirical models determine crop productivity based on the interaction between predictor values such as monthly rain and temperature summaries. Similarly, most of empirical models produce outputs at a coarse summary scale (Estes et al., 2013).

2.3.2.1 Empirical crop modelling

Statistical crop modelling

Statistical modelling involves the formulation of mathematical relationships between historical weather and crop yields. Most statistical crop models have been designed to operate on a multi-seasonal and regional scale and this enables light computing. They are thus suitable for assessment of inter seasonal and regional crop yield variability (Hertel and Rosch, 2010). Rainfall and temperature temporal summaries are the most common predictors whereas crop yield are most often the predictand (Estes et al., 2013). In contrast to mechanistic crop models, statistical models have reduced data requirements with rainfall and crop yields for calibration being the key parameters (Holzworth et al., 2014). Statistical models have limited applicability under future conditions since they are based on historical relationships which may not hold in future due to changes in climate and its variability (IPCC, 2007). The reduced data requirements minimise computing demand but concurrently limits assessment of crop management aspects such as crop variety and soil information. The reduced demand for data also makes their use particularly suited in Africa. In Africa data collection from field experiments is limited due to poor skill, financial resources and non-optimal management (Lobell and Burke, 2010). Statistical models have limited capability to simulate vegetative and reproductive development, plant water balance and pest dynamics (Krishna, 2003). Statistical models are nonetheless compatible with seasonal forecast information which is mostly issued as temporal and spatial summaries. They therefore cannot be used for predicting location specific crop yields due to the coarse spatial resolution. There are also challenges attributed to lack of point specific localised biophysical data (Apipattanavis et al., 2010). Empirical models are easier to parameterise but produce simulation outputs restricted to historical conditions under which they were parameterised.

Ricardian method

Coupling statistical models with additional tools such as socio-economic models will report crop yield changes in economic terms which improves their usefulness in climate variability management (Mendelsohn et al., 1994). The approach indirectly connects seasonal forecast information with crop models. Net farm revenues are regressed on independent variables affecting crop production such as market price, input costs, market access, water flow, rainfall and temperature (Kurukulasuriya and Mendelsohn, 2008). The approach has been used in the Eastern and Southern Africa in assessing economic impacts of different climate scenarios and opportunities for climate change management in small-scale farming systems (Mano and Nhemachena, 2006; Bello and Maman, 2015; Gadédjisso-tossou et al., 2016). The aim of linking seasonal forecast information to crop models is to assess crop productivity under climate variability. The method assesses the impact of climate change based on the net farm income, with farm land value being a key factor (Bello and Maman, 2015). Lower productivity due to increased climate variability will reduce the land value. The approach assumes that farm management decisions in climate change and variability are based on the profitability of the strategy. Decision making in small-scale farming systems is however based on many socio-economic and bio-physical aspects some of which cannot be accounted for by the Ricardian approach (Nhemachena and Hassan, 2008). The approach is however advantageous in regions or countries with functional land markets. Use of the approach in Southern Africa is therefore limited by unregulated and weak land markets. Land valuation is challenging in small-scale farming systems of Southern Africa since most of the land is state owned, hence there maybe inconsistences. The Ricardian approach assumes, land value is indirectly derived from commodity prices. The prices attached to the commodities are constant where in reality, prices fluctuate, leading to under and over-estimation of losses and gains respectively. The Ricardian approach is limited by the reliance on historical relationships which may not exist in the future. There is therefore potential limited reliability when predicting crop yields and profitability based on seasonal forecast information. This is due to increased frequency of extreme climatic events which may not have been accounted in the formulation of the statistical relationship. The Ricardian approach requires climate data in a summary format similar to the format in which seasonal forecasts are produced.

2.3.2.2 Mechanistic crop models

This is the most common approach used in simulating crop yield response to weather in the Southern African region (Zinyengere et al., 2013). Mechanistic crop models mimic plant phenological and physiological processes (Basso et al., 2013). These processes interact with input weather data, soil and crop management to simulate crop yields. Mechanistic crop model such as WOFOST accounts for about 260 characteristics. About 50 % are crop related characteristics, 35 % are soil related and 15 % are weather related variables. Similarly, output variables are related to the input variables (Gommes et al., 2012).

The most widely used mechanistic crop models in Africa are APSIM (Holzworth et al. 2014), DSSAT (Jones et al., 2003) and AQUACROP (Raes et al., 2009; Steduto et al., 2009). The APSIM model has been used for sugar cane yield prediction using seasonal forecast information (Nelson et al., 2002). Nelson et al., (1999) developed the Whopper cropper model which integrates seasonal forecast information and APSIM model derived crop yields under a range of farm management decisions. DSSAT cropping systems model is also a widely-used mechanistic crop models (Jones et al., 2003). DSSAT has been extensively used in yield prediction using daily climate change data in Southern Africa (Ngwira et al., 2014; Zinyengere et al., 2014). AQUACROP has been used in evaluating the impact of climate change on key crops such as bambara nut (Mabhaudhi et al., 2018) and maize (Berhane and Kefale, 2018; Dale et al., 2017) under different climate change scenarios (Akumaga et al., 2018). Crop models enable a quick preliminary assessment of the response of crops to given weather conditions under a wide range of farm management conditions (Holzworth et al. 2014). Mechanistic crop models mimic the cropping systems under study, and the reliability increases with the availability of high-quality experimental data for calibration. Mechanistic crop models simulate multiple crop management aspects such as crop rotation, intercrops, crop calendar, different crop types and varieties, fertility, irrigation, mulching and tillage (Jones et al., 2003; Holzworth et al., 2014). The management aspects that can be simulated with mechanistic crop models are similar to a range of different climate variability management strategies (Ajani et al., 2013). Mechanistic models require input weather data in the daily weather format. The key parameters are minimum, maximum temperature, rainfall and radiation (Holzworth et al., 2014; Jones et al., 2003). This is not compatible with seasonal forecast information, which is produced in temporal and spatial summaries (Hansen et al., 2006).

2.3.3 Seasonal forecast information and crop models

2.3.3.1 Challenges in linking seasonal forecast information and crop models

Extensive research involving seasonal forecasts interacting with crop models has been undertaken in North and South America (Jones et al., 2000; Fraisse et al., 2006; Morss et al., 2010; Wang et al., 2012; Shafiee-Jood et al., 2014). Hansen et al., (2009) and MacCarthy et al., (2017) integrated seasonal forecasts and crop models to predict maize productivity. Despite such extensive research, Hansen et al. (2006) highlighted the challenges in connecting seasonal forecast information to crop models. This was attributed to the incompatibility between seasonal forecast format and most mechanistic crop models. Specifically it was due to the temporal and spatial scale and format of seasonal forecast information and format of the climate input data required in mechanistic crop models (Hansen and Indeje, 2004). Seasonal forecasts are issued as spatial and temporal summaries. Mechanistic crop models, however require weather data in a daily step format rather than as seasonal weather summaries. In addition, crop growth and development is dependent on the minimum weather parameters (rainfall, solar radiation, minimum and maximum temperature) at a daily time step (Jones et al., 2003).

2.3.3.2 Approaches for linking seasonal forecast information and crop models

A range of methodologies have been used for improving the linkage between climate and crop models. Potential linkage methods include use of historical analogues, probability-weighted historic analogues, stochastic disaggregation, statistical yield prediction and global climate models (GCM) (Hansen and Indeje, 2004).

Global Climate Models (GCM)

GCMs used to project future and historical climate based on present and future land-sea-atmospheric dynamics. GCM produce climate data outputs at a daily time step. The outputs are therefore directly compatible with mechanistic crop models. GCM output from ECHAM 4.5 have been used as inputs to the SARRA-H, a mechanistic crop model for sorghum crop yield prediction in West Africa (Mishra et al., 2008). Similarly, Takale, (2017) used CFSv2 GCM based forecasts to predict maize productivity food security for planning purposes in Ethiopia using the DSSAT crop model. GCMs however have poor spatial resolution as they predict weather at larger spatial scales. Advances in atmospheric science have increased spatial resolution down to $0.833^{\circ}\times0.556^{\circ}$ but such conditioning distorts rainfall distribution (Maclachlan et al., 2015). This is normally biased towards increased frequency of rainfall events. Further conditioning has been undertaken to reduce frequency of rainfall events thus increasing the spatial and temporal resolution of GCMs in forecasting weather. This can be additive or multiplicative shifts (Ines and Hansen, 2006).

Additive or multiplicative simple shifts can be used to calibrate the GCM outputs to match the observed mean local climate (Ines and Hansen, 2006). The conditioning benefits are however uniform for all parameters. 1- Additive shifts are more appropriate for temperature and solar radiation. The additive effect however removes non-rainfall events which are typical of normal rainfall distributions. 2- Multiplicative shifts adjust the rainfall intensity to suit spatial means. This still however does not correct the rainfall distribution (Hansen et al., 2006). Other attempts have also been made to correct GCM daily weather bias through correcting rainfall frequency and intensity. In China, the non-hydrostatic Weather Research and Forecasting model (WRF) was nested inside the Climate Forecast System (CFS) model based GCM, to downscale seasonal forecast information. This reduced precipitation errors and bias by about up to 30 and 70 % respectively (Yuan et al., 2012). Ines and Hansen (2006) reduced the frequency and intensity of rainfall events from ECHAM 4.5 outputs to match the average long term frequency for specific time periods in East Africa using Empirical (GCM) Gamma Transformation technique. Schmidli et al. (2006) used simple multiplicative shifts to correct rainfall intensity. Winsemius et al., (2014) used conformal-cubic atmospheric model (CCAM) a regional climate model to downscale CGCM forecasts from a resolution of 200 km^2 to 60 km^2 over Southern Tropical Africa. In Australia, Schepen et al., (2014) downscaled and improved skill of GCM outputs to undertake spatial interpolation using statistical approaches such as calibration, bridging and merging. Merged calibration-bridging is however more effective compared to individual calibration-bridging approaches.

Stochastic disaggregation

Forecasts are often issued in the form of temporal summaries. To connect this information to mechanistic crop models, forecast summaries can be disaggregated into daily weather data. Stochastic weather generators create a series of synthetic daily weather data with statistical characteristics similar to expected climate. Stochastic disaggregation captures the high frequency variability of specific weather parameters whilst reproducing the low frequency of highly variable weather events. This can be undertaken through (1) calibration of a stochastic weather generator or (2) restriction of the simulated daily weather data parameters to those of the expected forecast (Apipattanavis et al., 2010).

(1) Stochastic weather generators are parameterised with the statistical properties of the forecast summary. Some of the methods utilised in calibration weather generator parameters include (a) estimating parameters from seasons with similar predictor values, (b) regressing parameters against predictors, (c) multi-variate statistical downscaling of GCM outputs and (d) estimation of parameters based on forecast shifts from climate means. Conditioning of parameters related to rainfall requires prior assumptions about the potential influence on rainfall statistical parameters. This provides a degree of reliability as the phenomenon would have been experienced prior. Reliance on historical data reduces the ability to reproduce non-linear simulations and climate events of high variability. Stochastic weather generation however requires multiple replicates to generate forecasts of acceptable statistical measure (Hansen et al., 2006).

(2) The alternative approach restricts the magnitude of daily weather parameter data to suit the temporal statistical characteristic of the forecast. This can be undertaken through (a) additive shifts which restrict non-rainfall parameters such as temperature and solar radiation values to match the target means; or (b) through trial and error approach to match the frequency and intensity of rainfall to the target means. This approach however does not make assumptions based on historical precipitation intensity and distribution which increases the chances of experiencing extreme rainfall events never experienced before. Restricting the magnitude of daily weather parameter data to suit the temporal statistical characteristic of the forecast increases the correlation between parameters of observed and stochastically generated precipitation outputs. Compared to other approaches stochastic disaggregation has a higher prediction error that also leads to over prediction of yields (Hansen et al., 2006). The ability of stochastic aggregation to produce daily meteorological data therefore improves the connectivity between mechanistic crop models and seasonal forecasts. Hansen and Ines (2005) have used this approach in disaggregating monthly forecasts to daily weather data for USA and Kenya for use as inputs into the CERES model.

Analogue method

The approach involves categorizing historical climate predictors and identifying the future climate predictors class within historical categories. Daily weather data from identified historical categories will be utilised in crop models. Daily weather data can be further conditioned to improve accuracy. This approach is suitable when historical data is sufficiently available. When there is limited historical weather data, the sample size is reduced, the categories not well defined, thus compromising the methodology and forecast quality.

Where there is high confidence in the predictor values resembling a specific historical season, the probability-weighted historic analogues approach is preferred (Hansen et al., 2006). This approach combines the analogue and regression approach. The *k*-nearest neighbour (K-NN) method weighs the predictor variables and assigns a probability on the likelihood of the occurrence of that particular season. Compared to stochastic disaggregation, the K-NN analogue based approach is relatively accurate with an MBE value of less than 2 (Hansen and Indeje, 2004).

To further improve the efficiency of the analogue approach, the analogue can be combined with the GCM approach. This approach creates Southern Oscillation Index (SOI) phases by clustering GCM generated forecasts of SOI. Forcing historical Sea Surface Temperatures (SST) on long term GCM data leads to the SOI predictions. The derived GCM SOI phases can therefore be compared to historical analogue years (Stone et al., 2000).

2.4 Discussion

2.4.1 Current application of seasonal forecast information

The use of seasonal forecast information is highly concentrated in large scale commercial farming systems. They possess greater literacy to interpret and financial capacity to apply seasonal forecast information. Most commercial farmers have access to real time seasonal forecasts with sufficient skill at satisfactory lead time (approximately 1 month) to make the corresponding farm management decisions (Winsemius et al., 2014). They mainly cultivate high value crops, where climate risks, such as mid-season dry spells and extreme temperature events, pose a greater financial risk. There is therefore a greater cost saving opportunity in using seasonal forecast information (Vogel, 2000).

There is limited use of seasonal forecast information in southern Africa small-scale farming systems. Reliable sources of seasonal forecast information such as radios televisions and newspapers, provide information in summaries which are relatively easier to package and communicate. Most of the information is usually availed to small-scale farmers through agricultural extension officers immediately prior to the beginning of the rainy season. There is therefore insufficient lead time to make corresponding farm management decisions. In addition, most of the information is however usually incompatible with the farmers' literacy levels. Some small-scale farmers may access seasonal forecasts through informal sources such as relatives and fellow farmers which leads to users accessing distorted and inaccurate forecast. Forecasts however do not provide further information of the actual farm management decisions a farmer should make in response to the predicted weather. Most small-scale farmers are resource constrained and may not use the information as some of the strategies may need extra financial resources not available to the farmers (Ziervogel, 2004). Small-scale farmers have however highlighted that access to seasonal forecast information at a greater lead time is less critical compared to the finance for implementing the corresponding farm management decisions (Vogel, 2000).

There is greater skill in forecasting extreme rainfall events compared to normal rainfall (Landman et al., 2012). Greater confidence in forecasting extreme rainfall events tend to benefit small-scale farmers where corresponding changes in productivity have a greater impact on physical food security compared to normal rainfall. Integration of seasonal forecast information and short-term weather forecasts potentially reinforces the limited confidence in normal rainfall predictions. In North-eastern South Africa, there is greater skill in predicting extreme high temperature events on a 3-months lead time during the summer period (October-March) and less skill during the winter (April-July) periods (Lazenby et al., 2014). Such seasonal forecast information could highly benefit small-scale farming systems in South Africa since most small-scale farmers cultivate crops during the rainy summer. On the contrary the low skill in predicting low temperatures does not auger well with farmers who cultivate winter crops such as wheat, mostly concentrated in south western South Africa.

There is a mismatch between producers and end users of seasonal forecast information. This is attributed to the bureaucracy in determining the regional forecast. Based on a wide range of seasonal forecasts, each year the Southern African Regional Climate Outlook Forum (SARCOF) discusses and agrees on the general regional forecast. National meteorological organisations adopt and fit the forecast to the local conditions and disseminate through national workshops, agricultural extension officers and media outlets such as radios, televisions and newspapers. Extension officers are therefore potentially more effective to communicate the forecast information to small-scale farmers as they have greater contact and a well-established rapport with the farmers. Due to the bureaucracy farmers receive the information immediately prior to the rainy season when there is less lead time to effectively disseminate this information to farmers and alter farm management decisions accordingly

(Ziervogel, 2004). A significant proportion of small-scale farmers therefore do not receive the seasonal forecast information at the proper time and in the proper format. Although extension officers remain the most appropriate dissemination medium, forecasts need to be communicated with greater lead time to allow timely dissemination and users action.

2.4.2 Choice of crop model

Crop models require calibration with historical data prior to yield prediction (Jones et al., 2003; Holzworth et al., 2014). The accuracy of yield prediction is highly dependent on proper calibration which in turn is hinged on the quantity and quality of parametrisation and calibration data. Mechanistic crop models such as APSIM and DSSAT require extensive detailed weather, atmospheric, soil, genotype and management data. The data may however not be uniformly available due to limited research skill and research funding. Researchers are therefore unable to collect all the data needed for model parameterisation and calibration.

On the contrary, empirical crop models do not need detailed calibration such as in mechanistic crop models as they require fewer input data like historical weather data and crop yields for model parameterisation and calibration. The latter approach may therefore be more suitable to African agricultural research (Jones et al., 2003; Holzworth et al., 2014). Use of an ensemble of crop models can however correctly simulate yields with limited data for calibration (Bassu et al., 2014). Statistical crop modelling and the Ricardian approach are better suited under such conditions as they require less input data. The Ricardian approach is however less suitable for small-scale farming as it is based on the value of the land. Most of the land under small-scale farming is state owned under the communal land tenure, which complicates land valuation (Bello and Maman, 2015).

Most mechanistic crop models require meteorological data in a daily format (Holzworth et al. 2014). They are therefore not directly compatible with seasonal forecast information which is issued out in temporal and spatial summaries. Downscaling and disaggregation of seasonal forecast information to the daily weather format increases the compatibility of seasonal forecasts with mechanistic crop models (Hansen et al., 2009). Statistical models and the Ricardian approach utilise climate data as summary format which is similar to the format in which most forecasts are issued as. They are therefore compatible with the default seasonal forecast format. Empirical models however fail to account for in-season weather variability since forecasts are produced at a coarse scale. Empirical approaches are therefore not effective in assessment of climate variability management.

Most crop models are calibrated based on historical conditions. Empirical models are based on linear mathematical relationships. The predictions are therefore statistically similar to the historical data. With climate models predicting an increase in climate variability, statistical crop models lack the capacity to account for short and long term expected changes in climate and its variability. Most process crop models are based on a combination linear and non-linear mathematical relationships. They however allow simulation of conditions that are not restricted to calibration conditions. They are therefore better suited for simulation under projected climate change and variability conditions. They can therefore predict outputs outside the range of the calibrated data. They can therefore account for infrequent climate events attributed to climate variability.

Based on the ability to mimic crop physical and physiological process, seamless simulation of management conditions and ability to account for infrequent climate events mechanistic crop models are therefore more feasible, accurate and efficient tools for integration of seasonal forecast information with crop models at a seasonal time scale for small-scale farmers in southern Africa.

2.4.3 Linking seasonal forecast information to crop models

Advances have been made in integrating seasonal forecasts and crop models. The techniques (Global Climate Models, stochastic disaggregation, analogue method and statistical yield prediction) highlighted in section 2.3.3.2 account for about 28-33 % of the variation in crop yields (Hansen and Indeje, 2004). Despite the advances, there is need for further improvements in the approaches to link seasonal forecast information to crop models to significantly account for the climate contribution to crop yields.

GCM based forecasts produce weather data at a daily time step format compatible with mechanistic crop models. This reduces the need for technical expertise in converting forecast summaries into the daily weather format compatible with mechanistic crop models as well as minimising errors associated in processing data. GCM based forecasts are easily accessible and manageable. Despite the compatibility, the coarse resolution associated with GCM forecast outputs presents challenges leading to spatially coarse yield predictions that do not account for local climatic variations which would be prime benefit for decision making. Such conditioning however distorts daily rainfall variability usually through increased rainfall frequency. Rainfall is a key driver of plant physiological and agronomic processes such as crop-water-atmospheric relations and soil erosion. Over-estimation of rainfall therefore leads to over prediction of crop yields. There is therefore need for further attempts to minimise yield prediction bias.

The statistical yield prediction approach predicts crop yields based on predictor variables through repeated conditioning of the crop model yield outputs. This therefore minimises compounding of errors associated with downscaling seasonal forecasts into the daily weather format and interaction with mechanistic crop models. The approach however assumes a direct linear relationship between the predictor and crop yields, which is not characteristic of normal crop growth and development (Hansen et al., 2006). Crop growth and development follow a non-linear pattern due to the multiple different parameters that determine the outcome of the processes. The approach therefore leads to poor estimation of crop yields.

There is greater confidence in the daily sequence outputs from parametric based stochastic disaggregation since they are based on historical weather patterns. The approaches however, cannot produce out-of-parameterised events such as non-previously experienced extreme rainfall, temperature, dry, heat spell (Hansen and Ines, 2005). This is a major downside in building an approach aimed at predicting phenomena requiring unusual decision making, among which are cases with low occurrence frequency and potentially unexperienced events such as climate change and variability. There are however greater chances of predicting parameters of extreme variability such as extreme high and low rainfall and temperatures using the non-parametric based mode of the stochastic disaggregation approach since it is not based on historical climate data (Hansen et al., 2006). This is therefore best suited to the southern African context where the region is experiencing increased frequency of climate variability. The non-parametric approach is flexible, therefore it can be applied in a range of climates with limited financial and technological resources research (Wilks and Wilby, 1999).

The analogue approach is advantageous when utilised at the spatial and temporal scale at which the historical weather data are available (Hansen et al., 2006). In southern Africa, weather data collection is dominant in urban areas, research sites and locations of special interest. The analogue approach has limited applicability in areas where there is limited weather data collection, especially in small-scale farming agro-ecologies. Although the approach is useful in conditions where historical climate data of high quality are available, it is difficult to use in African agriculture which faces challenges in skill, financial resources and management of weather data collection. Increased climate variability reduces the confidence in the analogue approach, as anthropogenic factors influence immediate future weather. There is greater confidence in the use of historical analogues when seasons under consideration are characterised by higher probability of the occurrence of climate phenomenon such as *La Niña* or *El Niño*.

All approaches can be utilised to link seasonal forecast information with mechanistic crop models. The GCM and analogue approach are the most effective as they produce seasonal forecast data at a daily time step compatible with mechanistic crop models and with minimum computational requirements. The analogue approach is effective as it is based on assumptions from specific spatial scales compared to GCM with larger spatial scales. GCMs can be fed straight into a crop model to undertaker simulations for quick and holistic simulations. Further processing of GCMs and other approaches will still not remove all the potential bias.

2.4.4 Current and potential application of integrated seasonal forecast information and crop models

Most of the research on integrating seasonal forecasts with crop models has been undertaken in North and South America (Manuela et al., 2007; Baigorria et al., 2008; Apipattanavis et al., 2010; Morss et al., 2010; Shin et al., 2010; Liang et al., 2012; Wang et al., 2012; Lee et al., 2013; Kouadio et al., 2014). In North America Jones et al., (2000) assessed the potential productivity of different cropping systems (rain fed and irrigated soybean, maize, peanut wheat) to the ENSO phases (*La Niña, El Niño* and *Neutral*) for potential intervention. This was based on the analogue approach which classified historical climate data (1949-2000) into 3 ENSO phases. The study used DSSAT, a mechanistic crop model, for simulating crop yields. Forecasts based on the *La Niña* ENSO phase led to at least a 15 % increase in wheat crop yields with extremes as high as 112 %. Timing of planting for pod initiation to coincide with high rainfall increases Soybean yields by 17 %. Shafiee-Jood et al., (2014) integrated seasonal forecast information based on 2 GCMs, (CFSv2 and ECHAM4) with the Soil and Water Assessment Tool (SWAT), a mechanistic crop model. The study assessed crop productivity and economic benefits from improved forecasting skill and the economic consequences of inaccurate forecast predictions. The study predicted maize and soybean yields of 7 and 3 t ha^{-1} respectively. This was lower than the 11 and 4 t ha^{-1} of maize and Soybean respectively required to attain profitability. Farmers were therefore advised not to participate in maize and soybean contract farming as they would not attain profitability. Fraisse et al., (2006) used a web-based tool 'AgClimate' that integrates seasonal forecasts with DSSAT. The seasonal forecast information was based on the different ENSO phases within North America. The tool provides information on productivity under different crop management strategies and ENSO phases. In Mexico, Ramírez-Rodrigues et al., (2016) assessed 3 forecasting methods: always-correct-season-type forecast (ACF), GCM based forecasts (GCMF), and an *El Niño* Southern Oscillation-based forecast (ENSOF) integrated with the APSIM model for reliability to determine the appropriate irrigation, nitrogen application and planting date regimes in wheat production. Based on ENSOF guided irrigation schedules, fertilizer costs reduced from US$300 t ha^{-1} to US$168 t ha^{-1} whilst maintaining a return per dollar invested of about US$1100. GCMF were however hampered by poor skill. Becker-Reshef et al., (2010) integrated downscaled Moderate Resolution Imaging Spectro-radiometer (MODIS) based seasonal forecasts with regression based empirical crop models to simulate potential wheat productivity for food security and policy management in Ukraine and Kansas.

Significant research integrating seasonal forecast information and crop models has also been undertaken in Europe (Capa-morocho et al., 2016). Under the DEMETER project, downscaled forecast data from Global coupled atmosphere–ocean Climate Models were integrated with Joint Research Centre crop model, a mechanistic crop model. This was utilised to assess opportunities for climate risk management intervention. The information can also be utilised for policy and planning especially in importing and exporting wheat for food security (Cantelaube and Terres, 2005). Mavromatis, (2016) evaluated wheat productivity under different sowing dates given seasonal forecast information derived from integrating step wise regression downscaled seasonal forecast data with the DSSAT crop model in Greece. Wheat yields varied with planting dates, but it was highly dependent on the spatial resolution of the different forecasts.

Significant research in integrating seasonal forecasts and crop models has been undertaken in Australia (Asseng et al., 2016). Nels*on et* al., (2002) developed the Whopper Cropper® a tool that integrates weather data at a daily time step with crop models to inform farm decision making. Crop yields are simulated using APSIM, a mechanistic crop model and seasonal forecast information is generated based on the analogue approach. The tool gives information on crop productivity of different crop types under different farm management decisions given specific seasonal forecast information. The tool has been used to evaluate the optimal sorghum sowing date which lies between 15 November and 15 December for Central Queensland, Australia.

In Africa, most of the research integrating seasonal forecast and crop models has been undertaken in East and West Africa (Dutra et al., 2013; Hansen et al., 2009; Ines et al., 2011; Ines and Hansen, 2006; Jabeen et al., 2010; Mishra et al., 2008; Roudier et al., 2016). Sultan et al., (2010) compared economic productivity based on statistical and dynamical seasonal forecasts integrated with the General Algebraic Modelling System (GAMS), a bio-economic model. The study evaluated, forecast specific farm management decisions with regards to crop selection in West Africa. Roudier et al., (2012) assessed the potential benefit of a range of climate risk adaption strategies such as millet varieties and sowing dates for small-scale farming in Niger, based on deterministic seasonal forecast information integrated with SARRA-H, a mechanistic crop model. Medium season variety millet varieties, sown on farmer determined dates with no fertilizer led to higher yields.

In East Africa, Hansen & Indeje (2004), assessed maize yields in East Africa given seasonal forecast information and the APSIM crop model. The study assessed the feasibility and effectiveness different techniques to link seasonal forecast information to the APSIM crop model. The study did not however determine the corresponding strategies that can be utilised to minimise climate risk upon successful linking of seasonal information to crop models. Within Southern Africa, few studies have been undertaken in linking seasonal forecasts with crop models. Zinyengere et al., (2011) integrated ENSO based seasonal forecast information with AQUACROP a mechanistic crop model. The study assessed a limited range of farm management decisions on maize productivity in semi-arid agro-ecologies of Zimbabwe. There is therefore need for continued evaluation of a wider range of forecast corresponding farm management decisions under small-scale farmer conditions and in contrasting environments characterising the greater Southern Africa. Most of the research in Southern Africa is limited to dynamics around seasonal forecast dissemination (Johnston et al., 2004) and skill assessment (Malherbe et al., 2014). There has been limited research on application of integrated seasonal forecasts and crop models.

2.4.5 Opportunities in integrating seasonal forecast information and crop models

Use of meteorological information in small-scale agriculture in Southern Africa has been traditionally limited to weather information (day to week forecasts) and limited for seasonal forecast information. There is potential value to small-scale farmers in providing information on potential farm management decisions corresponding to specific forecast. There is therefore need to evaluate the corresponding management decisions to specific seasonal forecast information. There is also need to evaluate farm management decisions for their effectiveness in reducing the impacts of weather hazards in small-scale farming systems, given seasonal forecast information. Given seasonal forecast information, mechanistic crop models are capable of directly and indirectly simulating crop productivity from key management farm management decisions such as those highlighted in Table 2.1. These practices can be utilised to manage climate variability in small-scale farming systems (Cooper et al., 2008).

Assessing predicted crop yields on a seasonal time scale potentially offers greater benefits to small-scale farmers to make prior farm management decisions such as cultivar; cropping system. Small-scale farmers have not enjoyed most of the benefits as most work in seasonal forecasting research has been undertaken as research in universities and research institutions. Such information is therefore potentially important in farmer decision making to improve productivity. Recent work on integration seasonal forecast information and crop models in Africa can be a starting point in Southern Africa. The techniques of integrating seasonal forecast information with mechanistic crop models are however not compatible with the literacy levels of most small-scale farmers. There is therefore need to bridge the gap between researchers and farmers. Most agriculture extension officers have higher literacy and they engage with small-scale farmers on a more frequent basis. They can therefore undergo training in operational seasonal forecasting and thereafter interprete to farmers.

Table 2.1: Practices that can be utilised in climate variability management in small-scale farming systems of Southern Africa.

Management category	**Strategy**	**Adaptation**	**Coping**
	Inter and multi cropping on the same piece of land (Mtambanengwe et al., 2012)	x	
	Changes in plant density by altering intra and inter-row spacing (Mtambanengwe et al., 2012)	x	
	Indigenous grains crops: millet; sorghum (Ajani et al., 2013)	x	
	Drought and heat tolerant crops and varieties (Bishaw et al., 2013)	x	
	Diversify crop types and crop varieties (Bishaw et al., 2013)	x	x
	Open pollinated varieties (Mubaya, 2010)	x	
	Agro-forestry (Asfaw et al., 2014)	x	
	Reducing crop acreage (Bryan et al., 2009)	x	
	Integrated insect pest management (Bishaw et al., 2013)	x	x
	Crop rotations (Ajani et al., 2013)	x	
	Cultivation of cover crops or live mulch (Ajani et al., 2013)	x	
Soil	Organic farming: fertilisers, manure; mulching (Ajani et al., 2013)	x	
	Conservation agriculture: Mulch; minimum tillage; Ripping (Mubaya, 2010)	x	x
	Improved nutrient use efficiency (Ajani et al., 2013)	x	x
Water	Fallowing (Benhin, 2006)	x	
	Water efficient crops-sorghum or millet (Mapfumo et al., 2014)	x	
	Mulching-grass, residues, muck, peat, compost, plastic (Benhin, 2006)	x	x
	Irrigation (Mapfumo et al., 2014)	x	x
	Water harvesting: Basins, ripping; pot holing (Bishaw et al., 2013)	x	x
	Chemicals to reduce evapotranspiration (Benhin, 2006)	x	x
Timing	Revising planting dates, early and late; new crop calendar (Ajani et al., 2013; Mijatovic et al., 2009)	x	
	Early harvesting; maturing crops and varieties (Mijatovic et al., 2009)	x	x
	Crops of different season lengths (Mapfumo et al., 2014)	x	
	Replanting (Mapfumo et al., 2014)		x
Improved information	Traditional forecasting: animals, birds, fruits (Ajani et al., 2013)	x	
	Global Climate Model based seasonal forecasting (Bishaw et al., 2013)	x	x
Financial	Crop insurance (Benhin, 2006)	x	

2.4.6 Seasonal forecast information and small-scale farm management decision making

Seasonal forecast information has been beneficial to some small-scale farmers in Southern Africa specifically in the North-Western province of South Africa. For instance, during the 1997/98 season, there was an intensive awareness campaign on the impending *El Niño* and its corresponding impacts on crops. Small-scale farmers responded through making corresponding farm management decisions e.g. reduction in land area, increased moisture conservation, off farm activities etc. (Vogel, 2000). This proves that given seasonal forecast information, small-scale farmers can make the appropriate tactical farm management decisions. Some of these climate variability management practices can be simulated using mechanistic crop models such as different cropping systems, alternate seed varieties, water harvesting, conservation agriculture, irrigation and nutrient efficiency (Table 2.1). Prediction of the corresponding crop yields resulting from these and other practices improves the farmer's decision capacity especially in climate variability management.

Seasonal forecast information predicting no deviation from the normal rainfall patterns would not prompt changes in farm management decisions. On the contrary forecasts predicting below normal rainfall would prompt farmers to be in a risk adverse mode, where they would choose for instance to reduce plant population and land area. Reduction in cropping density minimizes crop water demand, thus better use of the limited soil moisture. Reducing land area would minimize economic losses. In response to forecast information predicting high rainfall, farmers seeking to maximize productivity, would increase plant density and cropping area so as to maximize yields from the excess soil moisture (Mapfumo et al., 2014).

Plant breeders have developed a range of varieties that produce relatively high yields in different agro-ecological conditions. Given seasonal forecast information predicting low rainfall, farmers would have the opportunity to choose for cultivation small grains, short season or hardened crops, which maximize productivity (WAMIS, 2003). Dry season forecasts would prompt farmers to avoid use of expensive commercial seeds and instead use retained seed, since the chances of high financial returns are low. Forecasts predicting high rainfall, potentially leads farmers to sow long seasoned hybrid crops, that make maximum utilization of the growing conditions, thus higher yields (Cooper et al., 2008).

To increase the amount of water available to crops, at least 60 % of farmers in drier agro-ecologies from southern Africa use water harvesting techniques such as potholing (Mubaya, 2010). Seasonal forecast information predicting below normal rainfall will motivate farmers to prepare water harvesting techniques. On receiving forecast information predicting very high rainfall which leads to floods, farmers will not make potholes. In response to forecast information predicting below normal rainfall, farmers with access to draught could make rip lines between planting rows. The rills accumulate water during rainfall events, thus crops will access moisture stored within the rip lines (Twomlow et al., 2006).

Resource endowed farmers may prepare to use irrigation in response to forecast information predicting low rainfall (Mkuhlani et al., 2019a). Seasonal forecasts will determine when rains and or dry spells are expected. Farmers can therefore avoid irrigation immediately prior to rainfall events, thus increasing efficiency and profitability. Meteorological parameters such as wind also affect irrigation where winds exceeding certain thresholds will render irrigation ineffective or will need increased volumes and power to increase the wetting (WAMIS, 2003).

Use of seasonal forecast information potentially increases nutrient use efficiency in small-scale farming systems. Rainfall and temperature are the two main meteorological factors affecting fertilizer application efficiency. Excessive rainfall leads to excessive soil erosion and leaching thus causing pollution of underground water sources. Given seasonal forecast information predicting high rainfall, farmers can split apply fertilisers and use different fertiliser formulations to minimize losses. Low rainfall would lead to underutilization of the fertilizers. High temperatures cause volatilization of granular fertilizer and necrosis of foliage by foliar fertilizers (Ajani et al., 2013).

2.5 Chapter conclusion

The literature review highlighted how seasonal forecast information can be coupled with crop models as a tool to enhance climate variability management in small-scale farming systems of Southern Africa. Incompatibility of crop models and seasonal forecasts largely due to temporal and spatial incompatibility limits the exploitation of the value of integrating seasonal forecast information and crop models in climate variability management. GCM and analogues approaches are more feasible and effective in linking seasonal forecasts and crop models compared to stochastic disaggregation and statistical prediction. GCMs are based on the interaction between multiple predictor variables and the analogue is approach is hinged on historical weather data. GCMs are challenged by poor resolution but can be improved through conditioning. The analogue approach can be modified using probability weighted historical analogues. There is therefore greater confidence in forecasting climate change and variability compared to stochastic disaggregation and statistical prediction. In response to climate variability, and given specific seasonal forecast information, a wide range of farm management decisions can be made by small-scale farmers. These range from soil, water, crop and finance-based strategies. A significant portion of the management decisions can be potentially simulated using mechanistic crop models such as DSSAT. Compared to empirical crop models, mechanistic crop models are imbedded with management decision modules which enable evaluation of the various climate variability management strategies such as alternate crops; mulching and irrigation. Integration of seasonal forecasts and mechanistic crop models is essential in preliminary assessment of potential sustainable climate variability management strategies. Seasonal forecast information has been successfully integrated with crop models and utilised in farm management decision making in North and South America, Europe and East Africa. The potential benefits of integrating seasonal forecast information and crop models such as decision on the crop type and variety to cultivate given to small-scale farmers increases the need to undertake similar research in Southern Africa. Research on the integration of seasonal forecast and crop models in Southern Africa, potentially allows for preliminary assessment of the impact of various practices on a farm. Such information equips farmers with skills and knowledge on potential climate variability management strategies given certain specific seasonal forecast information. There is therefore need to undertake pilot research to test this hypothesis within Southern Africa using specific case studies. The research can potentially utilise DSSAT, a mechanistic crop model and GCM based forecasts. GCMs can be utilised as a technique to link seasonal forecast information with crop models. The range of strategies to be evaluated can potentially be derived from small-scale farmers using participatory techniques such as household surveys and focus group discussions.

Chapter 3

3.0 Classification of small-scale farmers for improved climate variability management in South Africa

3.1 Chapter summary

Adoption of research- based climate variability management practices among small-scale farmers in South Africa is limited. A study was therefore conducted to improve understanding of climate variability management using the farm typology, snowball and focus group discussion approaches. Farmers across all categories highlighted experiencing changing climate patterns. Resource-constrained farmers utilised non-finance demanding strategies such as mulch. Mixed farming households utilised crop and livestock-based practices such as manure. All farmers highlighted inadequate funding as a major challenge. Enterprising pensioners and horticulture-dependent farmers cited lack of climate information as an impediment. Combining this knowledge with seasonal forecast information potentially improves climate variability management.

3.2 Introduction

Small-scale farming is a major source of livelihood for most households in rural South Africa. At least 13 million people are supported by small-scale farming through 4 million farms, which occupy about 30 % of arable land in the country. Small landholdings of limited tenure and rights characterise the farming systems (Mpandeli and Maponya, 2014). These farmers face various challenges, such as soil infertility, limited access to inputs, poor literacy, and poor infrastructure and limited access to markets. Small-scale farmers have, however, highlighted climate variability as the most significant threat to their livelihood (Thomas et al., 2007).

Climate variability is a natural geo-physical phenomenon. Anthropogenic forcing has, however, led to increased frequency and intensity of unprecedented climate variability (Rosenweig and Solecki, 2005). This has manifested through a shift towards delayed onset and early cessation of rainfall resulting in a shorter growing season in South Africa (Weldeab et al., 2013). An increased frequency of mid-season dry spells, droughts and floods has also been observed (Brown et al., 2012). Mean temperatures increased by 0.7 ^{o}C during the period 1960-2003 in South Africa (Kruger and Shongwe, 2004). The patterns highlighted above are expected to continue with projected temperature increases of up to 4 ^{o}C from pre-industrial revolution levels by 2100 in Southern Africa (Serdeczny et al., 2016). In addition to increased variability, rainfall is projected to decrease by 10-20 % or more within the next 50 years within southern Africa (IPCC, 2014; Niang et al., 2014). The impacts of climate change are projected to be severe amongst resource-constrained households in semi-arid to arid agro-ecologies hence they should be the focus of most intervention practices (Singh et al., 2014).

In southern Africa, up to 50 % of annual maize yield losses during the past 25 years have been attributed to increased rainfall variability (Ray et al., 2015). In addition, increases in temperatures could lead to non-production of crops, such as tea, that require low temperatures for optimal growth and development (Ochieng et al., 2016). As a result semi-aridity is expected to increase by 5-8 %, thus reducing land area suitable for cropping (Boko et al., 2007). Consequently, there will be a 2-7 % loss in GDP in the sub-Saharan Africa region due to loss of agricultural productivity (IPCC, 2014).

Small-scale farmers have always responded to climate variability through use of traditional coping and adaptation practices (Ncube and Lagardien 2014). Despite use of traditional climate variability management practices small-scale farmers face recurrent losses in productivity due to drought and related climate hazards (Mpandeli et al., 2015). There is, therefore, a need for improved management of the impacts of climate variability in small-scale farming systems (Mapfumo et al., 2016).

The wide range of climate variability management options can be categorized as (1) government policy, (2) technological advancements, (3) farm financial management and (4) farm management practices (Smit and Skinner 2002). Government and the private sector are the key decision-makers in options related to policy and technological advancements in climate management. Small-scale farmers make decisions relating to farm financial and production management. Management options can be utilized individually or in combinations, so as to achieve effective and sustainable climate variability management (Cooper et al., 2008). Despite the availability of a wide range of adaption options, there is increased evidence that small-scale farmers are failing to manage climate variability due to poor uptake of the management strategies (IPCC, 2014).

The limited uptake of research-recommended strategies is partly attributed to the relatively high initial costs of changing cropping systems (FAO, 2001) and the non-suitability to specific agro-ecological conditions (Mazvimavi and Twomlow, 2009), weak institutional support (Ngwira et al., 2014), and the general risk aversion associated with small-scale farmers (Knowler and Bradshaw, 2007). The use of blanket recommendations ignoring the underlying socio-economic and cultural aspects is one of the leading causes of poor adoption (Twomlow et al. 2008). Small-scale farmers from diverse social strata require different incentives to adopt the different practices. There is, therefore need for a comprehensive review of the agro-ecological and socio-economic conditions under which specific coping and adaptation options are effective. There is also need for further assessment of adopted options and the corresponding factors responsible for their uptake. There is increased heterogeneity amongst some small-scale farmer communities in southern Africa due to differences in the predominant bio-physical and socio-economic characteristics. Given the heterogeneity of small-scale farmers, careful targeting of transfer of appropriate technology is required (Giller et al. 2009).

The farm typology approach can be utilised to increase the understanding of the diversity amongst small-scale farmers (Landais, 1998). Specifically, the approach allows for increased understanding of current socio-economic, bio-physical, agro-ecological and cultural conditions towards better determination, suggestion and recommendation of appropriate climate variability management strategies to small-scale farming communities (Berre et al., 2016). This approach accounts for, and disaggregates, the diversity of the farming systems to enhance understanding and analysis. Discerning this diversity is essential for diagnosis and recommendation, and identifying domain-specific intervention strategies in small-scale farming systems (Perret and Kirsten, 2000). This approach has been used in identifying farmer type-specific crop-livestock integration strategies and sustainable soil fertility improvement strategies in small-scale farmers of Zimbabwe (Chikowo et al. 2014; Mkuhlani et al. 2016). Using the farm typology approach in eastern Southern Africa, Makate et al. (2018) highlighted that resource-endowed and educated farmers prefer novel climate variability management strategies, such as seasonal forecast information. The approach is also applicable in conditions where there is limited in-depth socio-economic data, where qualitative descriptive approaches can be utilized. The Principal Component Analysis, an alternate approach however requires detailed socio-economic data which may not easily be available (Perret and Kirsten, 2000).

Improved climate variability management can be achieved through use of a broad range of management alternatives and technological advances, such as seasonal forecast information. To address the challenges of poor climate variability management attributed to incompatibility of practices with farmers, there is need for increased understanding of the current farmers' socio-economic conditions. This chapter highlights the potential use of the farm typology approach to increase understanding of the dynamics underlying climate variability management in small-scale farming systems. The study aimed to classify farmers based on predominant bio-physical and socio-economic characteristic using the farm typology approach and assessment of corresponding farmer perceptions, challenges and potential climate variability management strategies in small-scale farming systems using Lambani, Limpopo and Nkonkobe, Eastern Cape in South Africa as case studies.

3.3 Materials and methods

3.3.1 Study area

The study was based on two case study areas of Lambani, Limpopo and Nkonkobe, Eastern Cape communities in South Africa. Prior to the study an ethical approval was awarded from the University of Cape Town (FSREC 46–2018) to undertake research in the communities. The areas were selected for this study because most small-scale farming is under rain-fed agriculture. Both provinces are also home to significant proportions of resource-constrained small-scale farmers. These areas are also characterised by poor erratic rainfall. The research outputs are, therefore of importance to local small-scale farmers in these communities (Ncube et al., 2016).

Lambani is located in Vhembe district about 180 km to the north of Polokwane at 22º58′ S, 30º26′ E at an altitude of 596 m. In Lambani, mean temperatures range from 25 to 40 ºC and 22 to 26 ºC in summer and winter, respectively. Average precipitation is about 800mm per annum with most of the rainfall being received from October to March. The rainy season is characterized by mid-season dry spells with high rainfall variability (Mzezewa et al., 2010) (Figure 3.1). Dystrophic, red and yellow well-drained clays are the most predominant soils in the Lambani community (Soil Classification Working Group 1991). Small-scale farmers in Limpopo operate on land holdings averaging less than 1.5 ha, with some owning livestock. Maize is the most commonly cultivated cereal, whereas tomatoes, cabbages, beetroot, onions and butternuts are the major vegetable crops. Crop-production and livestock-rearing are mostly to meet household subsistence needs, with the balance being sold in order to raise income (Baloyi, 2010).

Nkonkobe is located within the Raymond Mhlaba municipality in the Eastern Cape province at 32°47′ S, 26°38′ E and altitude of 1200 m. The area receives an average of 540 mm of rainfall per annum (Figure 3.1), mainly between October and March. Seasonal temperatures range widely, from 4ºC to 38 ºC in winter and summer, respectively. Occasional incidences of frost and snow are experienced between May and July (Adekunle, 2014). Soil types vary due to the fluctuating topography, where the altitude ranges from 535 to 1200 m. Oak leaf soils are most common in the area (SCWG, 1991), with Valsriver and alluvial-derived micas being the other types (Mandiringana et al., 2007). The main farming activities are vegetable and livestock production for commercial and subsistence purposes. However, farming systems vary from sole crop or predominantly livestock production to mixed farming. Potatoes, tomatoes, cabbages, spinach, beetroot, carrots and maize are the commonly cultivated crops. Cattle are the predominant livestock species kept (Adekunle, 2014).

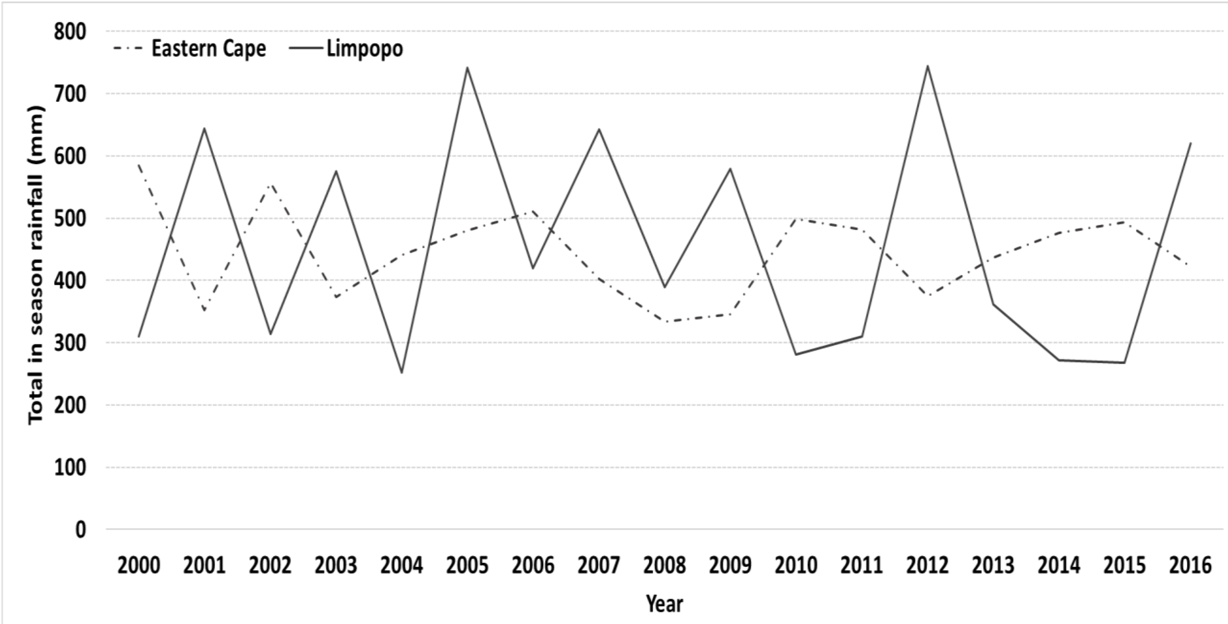


Figure 3.1: Seasonal total rainfall in the Fort beaufort, Eastern Cape and Punda maria, Limpopo from the 2000/1 to 2016/17 cropping seasons (South African Weather Services (SAWS)).

3.3.2 Farmer classification

Qualitative typology approach

The qualitative farm typology approach is based on key informants with in-depth knowledge of the subject being studied (Landais, 1998). The key informants are usually knowledgeable professionals or experts, which are local agricultural extension workers in this study (Kuivanen et al., 2016). Farmers were classified into different categories based on local agricultural extension workers' knowledge of the bio-physical and socio-economic characteristics of the different farmers in the area. In Lambani, five local agricultural extension officers based in Mhinga village were the key informants. They provided information on the various farmer categories in the area. Similarly, discussions on farmer diversity were held with four local agricultural extension workers operating in Nkonkobe district. Discussions were only conducted with extension workers who worked within the target communities. In both cases, the following socio-economic variables were used to help establish the farmer typologies: age of household head (HHH); household size; employment status; education of HHH; assets; total land holding; types of crops cultivated; size of area cropped; crop yields; livestock types; livestock numbers and food security status. These characteristics have been used in previous studies to classify small-scale farmers (Berre et al., 2016).

Snowball approach

The snowball sampling approach is a non-probability technique of selecting respondents. The approach selects and interviews key informants who then recommend specific individuals who can be interviewed. Prior knowledge of the population is crucial because it helps make validations of the initial referrals. The approach is suitable for assessing members of the population that are not easily accessible and identifiable (Atkinson and Flint, 2006).

In this study, discussions on small-scale farmer diversity were held with key informants, who were local agricultural extension workers, and this led to the classification of farmers into different categories. The key informants referred the researchers to specific farmers fitting the description of specific farmer categories. Focus group discussions (5-10 farmers per group), were conducted with farmers from each of the small-scale farmer categories. The focus group discussions extracted information on farmers' perceptions of climate patterns and strategies and challenges faced in managing climate variability. These perceptions were based on observations of both recent climate patterns and experienced historical patterns. Farmers highlighted the strategies and challenges being used and faced by small-farmers in managing climate variability. The potential to improve management of climate variability was determined through undertaking a qualitative assessment of the farmers' current strategies and challenges in managing climate variability.

3.4 Results

3.4.1 Farming systems in Lambani, Limpopo

The three predominant farmer categories in Lambani were mixed farming, horticultural farming and off-farm income-dependent (Table 3.1). Mixed farmers practice both crop and livestock production. They generated income through crop and livestock sales, as well as being recipients of government social grants for the elderly and remittances from children based in urban areas. They were also characterised by low literacy levels, high levels of self-employment and were mostly above 60 years old. Most horticulture farmers were in the age range 18-35 years, moderately educated and relied mostly on horticultural activities for their livelihood. They mainly cultivate tomatoes, cabbages and carrots on land less than 0.5 ha per household. Most off-farm income-dependent small-scale farmers were predominantly employed in the informal sector as motor mechanics, bricklayers, carpenters, etc. Their main sources of income and livelihood were off-farm activities and, to a limited extent, farming. Maize, vegetables and minor legumes were the most commonly cultivated crops in Lambani.

Table 3.1: Major small-scale farmer categories in the Lambani area of Limpopo Province in South Africa

	Mixed farming	**Horticulture farming**	**Off-farm income-dependent**
Age of HHH	>60	18-35	35-65
Household size	>5	~3	~5
Dependents	>3	~1	~3
Education of HHH	No education	Grade 12	Grade 12
Employment	Unemployed, usually pensioners	Unemployed	Informal employment
Major source of income	Crop and livestock farming	Farming	Off-farm activities
Other sources of income	Government grants and remittances	-	Crop farming
Arable land (ha)	>3	~1.5	~2
Cultivated area (%)	~75	~90	~50
Major crops	Maize	Vegetables: tomatoes	Vegetables, minor legumes
Minor crops	Vegetables, minor legumes	Green mealies	Maize
Maize yields (tha^{-1})	>1.5	0.25-0.5	<0.5
Cattle	>15	0	~5
Goats	~10	0	~5

Farmers across all the three categories experienced the impacts of climate variability in their farming activities as well as on their personal health. The crop enterprise was the most affected, as it is highly dependent on rainfall (Table 3.2). Horticultural farmers cited extreme low and high temperatures as evidence of climate variability. Mixed and off-farm income-dependent farmers experienced increased frequency of both extreme temperature events and increased rainfall variability.

Farmers across all categories used a wide range of strategies to manage climate variability (Table 3.2). The farmers indicated that irrigation was one of the major strategies they use in minimising the impacts of extreme temperature events and low rainfall on crops. The type of irrigation used differed amongst the different farmer categories with horticultural and off-farm income-dependent farmers using sprinkler derived systems. Some mixed farmers used flood irrigation, but its use was limited to horticultural crops. Mixed farming households used a combination of crop- and livestock-based strategies to manage climate variability. They used intercropping, water harvesting and mulching. Cattle manure was also applied to retain moisture as well as fertiliser in crop lands. Horticultural farmers indicated that, under high temperatures and or low rainfall conditions, they reduced fertiliser and pesticide application to minimise crop phytotoxicity. Off-farm income-dependent farmers either reduced cropping areas or did not plant at all. Drought-tolerant crops were, however, preferred whenever they eventually cultivated.

At least 60 % of farmers in Lambani indicated that they experienced financial challenges in managing climate variability. The funding is important for setting up, servicing and maintaining current irrigation equipment and technology. It is also important for purchasing fuel for farm equipment, electricity and other energy costs. Mixed farming and horticulture farming-based farmers faced financial challenges, largely attributed to shortage of capital. More capital would also enable them to better maintain and expand current irrigation systems. Some farmers practising utilising irrigation highlighted severe fluctuations in water availability largely due to the ENSO phenomenon. This has been characterised by frequent incidences of low volumes in the water bodies due to increased frequency of droughts and the *El Niño* phenomena. Off-farm income-dependent farmers had limited knowledge on farming and experienced shortages of labour (Table 3.2).

Table 3.2: Perceptions, strategies and challenges of different categories of small-scale farmers to climate patterns in Lambani, Limpopo province in South Africa

	Mixed farming	Horticulture farming	Off farm income dependent
Perceptions	Climate is changing Increased frequency and intensity of drought Rainfall pattern has changed High temperatures	Climate is changing Increased frequency and intensity of extreme low and high temperatures	Climate is changing Frequent low rainfall events Extreme low winter temperatures
Strategies	Intercropping with legumes Staggered planting dates Water harvesting e.g. potholes Irrigation e.g. flood, furrow Reduce cropping area Mulching Cattle manure	Irrigation Reduce fertiliser use Reduce pesticide use	Irrigation e.g. drip Drought- tolerant crop and crop types Reduce cropping area Do not plant
Challenges	Low water levels Siltation Financial resources Power shortages e.g. irrigation Climate information Maintenance Shortage of labour Lack of knowledge	Financial resources Shortage of water	Lack of knowledge Shortage of labour

3.4.2 Farming systems in Nkonkobe, Eastern Cape

There was greater farmer diversity in Nkonkobe, Eastern Cape compared to Lambani, Limpopo. This was manifested through realisation of five farmer categories in the Eastern Cape compared to the three categories realised in Limpopo (Table 3.3). The categories were: social welfare-dependent, enterprising pensioners, struggling subsistence, horticulture-dependent and cooperative crop farmers. Most social welfare-dependent farmers were unemployed, predominantly old-aged and had low literacy levels. They practice subsistence farming, where some of the produce is consumed in the homestead and the excess is sold for cash. The major sources of income were government-provided social grants for the elderly, remittances from family working in urban areas and occasional crop produce sales. The farmers cultivated maize and some vegetable crops such as tomatoes and cabbages on limited land sizes. They also owned about 14 cattle per household. Literacy levels were relatively high amongst enterprising pensioners and most of them once worked in either the private or public sectors. Most of the income was from the crop enterprise with livestock providing the least income (Table 3.3). They also received income from old-age pensions and remittances. The age range of most struggling subsistence farmers spanned from 20 to 90. Most of the struggling subsistence farmers had low literacy levels, were unemployed and headed large households averaging six members. They cultivated few crops, some of which included maize and a few legumes, on about 0.25 ha landholding per household. In this farmer category, ownership of livestock was limited to an average of one goat per household (Table 3.3). The main sources of income for struggling subsistence farmers were child support grants, old age pension and occasional crop sales. Most horticulture crop-dependent farmers were mainly middle-aged, had acquired secondary school education and relied on horticultural crop sales to raise income. Tomatoes, lettuce, cabbages, beans and peas occupied approximately 80 % of their arable land. Cooperative crop farmers were poorly educated and mainly produced tomatoes, lettuce and cabbages for sale. The age range of most cooperative farmers was 35-65 years old. Most of them had relatively easier access to grants and loans because they qualified for government-provided financial support, such as cooperative farming grants (Table 3.3).

Table 3.3: Major small-scale farmer categories in Nkonkobe municipality, Eastern Cape province, South Africa.

Variable	Social welfare dependent	Enterprising pensioners	Struggling subsistence	Horticulture-dependent	Cooperative crop farmers
Age of HHH	~71	>68	20-90	~37	35-65
Household size	>4	>4	~6	~5	~5
Education	Poorly educated	Educated	Poorly educated	Secondary school	Poorly educated
Employment	Unemployed	Retired private sector and public sector workers	Unemployed	Unemployed	
Key livelihood activities	Government grants and remittances	Crop produce and occasional livestock sales	Children and government grants	Horticultural crop sales	Horticultural crop sales
Other income sources	Semi-subsistence farming	Pension	Occasional crop produce sales	-	Non-horticulture crop sales
	Occasional crop produce sales	Remittances	-	-	-
Land area	2ha	>3ha	<1ha	<1.5ha	~10ha
Cultivated land	~0.25	>2.5	<0.4	~1.2	~7.5
Cattle	<2	>14	0	0	~2
Goats	0	>4	~1	0	0
Crops	Maize; Few vegetables	Maize; Tomatoes; Cabbages	Maize; Few legumes	Tomatoes; Cabbages; Peas; Beans	Tomatoes; Lettuce; Cabbages

NB: HHH-household head

All farmers across the different categories experienced the adverse effects of climate variability, which manifested in the form of increased frequency of dry spells and extreme low- and high-temperature events. Horticulture-dependent farmers highlighted experiencing reduced frequency and intensity of winter rains, coupled with increased frequency of extremely high summer temperatures. Struggling subsistence farmers cited increased variation in the onset of the rainfall season as a major concern (Table 3.4).

Farmers across all the categories, except for social welfare-dependent and enterprising pensioners, used irrigation as one of the strategies to minimise the impacts of climate variability. Social welfare-dependent and struggling subsistence farmers used crop-based climate variability management strategies, such as intercropping, mulching, water-harvesting and reduced cropping area. Horticulture-dependent farmers relied on water reservoirs, organic amendments and seed diversification to manage the challenges associated with climate variability. Irrigation and cattle manure were the most utilised strategies by cooperative crop farmers (Table 3.4).

All farmers except cooperative farmers faced financial constraints in managing climate variability. Social welfare-dependent farmers had limited access to irrigation infrastructure and labour for farm operations. Enterprising pensioners experienced water leakages and aging of irrigation infrastructure. They also highlighted limited access to climate information as a major challenge. This was confirmed by cooperative crop farmers when they highlighted poor access to extension services as a key challenge in managing climate variability. Enterprising pensioners and horticulture-dependent farmers highlighted challenges, such as lack of climate information as a major impediment in implementing climate variability management (Table 3.4).

Table 3.4: Perceptions, strategies and challenges of small-scale farmers to current climate patterns in Nkonkobe, Eastern Cape province, South Africa.

	Social welfare-dependent	Enterprising pensioners	Struggling subsistence	Horticulture-dependent	Cooperative crop farmers
Perceptions	Change in climate patterns Increased severity of droughts Reduced frequency and intensity of winter rains	Change in climate patterns Increased frequency of dry spells Extreme low and high winter and summer temperatures	Changing climate patterns Increased variation in start of rainfall season Extreme low and high temperature events	Changing climate patterns Reduced frequency and intensity of winter rains Extreme high temperature events	Reduced frequency and intensity of winter rainfall Increased frequency of high temperature events
Current strategies	Intercropping Reduce cropping area Mulch	Different crop types and varieties Irrigation Reduce fertiliser use Cattle manure	Mulch Water–harvesting Intercropping	Irrigation Water reservoirs Organic amendments Different crop types and varieties	Irrigation Application of manure
Challenges	Finance e.g. farm operations Irrigation e.g. tanks; pumps Labour e.g. operations	Improved irrigation equipment Climate information	Finance, e.g. reservoir; irrigation	Finance, e.g., improve operations Climate information	Improved access to extension services

3.5 Discussion

3.5.1 Perception of historical climate patterns across different farmer categories

Assessment of farmer perceptions is one of the steps towards sustainable climate variability management in small-scale farming systems. It provides information on the state of awareness of farmers to climate patterns in general, and rainfall variability and temperature.

Despite the differences in micro-climates of the locations where the study was undertaken, farmer perceptions were found to be relatively similar across all categories in both Limpopo and the Eastern Cape provinces. This was attributed to the general holistic climate of the southern African region, which has been experiencing increased frequency of high temperature events and high rainfall variability. Similarly, farmers highlighted experiencing increased frequency of extreme temperature events where temperatures across the southern African region have increased during the last 40 years due to global warming (Serdeczny et al., 2016). Increased frequency and intensity of droughts and delayed and unpredictable onset of rainfall, which corresponds to increased temporal and spatial variability realised from scientific research (IPCC, 2014), were also reported. In the current study, small-scale farmers did not, however, highlight change in wind patterns as part of changing climate patterns, although Muller and Shackleton (2013) reported that farmers have experienced changes in wind patterns over the past 20 years in the Eastern Cape province. The failure of farmers to realise changing wind patterns could be attributed to the non-significant changes in the wind speeds and direction under climate change. Farmers are therefore unable to take note of such minor changes. In addition, rainfall and temperature have a direct impact on agricultural productivity as well as livelihoods in contrast to wind. Farmers are therefore more likely to realise the changes in rainfall and temperature compared to wind. Most of the agricultural productivity is non-sensitive to changes in wind patterns.

Despite experiencing similar climate conditions, different farmer types highlighted slightly different perceptions of climate patterns, which is partially attributed to the different farming specialties. Horticulture is mainly affected by rainfall and temperature. Horticulture farmers produce crops all year round and are highly dependent on irrigation to supplement rainfall during the winter period. Winter rain cushions farmers from the high irrigation costs, which can be even higher during the winter. Horticultural farmers are, therefore, highly sensitive to changes in winter rainfall, as it has a direct impact on their farming activities. Due to decreased rainfall reliability, irrigation has evolved to be a key a source of water for crops. The potential negative impacts of increased rainfall variability are thus minimised by supplementary irrigation. Climate variability has increased the frequency of extreme temperature events. Occurrence of these events is associated with low rainfall or mid-season dry spells, and farmers usually respond with irrigation. Use of irrigation therefore minimises the effect of extreme temperature events so horticulture-dependent farmers are less likely to perceive extreme temperature events as a sign of climate variability.

Non-horticultural farmers, such as struggling subsistence farmers, are highly rainfed-dependent and usually cultivate grain crops, which are seeded from mid-October, the traditional rainfall onset period in southern Africa. Variation in rainfall intensity has a greater impact on non-horticultural farmers, as they have limited control over effects of the given weather elements due to lack of irrigation. Resource-constrained farmers are therefore highly sensitive to increased rainfall variability. Such farmers are, however, not susceptible to extreme temperature, as they mainly cultivate field crops, such as maize and groundnuts. These crops are less susceptible to extreme temperatures compared to horticultural crops. Field crops are, however, susceptible to lack of rainfall, the effects of which are worsened by the unavailability of irrigation, hence these farmers highlighted experiencing changing climate.

Mixed farmers specialise in cultivated crops, whilst simultaneously rearing livestock. They cultivate a variety of crops ranging from horticultural to field crops. Mixed farmers are, therefore, sensitive to changing climate patterns all year round since they experience both reduced winter rainfall, which affects vegetable crop production, and increased dry spells and droughts, which have an impact on summer crop production. Livestock would also be sensitive to changes in climate patterns. Rainfall has a direct impact on forage, where droughts or dry spells lead to forage and feed shortage. This has an impact on all sizes of ruminants especially large animals. Increased temperatures cause heat stroke in large ruminants. The impact is however reduced in small-ruminants.

3.5.2 Impact of small-scale farmer diversity on climate variability management strategies

Small-scale farmers have always used a wide range of strategies to manage the negative impacts of climate variability. Climate variability management strategies traditionally used by farmers are part of local knowledge, which have been passed from generation to generation and are often referred to as indigenous knowledge (Mapfumo et al., 2016). Climate change, industrialisation, modernisation and cultural degradation, coupled with the gradual disappearance and weak manifestation of indigenous climate indicators (behaviour of animal and plant species, springs and culturally revered forests, mountains and water bodies) have led to the gradual disappearance and reduced use of indigenous knowledge. As a result, this study realized small-scale farmer groups that use modernized strategies, such as inorganic fertilizers and modern irrigation.

The existence of various categories of small-scale farmers in Lambani and Nkonkobe is a manifestation of the diversity inherent in the sector. This is supported by findings from Perret and Kirsten (2000), who identified seven farmer categories of varying diversity in the Eastern Cape province. Similarly, in the Limpopo province, Mudau (2010) identified four different categories of small-scale farmers. Greater farmer diversity is attributed to the wide range of dominant socio-economic characteristics of the different farmer categories. This has consequences in the strategies that can be used amongst the farmers in the different farmer categories.

Farmers practising mixed farming were realised in both locations. Mixed crop-livestock farmers earn most of their income from crop and livestock sales. The bias towards more crop-livestock farming in both locations is attributed to the socio-economic cultural values of the African small-scale farming community, which depict accumulation of livestock as a sign of wealth (Nkomboni et al., 2014). Within the same system, farmers cultivate food crops for subsistence with the balance sold for cash, with some crop residues being used as animal feed (Wenhold et al., 2007). Farmers practising mixed farming can therefore, use a wide range of multiple crop- and livestock-based strategies to manage climate variability. This is strongly attributed to greater farming experience, which enables small-scale farmers to become efficient in the use of all available options to manage climate variability. They would have gathered knowledge and acquired experience from their predecessors and from informal on-farm experiments over a long period of time, which improve their decision-making. The ownership of livestock mostly leads to increased availability of manure and motivates the use of manure in conserving soil moisture with the aim of managing rainfall variability. Manure also has other multiple benefits, such as improvement in soil fertility. Most small-scale farmers who own livestock are therefore motivated to use cattle manure. Most climate variability management strategies are, however, crop-based, since most livestock-based strategies, such as use of livestock manure, are laborious. This may be challenging, considering that most farmers who practice mixed farming are old, hence are unable to provide the labour to gather, transport and apply manure. They are therefore potentially unable to make effective use of manure. They can, therefore, use their financial resources to hire labour to manage manure. They can also use the financial resources to invest in other non-labour requiring strategies, such as use of different crop types and varieties, and improved irrigation facilities. In contrast, manure use is one of the few strategies mostly used by cooperative crop farmers in the Eastern Cape. Cooperatives usually comprise of members from a wide age range with most of them being able-bodied individuals, who can undertake most of the farming activities. Use of manure is thus possible through the availability of labour to transport manure to the field. Use of manure is also motivated by the multiple benefits of its use where, in addition to moisture conservation, manure use minimises fertiliser use.

In contrast to resource-constrained farmers, such as social welfare-dependent farmers, off-farm income-dependent farmers utilise a combination of both adaptation and avoidance-based strategies. This is attributed to their ability to purchase drought-tolerant seeds, since they have the financial resources to do so. They can also afford to reduce cropping area or not to crop to cut losses, since they can purchase food with alternate sources of income. They have greater liquidity and relatively easy access to loans, which enables them to finance farming activities, despite being hamstrung by the limited labour and knowledge. They however have relatively less focus on farming, with most of the focus being on off-farm activities, which are their key source of income. Their ability to purchase food also makes them reluctant to invest time and financial resources in farming, resulting in labour shortages. These farmers are, therefore, likely to utilise finance-based climate variability strategies, such as irrigation. Most non-finance-based strategies are time and labour demanding, as a result most off-farm income farmers maybe unable to utilise them. Consequently, general farm management may be poor, resulting in poor productivity, leading to farmers purchasing food. Most resource-constrained farmers such as social welfare-dependent and struggling subsistence farmers are unemployed and have no other significant sources of finance. They are therefore unable to invest in farming hence they face food insecurity. They use limited inputs such as uncertified seeds and low fertilizer rates leading to reduced productivity (Pienaar and Traub, 2015). Such farmers can therefore utilise low cost natural climate variability management strategies such as mulch and intercropping.

Climate variability strategies utilised by resource-constrained farmers such as social welfare-dependent and struggling subsistence farmers are generally similar, regardless of the location. They mainly use indigenous crop-based climate variability management strategies such as mulching. The strategies mainly enhance soil moisture retention rather than adding more water into the soil. The strategies do not require financing and additional technical expertise; hence they are compatible with resource-constrained farmers, most of whom have lower literacy levels. The strategies do not, however, lead to significant increase in crop productivity, as there may not be sufficient soil moisture for crop production even after moisture retention, due to low precipitation attributed to climate variability. These farmers are more likely to continue using local natural climate variability management strategies as they cannot utilise other strategies, such as irrigation, and alternate crop types and varieties, as they have limited financial resources.

Horticulture-dependent farmers in both locations are highly dependent on sales from vegetable produce. Most of the horticultural farmers are young and therefore, very shrewd and enterprising. They introduce novel farming techniques to improve farming activities and productivity. They can, therefore, introduce novel strategies of managing climate variability such as drip irrigation. Most strategies utilised by horticulture-dependent farmers are short-term and are designed to minimise the immediate potential negative impacts caused by low rainfall and high temperatures. These farmers have significantly invested in irrigation. Irrigation significantly minimises the impacts of both shortage of water and the extreme temperatures. It therefore reduces need for other management strategies.

In the Eastern Cape, the current study realised horticulture-dependent and cooperative crop farmers, who were not realized in other farm typology studies by Perret and Kirsten (2000) and Kelly and Metelerkamp (2015). This may be attributed to the evolution of rural communities, which emanates from the communities' dynamism to adapt their livelihoods. This therefore likely, caused a significant proportion of farmers to venture into horticulture. Increased consumerism and acquisition of modern habits and tastes might also have motivated them to venture into agricultural enterprises that have quick economic returns. Small-scale farmers have always cultivated cereal crops solely for subsistence. Cereal crops however, have relatively low market prices, compared to vegetable crops hence horticulture-dependent farmers have developed a preference for higher value horticultural crops. For the same reasons, cooperative crop farmers have developed a preference for vegetable crops.

No social welfare-dependent and struggling subsistence farmers were realized in Lambani compared to Nkonkobe. Limpopo and Eastern Cape provinces are home to the most resource-constrained households in South Africa, but Limpopo farmers have higher agricultural productivity than Eastern Cape farmers (Bhorat and van Der Westhuizen, 2012). There is, therefore, less dependence on social grants amongst farmers in Limpopo compared to Eastern Cape province. Advances in age, and shortage of labor and inputs, which characterize social welfare-dependent and struggling subsistence farmers, potentially lead to reduction in agricultural activities. Reduced cultivation is also attributed to receiving government grants for sustenance, which therefore reduces their willingness to undertake farming activities and the need to undertake any other cropping improvement strategies.

3.5.3 Challenges in managing climate variability

Small-scale farmers are aware of the changing climate patterns, but not all farmers revisit their management decisions and make the corresponding amendments to the cropping systems in managing climate variability (Gbetibouo, 2009). This research realised that the failure to adapt is highly attributed to a range of challenges chief among them being lack of financial resources, especially amongst mixed-farming and horticulture-farming households in Limpopo, but also in the Eastern Cape. Finance is required for irrigation and seed.

Farmers need finance to repair, maintain or upgrade irrigation equipment and systems to improve crop water supply. Poorly maintained and funded irrigation schemes are highly inefficient as they lead to losses through water leakages. Climate variability further reduces the amount of water available for irrigation due to reduced precipitation. This is worsened by siltation in water bodies, which further reduces amount of water available for utilisation by farmers. There is therefore a need for farmers to make use of water reservoirs for irrigation. These farmers can also engage the local and national government to undertake de-siltation activities to increase water retention in water bodies as most water bodies are owned by national governments. Off-farm income-dependent small-scale farmers do not highlight finance as a challenge in managing climate variability as they already have relatively greater financial resources.

Most of the challenges, such a shortage of power, highlighted by farmers practising mixed farming and horticultural farming, were related to irrigation. Such farmers can either use low-cost strategies such as traditional varieties, cover crops, mulch, and ponding, which are suitable for use where financial resources are limited. They can, however, take loans to finance irrigation or acquire drought-tolerant cultivars. There is an abundance of seed whose productivity varies under different agro-ecological conditions. Farmers can therefore acquire specific cultivars in anticipation of certain climate forecasts. Such seed is however costly and only resource-endowed farmers can, therefore, use such strategies in managing climate variability.

The increased popularity of irrigation as a solution to rainfall variability seems to have over-shadowed the challenges associated with the use of other strategies. For instance, the use of mulch challenged by crop-livestock competition for crop residues was not raised. Irrigation has greater stature amongst small-scale farmers, as it enables production of horticultural crops which are usually cultivated throughout the whole year. Cultivation of horticulture crops are increasingly popular due to the greater and quicker financial returns. Most farmers' challenges are therefore, related to irrigation. There is, therefore need to introduce and promote other strategies, such as staggered planting, cultivation of different crop types and promotion of the use of mulch. These and other strategies can be utilised by farmers at relatively lower cost and are flexible to farmers compared to use of irrigation.

Small-scale farmers view irrigation as a panacea to all other farming challenges. Finance is required to acquire, maintain or upgrade irrigation equipment. The aspect of finance as a challenge, however appears to have been over-emphasised by small-scale farmers in both Limpopo and the Eastern Cape. There has been an increase in the number of donor projects targeting small-scale farmers and other less privileged households. Small-scale farmers, therefore, assume that most visitors to the areas are donors bringing finances. Farmers may, therefore, have highlighted finance as an issue in the expectation of receiving funds and agricultural equipment from donors. Other small-scale farmers, especially resource-constrained farmers may, therefore, view irrigation as the solution to poor production. Irrigation is, however, not the panacea of African small-scale agriculture, as it is affected by several factors, such as knowledge, access to extension services and access to inputs. As a result, African small-scale farmers experience recurrent crop yield losses. Provision of funds to set up irrigation among these resource-constrained farmers may, therefore, not be sustainable due to the additional negative impacts attributed to other challenges which would significantly lower yields despite irrigation.

Most of the farmers have also highlighted finance as a challenge. Most farmers who attain higher agricultural productivity and have decent livelihoods make use of irrigation. Other small-scale farmers, especially resource-constrained farmers, may therefore, view irrigation as the ultimate solution to poor production. However, irrigation is not always a viable solution due to other multiple challenges, as explained in the preceding paragraph. These farmers can, therefore, utilise low cost strategies, such as mulching, intercropping, and cultivation of different crops.

In contrast to Limpopo, some farmers in Eastern Cape, especially enterprising pensioners, and cooperative crop and horticulture-dependent farmers highlighted the need for information. Cooperative crop farmers highlighted limited access to information about crop agronomy. Agricultural productivity is affected by many factors which include poor soil fertility, insect pests and diseases. Climate variability management is effective when other factors affecting productivity are also addressed. There is, therefore need for improved agronomic management, efficiency and productivity before introducing climate variability management strategies. This therefore increases sustainability of climate variability management. Enterprising pensioners and horticulture-dependent farmers also highlighted lack of climate information as a challenge in managing climate variability. Provision of climate information prior to planting enables farmers to make management decisions enhancing coping with, and adaption to, climate variability. Mpandeli (2006) also emphasised that one of the sustainable strategies of coping with, and adapting to, climate variability is the provision of climate information as seasonal forecast information. It can also be highlighted that small-scale farmers have used indigenous climate forecasting methods in managing climate variability. Increased climate variability and change (Min et al., 2011), coupled with the gradual disappearance and weak manifestation of indigenous climate indicators which have traditionally been used by small holder farmers (Mapfumo et al., 2016), has increased the need for the use of scientific seasonal forecasts to improve farmers' preparedness to seasonal weather variability.

Effective use of science-based seasonal forecasting is highly dependent on factors such as access to seasonal forecast information, timing of forecasts and literacy levels. Farmers with high literacy are therefore more able to access and interpret seasonal forecast information. On the contrary, poorly resourced and illiterate farmers cannot make effective use of forecasts. Even after timely receipt of the forecasts, the farmers are highly unlikely to put in place the corresponding management practices, due to financial challenges. Use of extension officers can therefore make the use of forecasts relatively easier amongst all farmer types. Extension officers are highly literate and can interpret and offer support on the use of forecasts to farmers.

3.6 Chapter conclusion

The study shows increased farmer diversity in small-scale farming systems of Limpopo and Eastern Cape provinces of South Africa as realized by the different major farmer categories. Diversity is attributed to the varying socio-economic characteristics of the farmers. Due to socio-economic diversity, farmers also make use of different climate variability management strategies. Resource-endowed farmers can employ strategies that require financing such as irrigation. In contrast, resource-constrained farmers should favour non-finance-requiring strategies, such as mulching and intercropping. Despite not fully comprehending the scientific dynamics behind climate variability, small-scale farmers are fully aware of the changing climate patterns and increased climate variability. The degree of awareness corresponds with the farmers' goals and current farming systems. Across farmer categories, most of the farmers highlighted finance as the major challenge in managing climate variability. The importance of irrigation is, however, intertwined with the need for production of crops outside the main rainfall season for financial benefits and consequently, livelihood purposes

Increased farmer diversity has a bearing on the vulnerability and effectiveness of climate variability adaptation strategies, as it determines the farmers' ability to effectively execute some of the adaptation strategies. Consideration of farmer diversity through assessing socio-economic and bio-physical characteristics is critical in prioritising or assessing climate variability adaptation options in small-scale farming conditions. Farmers can, however, only utilize strategies that are compatible with their socio-economic characteristics. The degree of awareness corresponds with the farmers' goals and current farming systems. Farmers' awareness of climate variability stimulates self-mobilisation, enables informed decision-making and increases the capacity and ability to manage climate variability in small-scale farming systems through behavioural change, especially during the initial stages of adaptation. The study exposes a critical challenge of the need for climate information amongst resource-constrained farmers, which is rarely emphasised in socio-economic research. Evaluation of the challenges is therefore key in assessing the potential approaches for future climate variability management in small-scale farming. This may be accomplished by advisory approaches or recommendation in farm management decision-making. Alternatively, this can be a route to assess the effectiveness of modern tools for climate variability management, such as seasonal forecast information. Through its representation of local heterogeneity of farm types, this study highlights the values of seasonal forecasting information to benefit the full range of small-scale farmers in better managing climate variability. According to their specific conditions, farmers can better appreciate weather forecast/predictions and develop an understanding of its crop consequences over the season.

Chapter 4

4.0 Decision-making process based on integration of seasonal forecast information and crop models in South Africa

4.1 Chapter summary

Integrating seasonal forecast information and crop models increases the farmer's ability to make farm management decisions relating to climate variability. This chapter therefore sought to (i) formulate a decision-making process and decision scenarios and (ii) test if any useful pre-season management information can be identified to inform small-scale farmers decision making. A prior study reviewed potential approaches for integrating seasonal forecast and crop models (Chapter 2). A process-based approach consisting of coupled Global Climate Model (GCM) that produces seasonal forecast information in a format compatible to mechanistic crop models was found to be suitable. The GCM based Climate Forecast System version 2 (CFSv2) and the Decision Support System for Agro-Technology Transfer (DSSAT) v4.7 were therefore integrated based on the GCM approach. GCM based Climate Forecast System version 2 (CFSv2) model produced seasonal forecast information for Nkonkobe, Eastern Cape and Lambani, Limpopo, South Africa. The study used 23 sets of seasonal forecast information for the period 1-23 October for the 2017/18 season. The study assessed 48 potential combinations of climate variability management practices including; organic soil cover, crop variety, fertilizer, and irrigation for a set of farmer typologies. Crop yield simulations were therefore conducted form the 23 different seasonal forecasts and 48 different practices. Decision scenarios were formulated by assessing the pattern of yield response to the interaction between seasonal forecasts and the different combination of farm practices across the different crops, farmer types and locations. Overall, there were no notable differences in farm management decision scenarios amongst the different types of farmers in both locations. The study realized 3 major potential decision scenarios using seasonal forecast information and crop models. In about 9 % of all the decision scenarios, there was low decision capacity and low climate sensitivity. In about 40 % of the decision scenarios, there was high decision capacity and high climate sensitivity as the performance of farm management decisions varied with seasonal forecast. In about 51 % of the scenarios, there was high decision capacity and low climate sensitivity where the ideal farm management practices

were uniform across all forecasts. Decision making is therefore relatively easy in such a scenario as the ideal set of practices are uniform across a range of different forecasts. The set of management practices including organic ground cover, long season varieties, fertilizer and irrigation had the highest yields across all crops in both locations. Crop yields were greater with earlier planting and decreased with late planting in the Eastern Cape. The pattern was opposite in Limpopo. In conclusion it is feasible to integrate seasonal forecast information and crop models to enable operational farm management decision making in South African conditions. Decision making is relatively easier where the ideal farm management practices are uniform across most climate forecasts compared to where they are uniform as well as climate dependent. Despite the great variation in climate forecasts, generally the management practices leading to higher yields include irrigation, long seasoned varieties, organic amendments and under higher fertilizer application. Farmers from different socio-economic backgrounds can utilize components from combination of practices that lead to higher yields.

4.2 Introduction

Small-scale farmers are vulnerable to climate variability as they are highly dependent on rainfed agriculture. Climate variability has been gradually increasing since pre-industrial revolution and is projected to significantly increase in the future (IPCC, 2014). Specifically, projections show intra- and inter-seasonal increase in frequency of extreme temperature events and increased variability in the onset and cessation of rainfall (Tadross et al., 2009).

Climate variability has contributed to significant crop yield losses of at least 50 % for crops such as maize and soybean since 1980 (Ray et al., 2015). Climate variability is projected to increase inter-seasonal maize yield variability by as high as 85 % in Southern Africa (Mkuhlani et al., 2019b). Increased inter-annual maize yield productivity increases food insecurity especially amongst resource constrained small-scale farmers (World Bank, 2007). Seasonal forecast information potentially enables small-scale farmers to make farm management decisions in preparation for the incoming agricultural cropping season (Chung et al., 2014).

Farmers can make farm management decisions as well as allocate farm resources based on seasonal forecast information (Ziervogel, 2004). Seasonal forecasts usually include information on temperature and rainfall but parameters such as wind, humidity can also be included depending with intended use and target users (Zhang, 2014). To increase the value of forecasts, seasonal forecast information can be integrated with crop models producing crop yield forecasts. Crop yield forecasts are of potential value to small-scale farmers as this enables them to evaluate crop response to projected seasonal forecast information. This therefore potentially improves the farm management decision making process. Linking seasonal forecast information with crop models however presents challenges. This is attributed to the spatial and temporal format of seasonal forecast which is incompatible with the daily time step input format required by process based crop models (Hansen et al., 2009).

Advances have been made in linking crop models and seasonal forecast information to enhance farmer decision making. Integrated seasonal forecast information and crop models have been widely used in farming (Ines & Hansen, 2006; Mishra et al., 2008; Hansen et al., 2009; Sultan et al., 2010; Asseng et al., 2012a; Asseng, et al., 2012b). Using integrated seasonal forecast and crop models, farmers can potentially make farm management decisions (Mishra et al., 2008). Specifically, farmers can make decisions such as crop type, variety and organic ground cover that potentially lead to high productivity. Such research potentially minimizes the impact of climate variability through prior determination of the feasible climate variability management practices. Given the increased variability in the commencement of rains, researchers can enhance decision making on the planting date. Small-scale farmers also face challenges in managing fertility whose effect is correlated with climate. Researchers can therefore evaluate the fertilizer type and rates corresponding to the projected weather (Zinyengere et al., 2011). Agricultural extension workers can sustainable medium of dissemination of such information as they are literate and in constant touch with farmers (Ziervogel, 2004). These assertions however need to be evaluated under local conditions.

The research therefore sought to assess the feasibility and application of integrating seasonal forecast information and process-based crop models under South African conditions using 2017/18 rainfall season as a case study. Specifically, in this chapter, the study (i) defined a decision-making process and formulated decision scenarios for potential use in climate variability management. This was undertaken through assessment of crop yield response patterns from the interaction of range of seasonal forecasts and farm management practices across different crops, farmer type and locations. (ii) identify pre-season management information that can inform small-scale farmer decision making. (iii) Identify management practices leading to higher productivity under a range of seasonal forecasts.

4.3 Materials and methods

4.3.1 Sites

The study was based on Nkonkobe and Lambani communities in the Eastern Cape and Limpopo provinces, South Africa. The sites were described in detail in Section 3.3.2.

4.3.2 Seasonal forecast information

Seasonal forecast information used in this study were outputs from the Climate Forecast System version 2 (CFSv2) model. CFSv2 is a coupled ocean-atmosphere-land model, developed by the National Centers for Environmental Prediction (NCEP). The model has a resolution of about 0.9◦x 0.9◦ (Yuan et al., 2011). CFSv2 was used as it was easily accessible through simple web downloads compared to other forecasts which were only accessible upon purchasing. Some of the forecasts also demanded high computational and technical capacity and involved significant bureaucracy in accessing. Seasonal forecast information was included in *Netcdf format* files. Using *Python*, seasonal forecast data was extracted for Nkonkobe, Eastern Cape (32°47′ S, 26°38′ E) and Lambani, Limpopo (22º58' S, 30º26' E). The study extracted 23 seasonal forecast data sets, for each day for the period, 1-23 October 2017. The extracted weather data included: minimum and maximum temperature, rainfall and solar radiation for the two locations. Each of the seasonal forecast data set was for 9 months from the date of forecasting. Previous research has shown that there is greater forecasting skill in Limpopo compared to the Eastern Cape in South Africa. This is attributed to the limited capacity of GCMs to account for most factors defining weather in the Eastern Cape compared to Limpopo, where there is less oceanic influence (Landman et al., 2012; Landman and Beraki, 2012).

4.3.3 Farmer classification

Small-scale farmers in Lambani, Limpopo and Nkonkobe, Eastern Cape were classified using the qualitative farm typology approach based on the predominant socio-economic characteristics. Further details are provided in section 3.3.2.

4.3.4 Calibration of the crop model

DSSAT v4.7, a process based mechanistic crop model was utilized to simulate crop yields (Jones et al., 2003). Such models are capable of predicting most aspects of crop growth and development through mimicking plant phenological and physiological processes (Basso et al., 2013) (Chapter 2). Process based crop models simulate crop management aspects such as: crop rotation, intercrops, crop calendar, different crop types and varieties, fertility, irrigation, mulching and tillage (Jones et al., 2003; Holzworth et al., 2014). These management aspects that can be simulated by the DSSAT model are similar to some of the farm management practices that are the focus of the current study.

The DSSAT 4.7 model was calibrated based on the measured and observed biophysical and socio-economic data collected from farmers during community engagement activities such as household surveys and focus group discussions for both Lambani and Nkonkobe. Daily weather data for: maximum and minimum temperatures, rainfall and solar radiation; was acquired from the South African Weather Service for 2010-2016. The model was also parameterized with soil data parameters such as soil texture, mineral and nutrient content, soil water dynamics for both Lambani, Limpopo (Table 4.1a) and Nkonkobe, Eastern Cape (Table 4.1b) (Fanadzo et al., 2010; SCWG, 1991; Mzezewa et al., 2010). Crop yield data for maize, cabbage, tomato, dry and green bean was acquired through farmer interviews, whereas phenological data was extracted during interviews with agricultural extension workers and literature. Effective calibration of the DSSAT model would include evaluation of the model’s capability to simulate phenological aspects such as emergence, silking and maturity dates for each crop, season and location. Such data was however not available from farmers, hence the study relied on the relevant literature.

The root mean square error (RMSE) was utilized to evaluate the ability of the DSSAT model to effectively simulate crop yields. The RMSE compared simulated and measured crop yields from 2011/12 to 2015/16 seasons. The RMSE was computed using equation (1):

$$\text{RMSE}=\sqrt{\sum_{i=1}^{n}\frac{(P_i-O_i)}{n}}\cdot\frac{100}{O_i} \qquad (1)$$

A value above 30 % is an indication of the model's inability to appropriately simulate the parameters under study (Moriasi et al., 2007). RMSE values for all crop yields across the different farmer categories and agro-ecologies were less than 30 % (Table 4.2a and b). The calibrated DSSAT model was therefore considered as suitable to predict crop yields in the conditions described above.

Table 4.1a: Characteristics of soil data used to calibrate the DSSAT v4.7 model for Lambani, Limpopo South Africa

Characteristic	**0 – 30 cm**	**30 – 120cm**	**>120cm**
Lower limit (cm^3/cm^3)	0.12	0.12	0.13
Upper limit (cm^3/cm^3)	0.26	0.26	0.29
Saturation (cm^3/cm^3)	0.49	0.49	0.49
Extractable water (cm^3/cm^3)	0.14	0.14	0.16
Root distribution (cm^3/cm^3)	0.78	0.42	0.11
Bulk density (g/cm^3)	1.1	1.1	1.20
pH	5.5	5.4	5.3
Nitrogen (%)	0.06	0.06	0.09
Organic carbon (%)	1.94	1.09	1.7

Table 4.1b: Characteristics of soil data used to calibrate the DSSAT v4.7 model for Nkonkobe, Eastern Cape, South Africa.

Characteristic	**0 – 30 cm**	**30 – 120cm**	**>120 cm**
Lower limit (cm^3/cm^3)	0.137	0.137	0.06
Upper limit (cm^3/cm^3)	0.27	0.27	0.16
Saturation (cm^3/cm^3)	0.38	0.38	0.27
Extractable water (cm^3/cm^3)	0.14	0.14	0.16
Root distribution (cm^3/cm^3)	-	-	-
Bulk density (g/cm^3)	1.6	1.6	1.6
pH	6.0	6.0	6.0
Nitrogen (%)	0.13	0.05	0.01
Organic carbon (%)	0.7	0.22	0.02

Table 4.2a: Root mean square error (RMSE) values comparing measured and model simulated yields across different crops and farmer categories in Limpopo, South Africa.

Season	Crop	RMSE Grain (%)	RMSE Stover (%)
Mixed farmers	Maize	29.0	17.7
Horticultural dependant farmers		17.5	29.1
Off farm income dependant farmers		24.4	12.4
Mixed farmers	Tomato	28.2	25.3
Horticultural dependant farmers		29.0	28.5
Off farm income dependant farmers		23.8	28.0
Mixed farmers	Groundnut	26.7	16.3
Mixed farmers	Dry beans	23.6	19.5
Horticultural dependant farmers	Cabbage	-	12.6

Table 4.2b: Root mean square error (RMSE) values comparing measured and model simulated yields across different crops and farmer categories in Eastern Cape.

Farmer category	Crop	RMSE Grain (%)	RMSE Stover (%)
Social welfare dependant farmers	Maize	29.8	21.1
Enterprising pensioners		27.4	13.6
Struggling subsistence farmers		17.0	28.7
Horticultural dependant farmers		29.5	16.9
Social welfare dependant farmers	Groundnuts	28.0	25.5
Enterprising pensioners	Tomatoes	28.1	16.2
Horticultural dependant farmers		27.0	23.1
Cooperative crop farmers		21.9	19.3
Enterprising pensioners	Cabbages	-	22.2
Horticultural dependant farmers		-	5.7
Cooperative crop farmers		-	6.7
Struggling subsistence farmers	Dry beans	18.3	19.2
Horticultural dependant farmers	Green beans	28.8	14.1

4.3.5 Integration of crop models and seasonal forecast information

A prior review of past studies was conducted to assess the approaches to integrate seasonal forecast information and mechanistic crop models. The review assessed the most feasible approach to integrate seasonal forecast and crop models under southern African conditions (Chapter 2). The review realized the GCM approach is more appropriate to integrate seasonal forecast and crop models at relatively high resolution. The approach produces seasonal forecast data at a daily time step and compatible with input data requirements for process-based crop models. GCM based forecasts are easily accessible and requires less computational capacity and skills to access the data (Hansen and Indeje, 2004). Accessibility of the GCM based forecasts is dependent on the institution hosting the model. Multiple institutions undertake climate modelling using various GCMs. Some institutions can therefore make the GCM output data available in different formats as well as at what costs. The statistical prediction assumes a direct linear relationship between the predictor and crop yields, which is not characteristic of normal crop growth and development (Hansen et al., 2006). The approach therefore leads to poor estimation of crop yields. Stochastic disaggregation cannot produce out-of-parameterized events non-previously experienced extreme rainfall, temperature, dry and heat spells (Hansen and Ines, 2005). Stochastic disaggregation demands greater computational capacity to extract the data. The analogue approach has limited applicability where there is limited weather data collection. Increased climate variability reduces the confidence in the analogue approach, as anthropogenic factors influence immediate future weather.

4.3.6 Farm management practices

The research evaluated combinations of five management practices: planting dates, fertilizer use, organic amendments, different crop types and varieties. The study assumed that small-scale farmers rarely use a single strategy to manage climate variability, but rather use a combination of the different practices (Nda-Nmadu and Dankyang, 2015). About 48 different potential combinations of applied practices were therefore used for this study (Table 4.3). Each of the combination of practices was evaluated for productivity under the bio-physical and socio-economic conditions of each small-scale farmer category. The study assumed that the amount of fertilizer applied to the crops was directly proportional to the degree of farmer resource endowment. Resource constrained farmers would therefore be unable to purchase and apply high fertilizer rates. On the contrary resource endowed farmers were able to apply high fertilizer rates. The amount of fertilizer applied by each farmer category in the different scenarios were listed in Table 4.4. The DSSAT model can only effectively account for nitrogen compared to other elements hence the fertilizer was described in nitrogen terms only (Jones et al., 2003). The pattern was similar in seeding rate where resource constrained farmers have limited financial resources such that they are unable to purchase seed leading to lower seeding rates and planting populations (Table 4.5a and b). Simulations were conducted for maize, cabbages, dry bean, green bean and tomatoes. These crops were selected as they were cultivated by farmers across all farmer types and locations. The study could not however simulate crops such as lettuce, butter nuts, onions and sweet potato (Jones et al., 2003).

Table 4.3: Potential combination of the climate variability practices amongst small-scale farmers.

Practices				Combination of practices
Variety	**Organic amendments**	**Fertilizer**	**Irrigation**	**Combination code**
Short (SH)	No amendments (NO)	Fertilizer (FE)	Irrigation (IR)	SH-NO-FE-IR
			No irrigation (NR)	SH-NO-FE-NR
		No fertilizer (NF)	Irrigation (IR)	SH-NO-NF-IR
			No irrigation (NR)	SH-NO-NF-NR
	Grass mulch (GR)	Fertilizer (FE)	Irrigation (IR)	SH-GR-FE-IR
			No irrigation (NR)	SH-GR-FE-NR
		No fertilizer (NF)	Irrigation (IR)	SH-GR-NF-IR
			No irrigation (NR)	SH-GR-NF-NR
	Maize mulch (MM)	Fertilizer (FE)	Irrigation (IR)	SH-MM-FE-IR
			No irrigation (NR)	SH-MM-FE-NR
		No fertilizer (NF)	Irrigation (IR)	SH-MM-NF-IR
			No irrigation (NR)	SH-MM-NF-NR
	Compost (CO)	Fertilizer (FE)	Irrigation (IR)	SH-CO-FE-IR
			No irrigation (NR)	SH-CO-FE-NR
		No fertilizer (NF)	Irrigation (IR)	SH-CO-NF-IR
			No irrigation (NR)	SH-CO-NF-NR
Medium (ME)	No amendments (NO)	Fertilizer (FE)	Irrigation (IR)	ME-NO-FE-IR
			No irrigation (NR)	ME-NO-FE-NR
		No fertilizer (NF)	Irrigation (IR)	ME-NO-NF-IR
			No irrigation (NR)	ME-NO-NF-NR
	Grass mulch (GR)	Fertilizer (FE)	Irrigation (IR)	ME-GR-FE-IR
			No irrigation (NR)	ME-GR-FE-NR

		No fertilizer (NF)	Irrigation (IR)	ME-GR-NF-IR
			No irrigation (NR)	ME-GR-NF-NR
	Maize mulch (MM)	Fertilizer (FE)	Irrigation (IR)	ME-MM-FE-IR
			No irrigation (NR)	ME-MM-FE-NR
		No fertilizer (NF)	Irrigation (IR)	ME-MM-NF-IR
			No irrigation (NR)	ME-MM-NF-NR
	Compost (CO)	Fertilizer (FE)	Irrigation (IR)	ME-CO-FE-IR
			No irrigation (NR)	ME-CO-FE-NR
		No fertilizer (NF)	Irrigation (IR)	ME-CO-NF-IR
			No irrigation (NR)	ME-CO-NF-NR
Long (LO)	No amendments (NO)	Fertilizer (FE)	Irrigation (IR)	LO-NO-FE-IR
			No irrigation (NR)	LO-NO-FE-NR
		No fertilizer (NF)	Irrigation (IR)	LO-NO-NF-IR
			No irrigation (NR)	LO-NO-NF-NR
	Grass mulch (GR)	Fertilizer (FE)	Irrigation (IR)	LO-GR-FE-IR
			No irrigation (NR)	LO-GR-FE-NR
		No fertilizer (NF)	Irrigation (IR)	LO-GR-NF-IR
			No irrigation (NR)	LO-GR-NF-NR
	Maize mulch (MM)	Fertilizer (FE)	Irrigation (IR)	LO-MM-FE-IR
			No irrigation (NR)	LO-MM-FE-NR
		No fertilizer (NF)	Irrigation (IR)	LO-MM-NF-IR
			No irrigation (NR)	LO-MM-NF-NR
	Compost (CO)	Fertilizer (FE)	Irrigation (IR)	LO-CO-FE-IR
			No irrigation (NR)	LO-CO-FE-NR
		No fertilizer (NF)	Irrigation (IR)	LO-CO-NF-IR
			No irrigation (NR)	LO-CO-NF-NR

Table 4.4a: Nitrogen fertilizer applied (kg ha^{-1}) to different crops within the different farmer categories in the Eastern Cape province.

Crop	Application at Days after planting	Social welfare dependant (kg ha^{-1})	Enterprising pensioners (kg ha^{-1})	Struggling subsistence (kg ha^{-1})	Horticultural dependant (kg ha^{-1})	Cooperative crop (kg ha^{-1})
Cabbage	0	21	49	28	70	63
	14	22.5	52.5	30	75	67.5
	28	22.5	52.5	30	75	67.5
	45	22.5	52.5	30	75	67.5
	60	22.5	52.5	30	75	67.5
Dry bean	0	4.2	9.8	5.6	14	12.6
	42	8.4	19.6	11.2	28	25.2
Green Bean	0	11.1	25.9	14.8	37	33.3
	30	16.8	39.2	22.4	56	50.4
	60	16.8	39.2	22.4	56	50.4
Maize	0	7.5	17.5	10	25	22.5
	35	20.7	48.3	27.6	69	62.1
Peanut	0	3.3	7.7	4.4	11	9.9
Tomato	0	15	35	20	50	45
	42	21	49	28	70	63
	84	15	35	20	50	45
	120	15	35	20	50	45

Table 4.4b: Nitrogen fertilizer applied (kg ha^{-1}) to different crops within the different farmer categories in the Limpopo province.

Crop	Days after planting	Mixed (kg ha^{-1})	Horticultural dependant (kg ha^{-1})	Off farm income dependant (kg ha^{-1})
Maize	0	51.8	70	37.1
	14	55.5	75	39.75
	28	55.5	75	39.75
	45	55.5	75	39.75
	60	55.5	75	39.75
Dry bean	0	10.36	14	7.42
	42	20.72	28	14.84
Maize	0	18.5	25	13.25
	35	51.06	69	36.57
Peanut	0	8.14	11	5.83
Tomato	0	37	50	26.5
	42	51.8	70	37.1
	84	37	50	26.5
	120	37	50	26.5

Table 4.5a: Plant density utilized in simulations for crops within the different farmer categories in the Eastern Cape province.

Crop	Social welfare dependant (plant population per m^2)	Enterprising pensioners (plant population per m^2)	Struggling subsistence (plant population per m^2)	Horticultural dependant (plant population per m^2)	Cooperative crop (plant population per m^2)
Cabbage	0,9	2,1	1,2	3	2,7
Dry Bean	5,4	12,6	7,2	18	16,2
Green Bean	7,5	17,5	10	25	22,5
Maize	1,3	3,1	1,8	4,4	4,0
Peanut	4,5	10,5	6	15	13,5
Tomato	0,6	1,4	0,8	2	1,8

Table 4.5 b: Plant density utilized in simulations for crops within the different farmer categories in the Limpopo province.

Crop	Mixed (plant population m^{-2})	Horticultural dependant (plant population m^{-2})	Off farm income dependant (plant population m^{-2})
Cabbage	2.2	3	1.6
Dry Bean	13.3	18	9.5
Maize	3.3	4.4	2,3
Peanut	11.1	15	8.0
Tomato	1.5	2	1.1

After calibration of the DSSAT crop model, crop yield simulations were conducted based on the 48-different potential climate variability management practices (Table 4.3), under 23 sets of different seasonal forecast and under different farmer types (Figure 4.1).

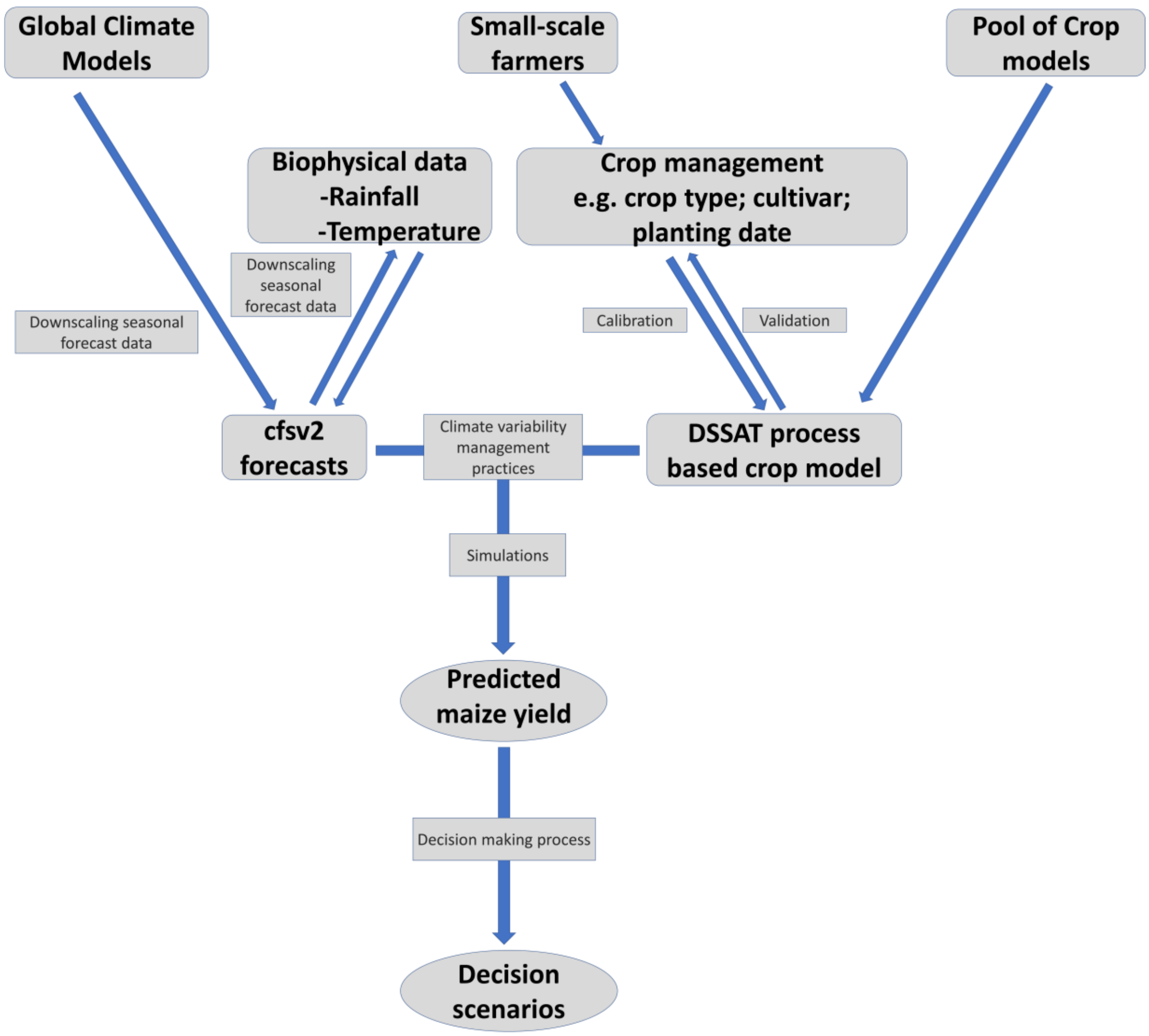


Figure 4.1: Conceptual framework of the process of integrating seasonal forecast information and crop models for decision making in small-scale farmers.

4.3.7 Decision making process

Part of the study aimed to formulate the process of identifying potential decision scenarios to improve decision-making. Crop yields simulations outputs for the different management practices and seasonal forecasts were plotted in 'heat maps' for the different crops, farmer types and location. The yield patterns were identified by the range of colour bands, with low; 'high' and ‘higher’ yields being shown by ‘red’, ‘yellow’ and ‘white’ colours respectively. The interaction effect of the farm management practices and forecasts displayed in the heat maps provided a platform for formulation of the decision scenarios. They were formulated based on assessing the pattern of yield response to the interaction between seasonal forecasts and the different combination of farm practices. The process attempted to identify a range of preferred decision capacity scenarios which can be (1) *low decision capacity and low climate sensitivity*, (2) *high decision capacity and low climate sensitivity*, (3) *high decision capacity and high climate sensitivity*. (4) *low decision capacity and low climate sensitivity*.

4.4 Results

4.4.1 Seasonal forecast variation

Temperature

The CFSv2 model was used to forecast rainfall and temperature for the 2017/18 season for both Limpopo and Eastern Cape. The forecasts outputs for minimum and maximum temperature are displayed in boxplots (Figure 4.2-4.3; Annexure 1-2). There was notable variability in daily minimum temperature across both locations. In the Eastern Cape, variation was greater in October and June (Figure 4.2) and lower from November to May but constant throughout the season in Limpopo (Annexure 1). There is therefore greater variation in minimum summer temperatures the Eastern Cape compared to Limpopo.

There was greater variation in summer maximum temperatures for both Eastern Cape (Annexure 2) and Limpopo for the period, October to January (Figure 4.3). In Limpopo variation in maximum temperatures was higher from October to March but was lower from April to July (Figure 4.3).

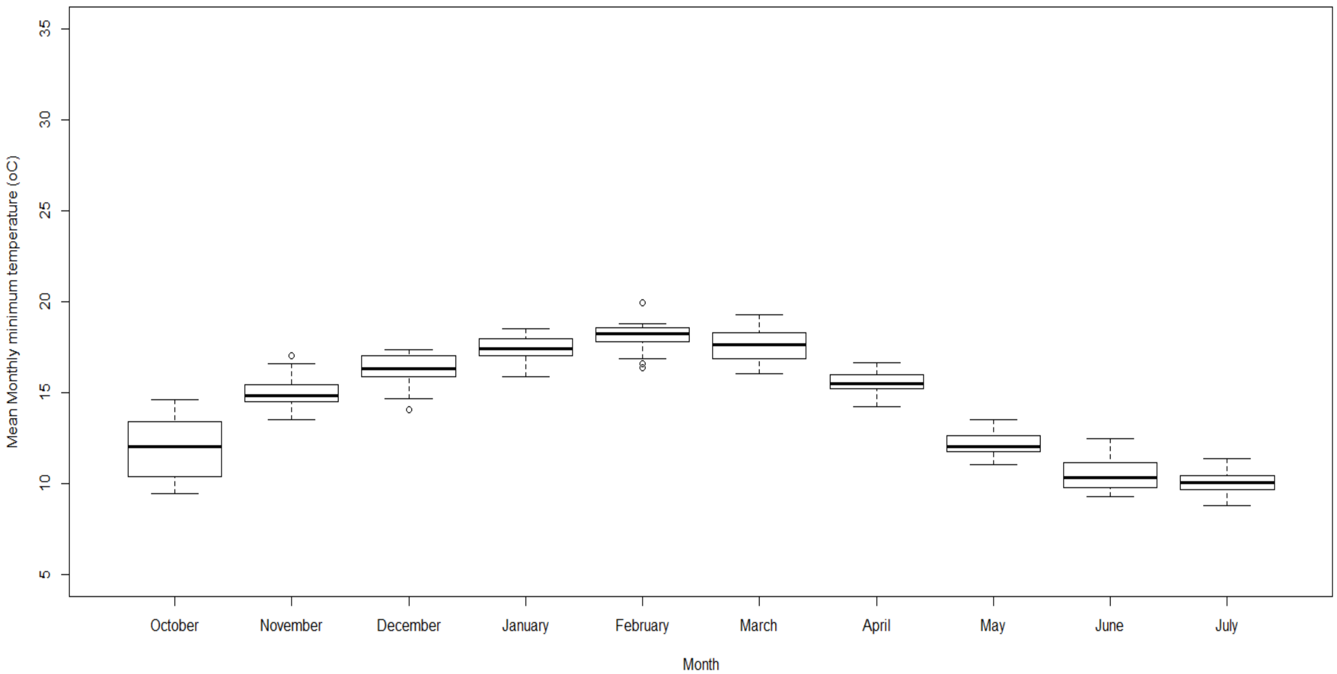


Figure 4.2: Mean minimum monthly temperatures from 23 seasonal forecasts for the 2017-18 cropping season in Nkonkobe, Eastern Cape, Limpopo, South Africa

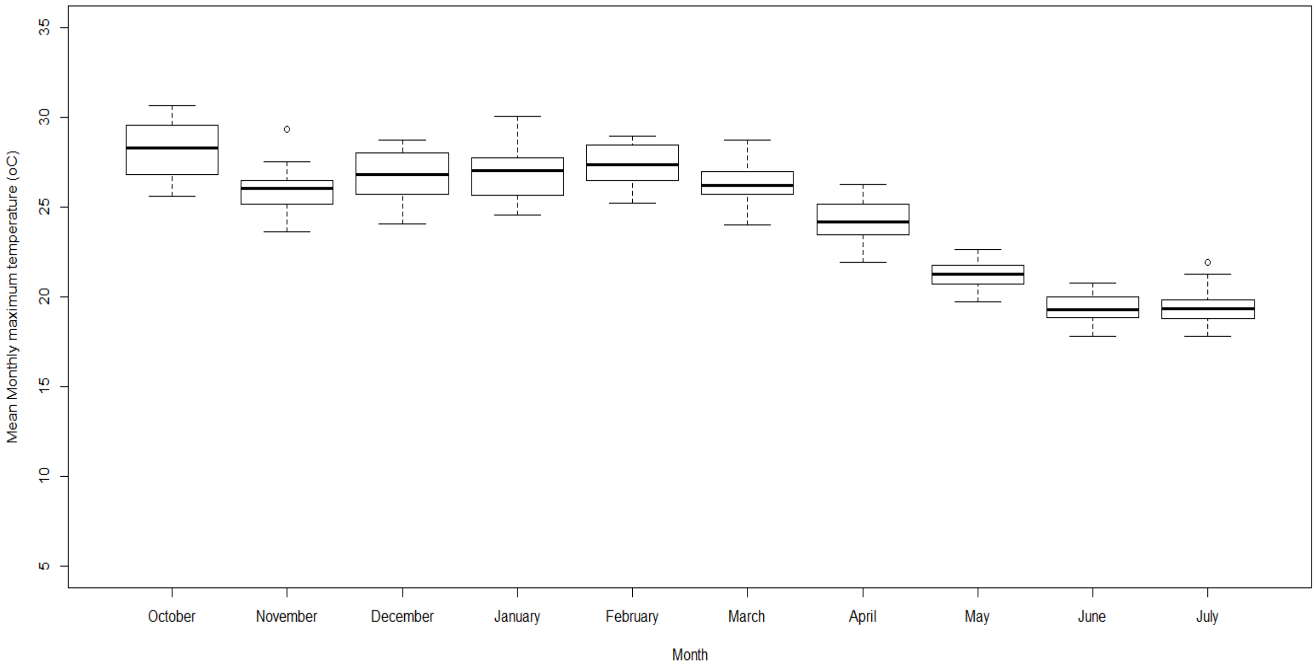


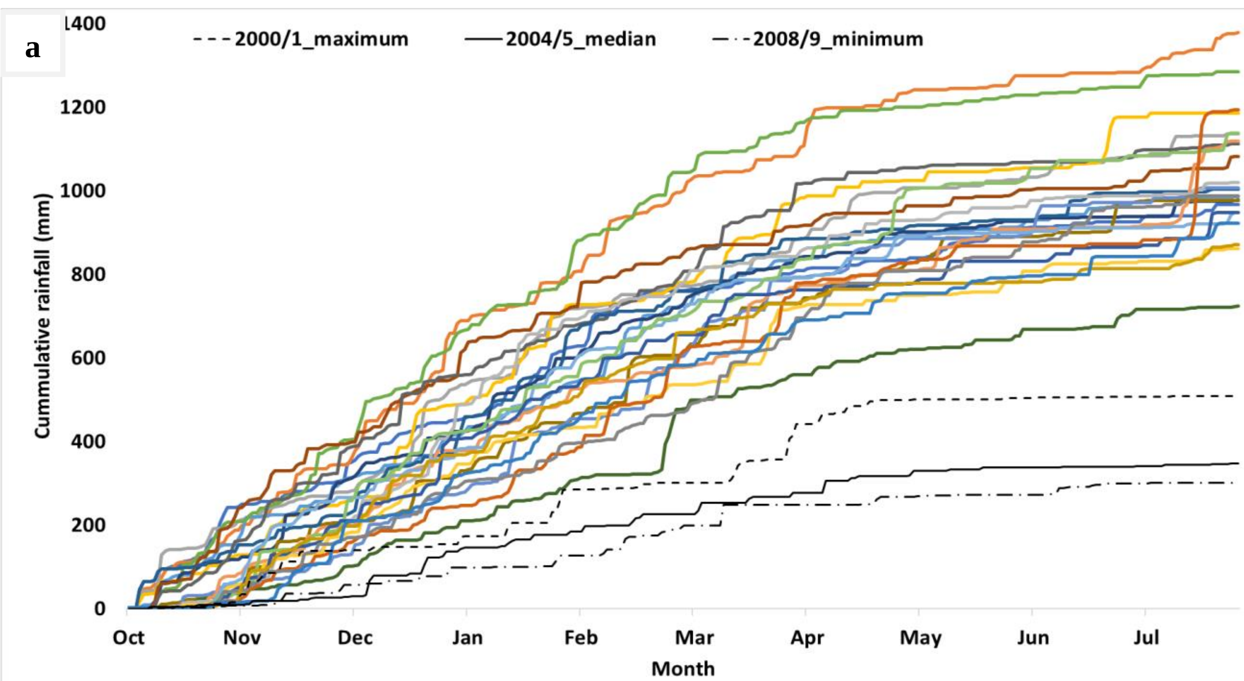
Figure 4.3: Mean maximum monthly temperatures from 23 seasonal forecasts for the 2017/18 cropping season in Lambani, Limpopo, South Africa

Rainfall

The measured daily historical rainfall trends for the period, 2000-2016 were compared to the 23 rainfall forecasts for the 2017/18 season. The outputs are displayed in line graphs (Figure 4.4a and b). Rainfall forecasts show notable seasonal variation between Eastern Cape and Limpopo, South Africa. Almost all seasonal forecasts in Eastern Cape were outside historical rainfall trends. In contrast, in Limpopo, about 90 % of the forecasts were within historical range (Figure 4.4).

For the Eastern Cape, the cumulative forecasted rainfall ranged from 720 mm to 1400 mm per season. The lowest cumulative in-season historically measured rainfall was 300 mm in 2008/9 compared to the maximum historical in-season rainfall of 510 mm in 2000/1 (Figure 4.4a).

In the Limpopo province, the minimum cumulative historical measured rainfall was 245 mm in the 2004/5 season compared to the maximum of 745 mm in the 2012/13 season. Of all the 23 rainfall forecasts only 2 had a cumulative seasonal rainfall greater than 745 mm, thus the seasonal rainfall forecasts were mostly within the boundaries of historically measured cumulative rainfall (Figure 4.4b).



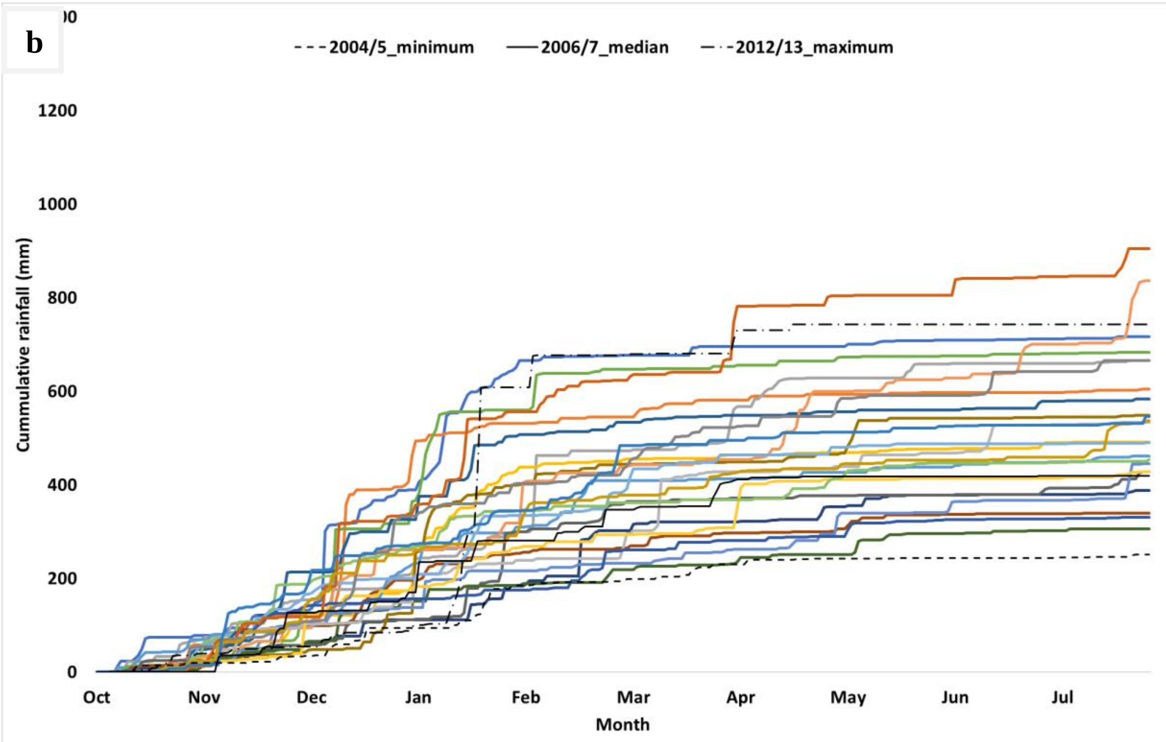


Figure 4.4: Cumulative rainfall from 23 seasonal forecasts for the 2017/18 cropping season and historical seasonal minimum, median and maximum seasonal rainfall in (a) Nkonkobe, Eastern Cape, (b) Lambani, Limpopo, South Africa.

4.4.2 Crop yield variation in response to seasonal forecast

The study evaluated the productivity of 48 different practices under a range of seasonal forecasts and sowing dates throughout the season (Table 4.3). The study utilized box plots to assess crop yield variation from the 23 different forecasts within each planting period (Figure 4.5-4.7; Annexure 3-5). For comparing yield variation resulting from the 23 different forecasts, the study selected the strategy with compost, long seasoned variety, fertilizer and irrigation CO-LO-FE-IR across the different crops and locations (Table 4.3).

Overall, there was notable variation in crop yield across the different seasonal forecasts in all crops and locations. In both locations the yield variation was greater in crop yields derived from late planting dates. In all crops except maize, yield variation was greater in the Eastern Cape compared to Limpopo. The highest maize yields were obtained in Limpopo compared to the Eastern Cape (Figure 4.5-4.7). In the Eastern Cape, crop yields generally decreased with delayed planting dates whereas the yields increased with delayed planting dates in Limpopo. In addition, the sowing window was generally narrow in the Eastern Cape compared to Limpopo for all crops except for Cabbage. It extended to April for most crops whereas it was early in December in the Eastern Cape (Figure 4.5-4.7).

In the Eastern Cape, early seeding led to higher yields in the Eastern Cape across all forecasts. In a cropping season that spanned from October to May, yields gradually decreased due to delayed planting conducted towards the end of the season. Sowing after December leads to low maize yields. On the contrary, in Limpopo, yields were relatively lower early in the season but gradually increased due to delayed sowing conducted towards the end of the season, peaking in the middle of the season in most cases (Figure 4.5-4.7).

Specifically, there was significant maize yield variation in both locations. Maize yield variation amongst the 23 seasonal forecasts was lower from yields resulting from earlier planting dates, in both locations. Maize yield variation was relatively higher with later planting dates towards end of the season. Maize yield variation amongst the different seasonal forecasts was zero in early-December and mid-February for Eastern Cape and Limpopo respectively, as the yields were zero in each of the forecasts and each planting window (Figure 4.5a and b). In the Eastern Cape the highest yields of about 4300 kg ha^{-1} were obtained by sowing early in the season i.e. early October. On the contrary, maize yields were lower from late planting dates towards the end of the season (Figure 4.5a). This was in contrast to Limpopo, where maize grain yields were lower on early planting and relatively higher on late planting in mid-January (Figure 4.5b). The maize planting window was longer in the Limpopo province compared to the Eastern Cape. The planting period was mid-October to mid-December for Eastern Cape and extended to mid-February for Limpopo (Figure 4.5).

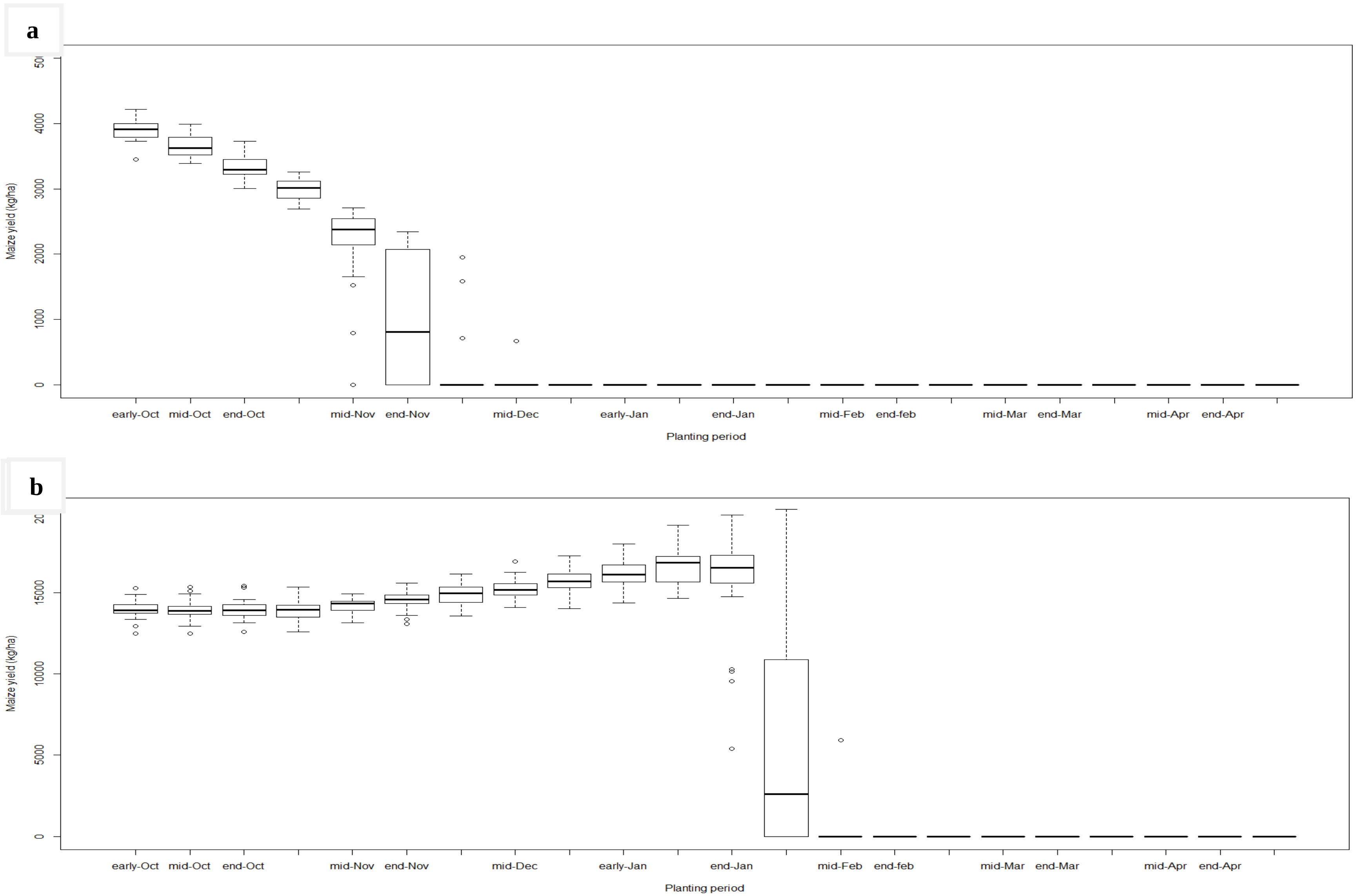


Figure 4.5: Distribution of maize grain yields from the different seasonal forecasts within different planting periods for the 2017/18 season in the (a) Eastern Cape, (b) Limpopo provinces, South Africa.

Similar to maize, there was notable variation in dry bean yields in both locations. Dry bean yield variation amongst the 23 seasonal forecasts was greater in late planting, towards the end of the season for both locations. There were however differences, where in the Eastern Cape yield variation amongst the seasonal forecast reduced with delayed planting towards the end of the season. This was in contrast to Limpopo where yield variation was greater in planting dates around mid-December, which is in the middle of the planting window (Annexure 3). In the Eastern Cape, dry-bean yields were higher with early seeding in mid-October and they gradually reduced with delayed planting towards of the end of the season. In contrast, early seeding did not lead to higher yields in Limpopo. Instead the yields fluctuated whilst increasing with delays in planting peaking in mid-November and mid-March. In contrast to maize the planting window for both Eastern Cape and Limpopo was similar for dry-bean ending in early-March and mid-April respectively (Annexure 3).

There was notable green bean yield variation throughout the season. Yield variation was however more notable in November and January. The planting window extended until January which was shorter than dry beans. The maximum yields were obtained from seeding in the periods, early and late November (Annexure 4).

There was notable variation in peanut yields in both locations. The greater peanut yield variation amongst the 23 seasonal forecasts was realized in yields resulting from delayed planting dates towards end of the season for both locations. Highest yields were obtained in early-November for both locations. There were however notable differences in the planting window, where it extended to early December and end of February respectively (Figure 4.6).

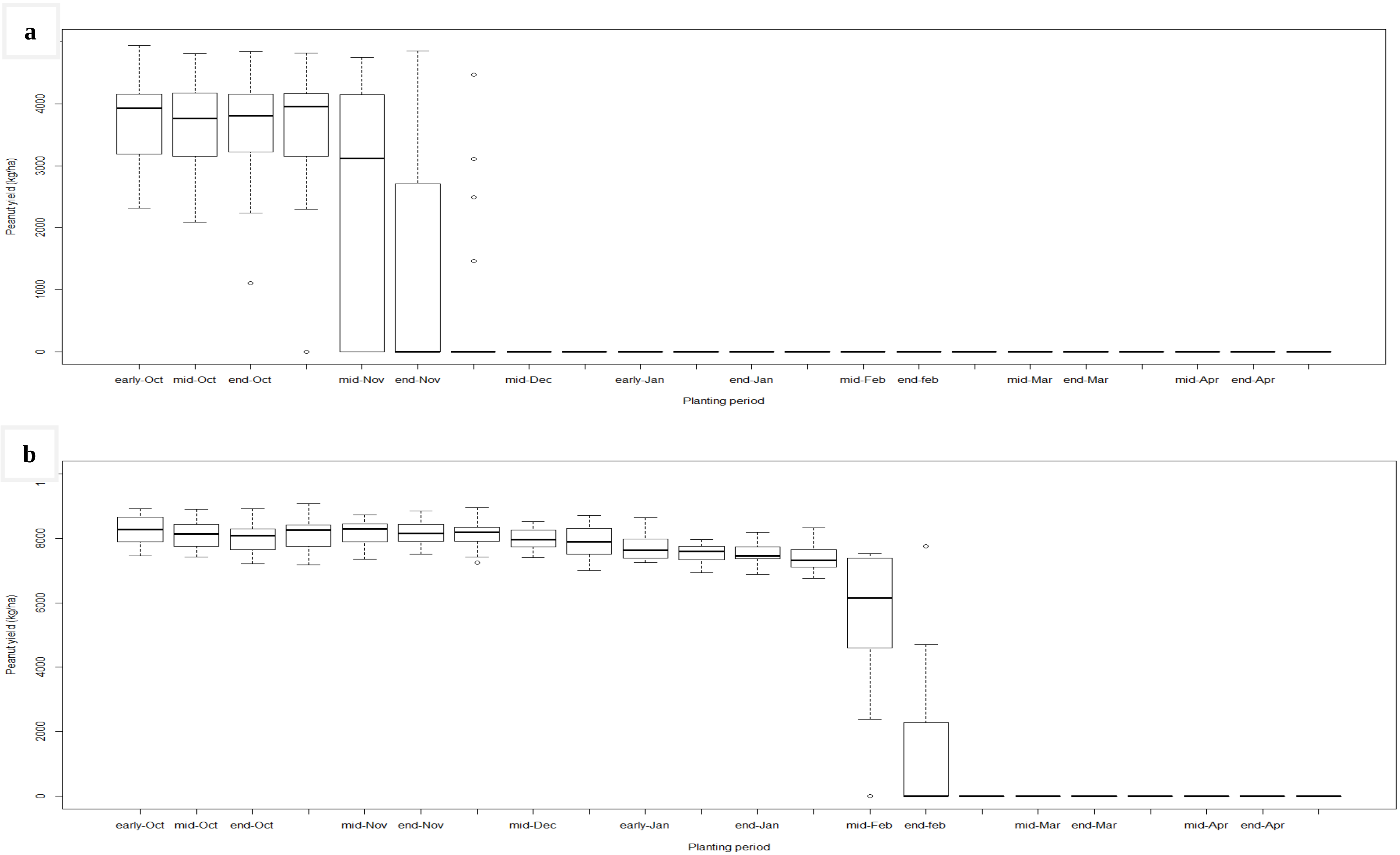


Figure 4.6: Distribution of peanut grain yields from the different seasonal forecasts within each planting period for the 2017/18 season in the (a) Eastern Cape, (b) Limpopo provinces, South Africa.

There was notable tomato yield variation across the 23 different seasonal forecasts within each planting period in both locations. In the Eastern cape, yield variation decreased with delayed planting dates (Annexure 5a). In contrast, the tomato yields across the different seasonal forecasts fluctuated in different planting dates throughout the season but peaked with later planting dates towards the end of the season (Annexure 5b). The highest yields in the Eastern cape are obtained on planting in early October compared to Limpopo where planting in late January led to the highest yields. The sowing window also differed where in Eastern cape the window extended to early February but extended to mid-March in Limpopo (Annexure 5b).

There was notable variation in Cabbage yield across all the planting periods in both locations. The variation was however greater in the Eastern cape compared to Limpopo. In Limpopo the highest yields were realized from sowing towards end of December whereas the highest yields were obtained from sowing towards the end of the season around the end of January in Limpopo. In contrast to all crops the planting window was greater in the Eastern cape compared to Limpopo. The planting window extended to April in the Eastern cape whereas it extended to early February in Limpopo (Figure 4.7).

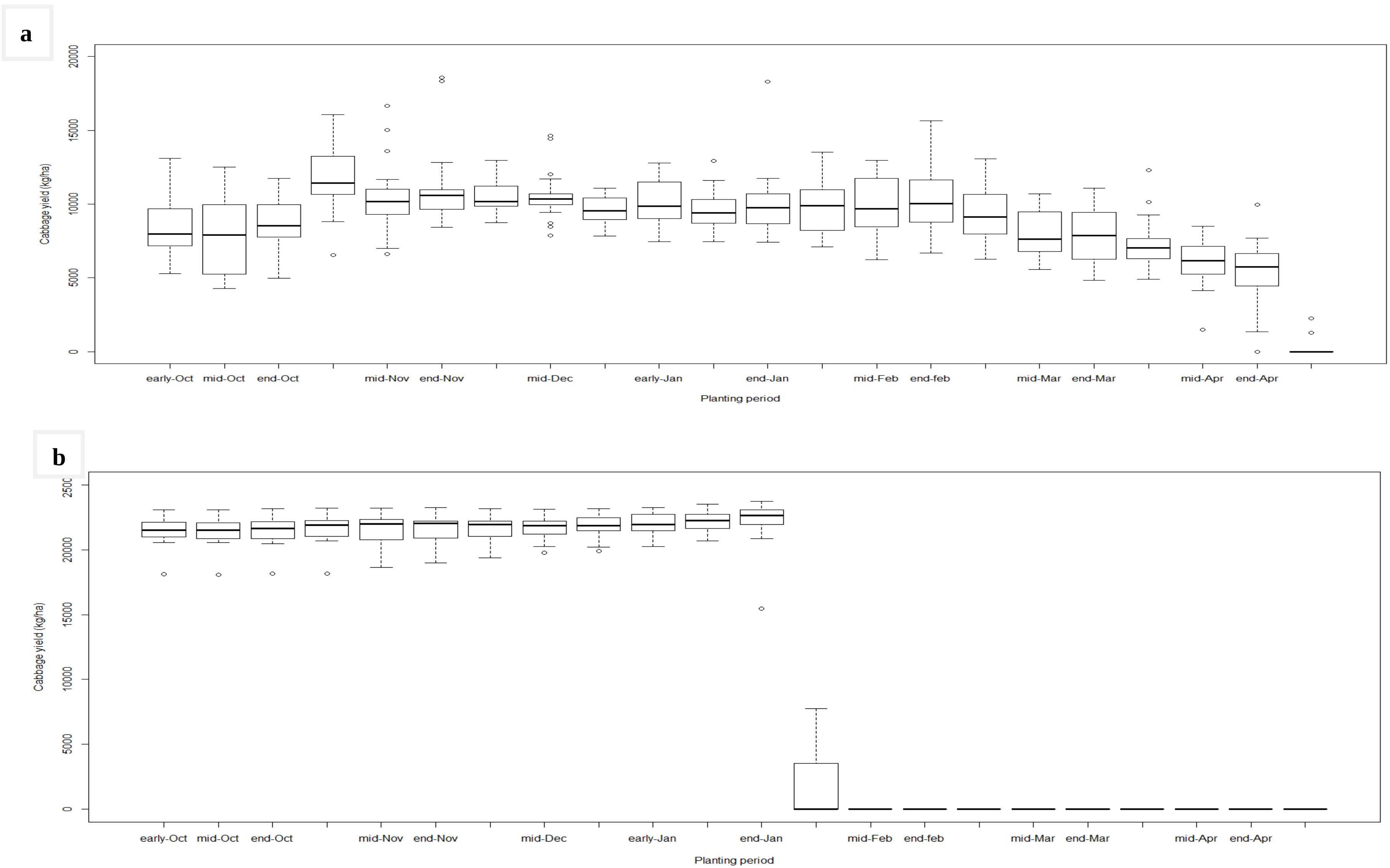


Figure 4.7: Distribution of cabbage yields from the different seasonal forecasts within each planting period for the 2017/18 season in the (a) Eastern Cape, (b) Limpopo provinces.

4.4.3 Crop forecast based decision-making process

Formulation of the decision-making process was undertaken by assessment of the yield patterns from a set of farm management practices under a range of different seasonal forecasts for each crop and different farm types. The study used heat maps to provide a visual illustration of the dynamics within the different farm management decision capacity scenarios. The yield differences from the different farm management practices and seasonal forecasts, were illustrated using heat maps. In these heat maps, the 'red' and 'yellow' colors indicated relatively 'low' and 'high' crop yields respectively. The dendrogram on either axis clustered the farm management practices and seasonal forecasts leading to similar crop yields. To formulate the decision process, heat maps displaying similar trends were classified into different categories.

Overall the study identified 3 broad decision scenarios which are: (1) *low decision capacity and low climate sensitivity*; (2) *high decision capacity and low climate sensitivity*; and (3) *high decision capacity and high climate sensitivity*. The study did not however identify another potential scenario, (4) *low decision capacity and high climate sensitivity*.

Low decision capacity and low climate sensitivity

In this scenario there was a reduced capacity to inform decisions and lower sensitivity to climate predictions. The scenario describes conditions where there is uniform response to varying farm management as well as uniform response to varying seasonal forecasts. This was manifested through uniform performance of all farm management practices across all forecasts. This was an indication of the uniform response of the management practices to the range of seasonal forecasts (Figure 4.8-4.9).

Specifically, there were instances where neither varying farm management practices nor varying seasonal forecasts led to differences in crop productivity, as highlighted by the uniform 'red' color, which was an indication of relatively low yields (Figure 4.8-4.9). The crop yields were relatively low across most farm management practices and different seasonal forecasts. Such decision scenarios account for about 9% of all cases (Figure 4.8).

The pattern was more specific for tomato, for mixed farmers in Limpopo, South Africa (Figure

4.8). Yields from such farm management practices were similar and also relatively low. There were some instances where there were slight differences in the ideal farm management practices as indicated by the alternating ‘faint red’ and ‘dark red’ colours. Despite the minor differences, this highlights the lower capacity to inform to the decision making (Figure 4.9).

Despite the uniform tomato yields from the different farm management practices, between cooperative crop farmers in the Eastern Cape (Figure 4.9) and mixed farmers in Limpopo (Figure 4.8), there were however minor yield differences for cooperative farmers in the Eastern Cape (Figure 4.9). A set of practices including irrigation showed slightly higher yields compared to other practices, but the differences were however minor as observed by the uniform ‘red’ colour (Figure 4.9).

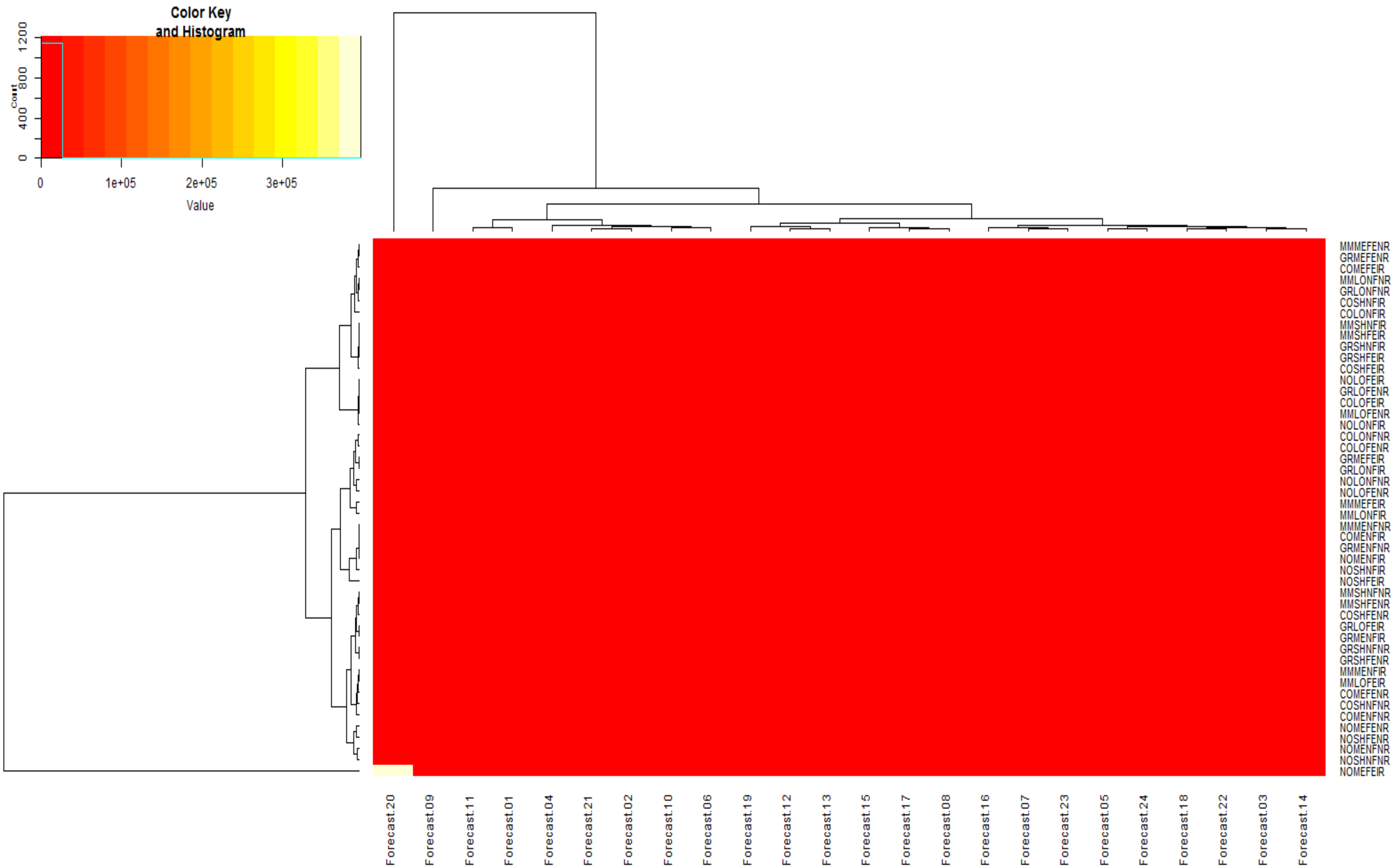


Figure 4.8: Tomato yield pattern under different combinations of farmer practices and seasonal forecasts amongst mixed farmers in Limpopo, South Africa.

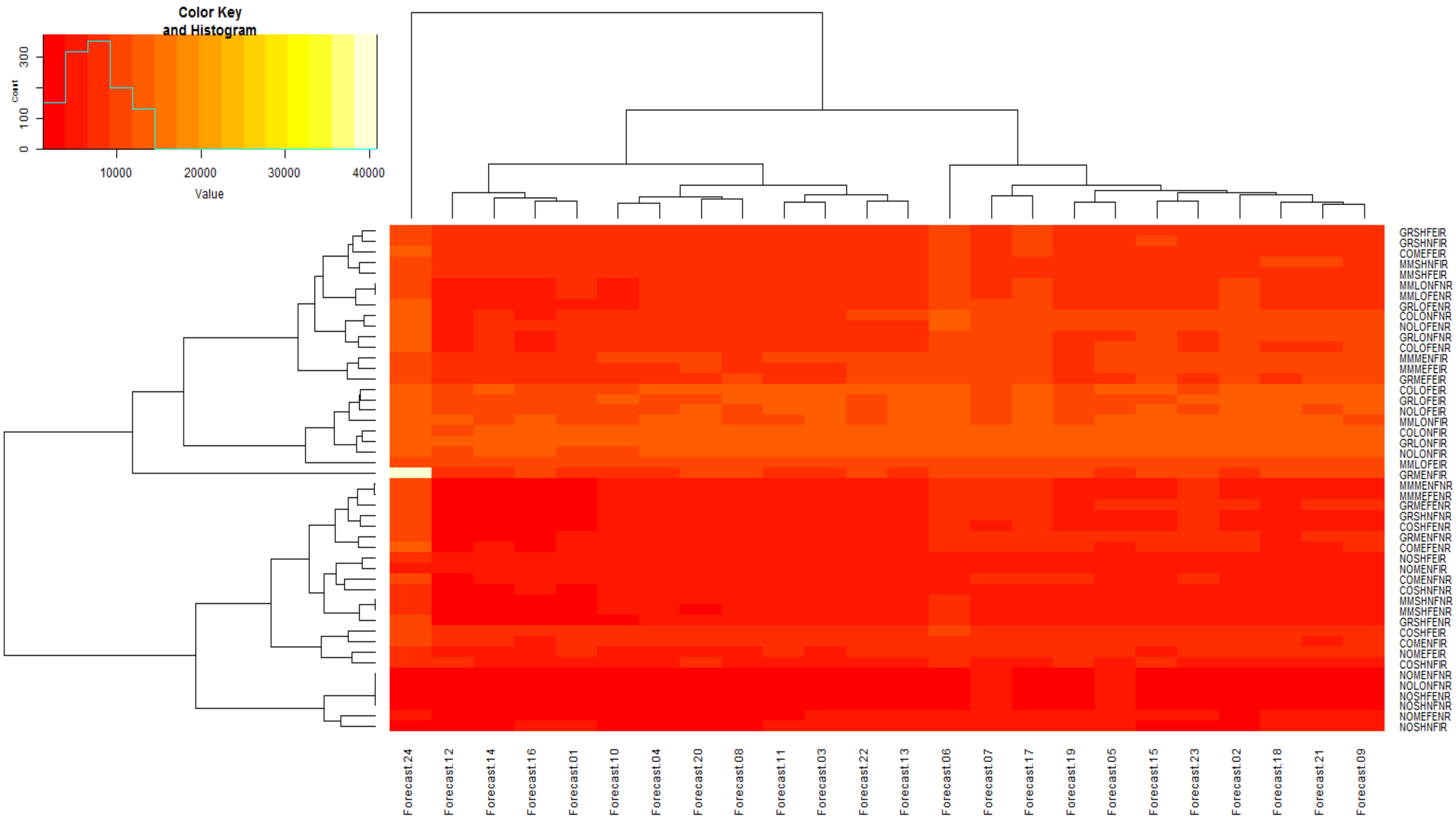


Figure 4.9: Tomato yield pattern under different combinations of farmer practices and seasonal forecasts amongst cooperative farmers in the Eastern Cape, South Africa.

High decision capacity and low climate sensitivity

The scenario highlights cases where there is a high decision capacity and low sensitivity to the varying climate prediction. Such a scenario highlights a greater potential to inform decision making. The scenario is characterized by yields largely affected by changes in farmer practices, and less affected by the change in seasonal forecasts. Specifically, there were some instances where a group of management practices leading to the highest yields were consistently similar across all seasonal forecasts. This therefore suggests that these practices are resilient to varying seasonal forecasts as they lead to consistently higher yields despite variation in forecasts (Annexure 6-12). The pattern was observed in about 51 % of all the cases (Figure 4.10-4.11) (Annexure 6-16).

The set of management practices with organic amendments, fertilizer and irrigation consistently had higher yields across all forecasts. The practices with no irrigation consistently led to low yields as illustrated by the deepening red color. Such management practices were GR-LO-FE-IR. The pattern was consistent across all the forecasts and farmer types (Figure 4.10).

Specifically, for social welfare dependant farmers in the Eastern Cape, South Africa, the farm management practices that consistently led to higher maize yields included long seasoned varieties, organic amendments, fertilizer and irrigation. In this scenario, there were some instances, where the highest yields were derived from farm practices with no fertilizer. This was particularly in combination of practices with compost manure. This was in contrast to Figure 4.10 where all farm management decisions with no fertilizer led to lower yields across all forecasts. The lowest maize yields were derived from a combination of practices with no irrigation and mostly with short season varieties with no fertilizer and irrigation. Some combination of practices with no irrigation also led to relatively higher yields across all seasonal forecasts. The pattern was consistent across all crops, farmer types in both locations except in the peanut crop.

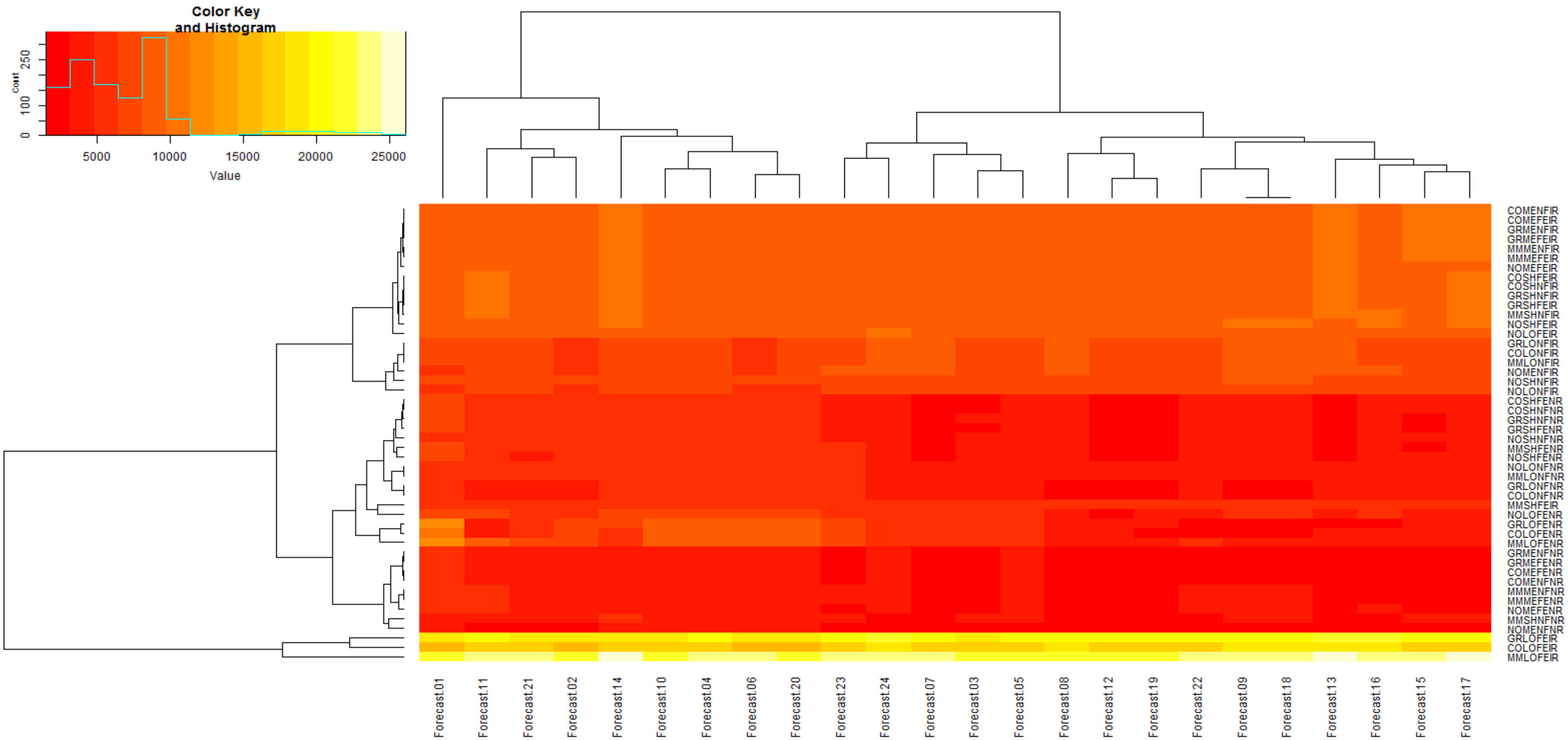


Figure 4.10: Maize yield patterns under different combinations of farmer practices and seasonal forecasts amongst mixed farmers in Limpopo, South Africa.

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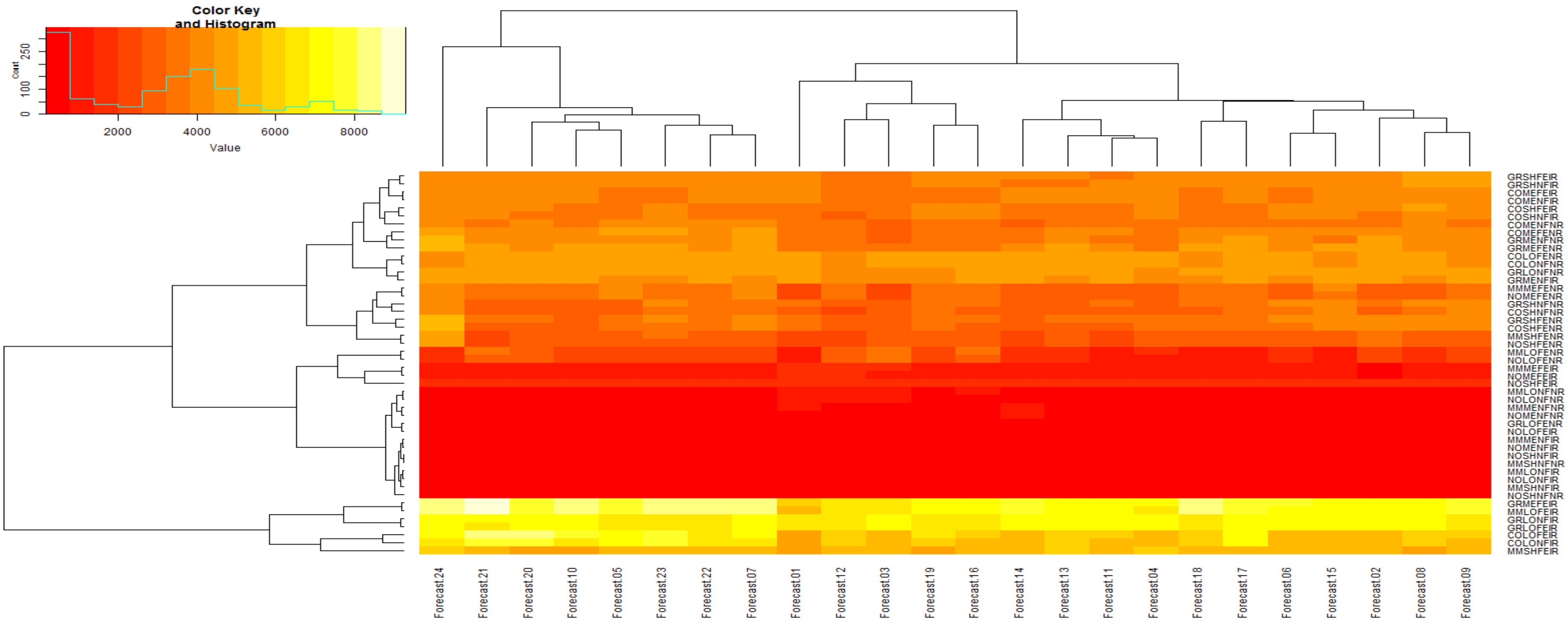

Figure 4.11: Maize yield patterns under different combinations of farmer practices and seasonal forecasts amongst social welfare dependant farmers in the Eastern Cape, South Africa

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High decision capacity and high climate sensitivity

The scenario was characterized by yields highly impacted by changes in farmer practice, as well as by changes in seasonal forecasts. The high decision capacity resulting from the clear and contrasting impact of varying practices is devalued by the uncertainty of the different sets of seasonal forecasts. This was identified through the contrasting colour codes with 'yellow' to 'white' showing higher yields and 'red' showing lower yields. The clear contrasting colors is an indication of the easiness of making farm management decisions. Despite the high sensitivity of yield to seasonal forecasts, the best yields are still achieved with a limited set of practices, which would remain valuable for decision making (Figure 4.12-4.13) (Annexure 16-18, 21-27).

Specifically, there were instances where the productivity of farm management decisions varies with forecasts. Some farm management practices led to higher crop yields under certain seasonal forecasts but led to lower yields under different forecasts. The pattern was consistent in about 40% of all the cases (Figure 4.12-4.13) (Annexure 16-18, 21-27).

In the Eastern Cape, under off farm income farmers, in peanuts, farm management decisions including long seasoned varieties, fertilizer and irrigation led to higher yields amongst all forecasts except from forecasts 01 and 11 (Figure 4.12). Forecasts 24, 03 and 21 had higher peanut yields under maize mulch, medium varieties, no fertilizer and no irrigation, whereas other forecasts showed lower yields under the same practices. Management practices with medium varieties, organic amendments and irrigation such as CO-ME-NF-IR and GR-ME-NF-IR led to higher peanut yields in some forecasts such as forecast 24, 12 and 13 compared to other forecasts which showed relatively lower peanut yields (Figure 4.12).

The pattern was similar and more pronounced for green beans amongst mixed farmers in Limpopo, South Africa (Figure 4.13). Most of the management practices leading to lower yields did not include irrigation and the pattern was uniform and consistent amongst all forecasts e.g. CO-ME-FE-NR. There was also a combination of management practices such as GR-LO-FE-NR that led to lower yields amongst 42 % of the forecasts and also led to higher yields amongst 52 % of the forecasts. Most of the practices leading to higher green bean yields under mixed farmers in Limpopo, South Africa included irrigation with no organic ground cover as well as different varieties (Figure 4.13).

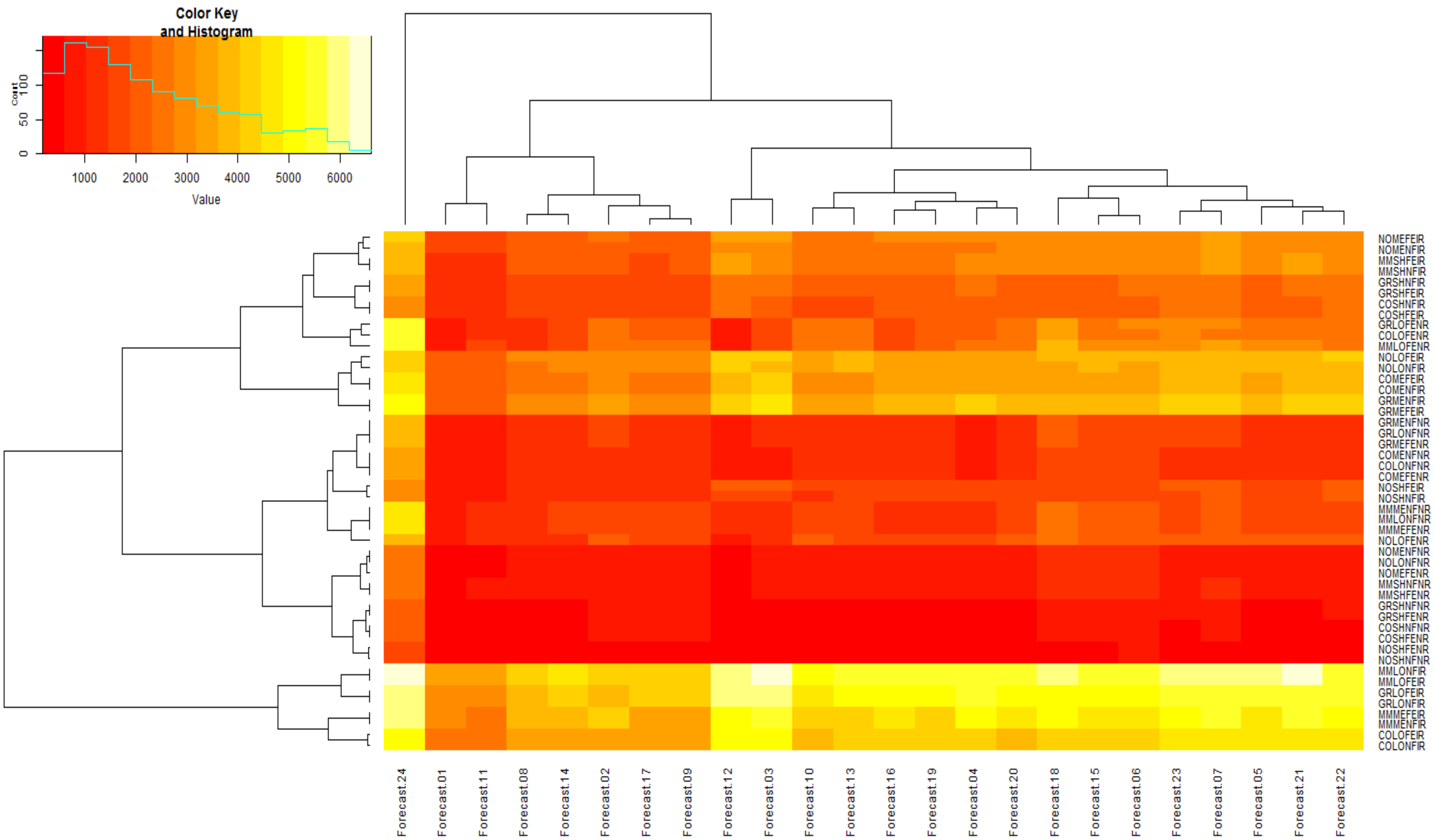

Figure 4.12: Peanut yield patterns under different combinations of farmer practices and seasonal forecasts amongst off farm income farmers in the Eastern Cape, South Africa.

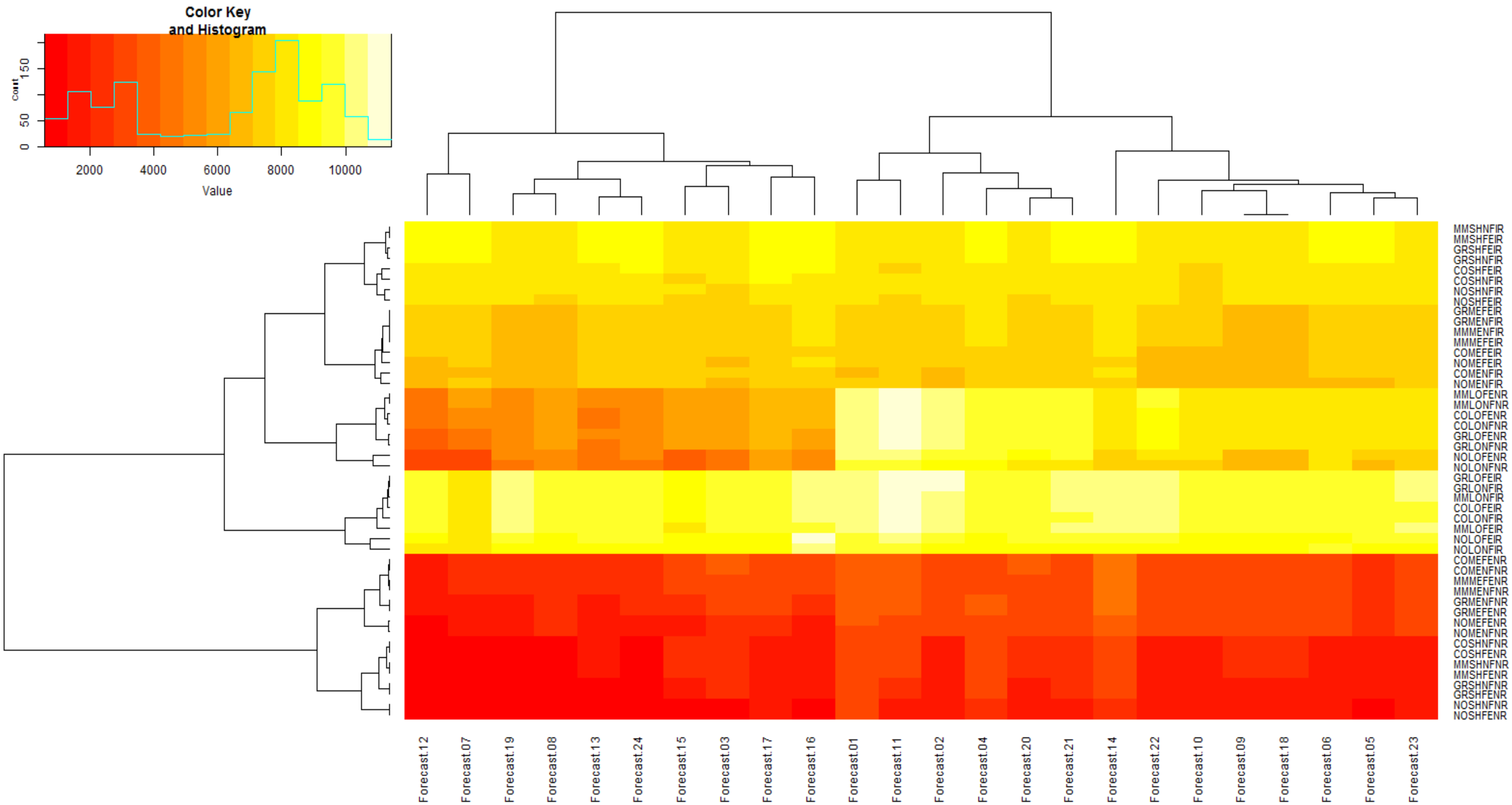

Figure 4.13: Green bean yield patterns under different combinations of farmer practices and seasonal forecasts amongst mixed farmers in Limpopo, South Africa.

4.5 Discussion

4.5.1 Consequences of forecast variability on crop productivity

Yield variation across the different crops and locations was partially attributed to the variation in the CFSv2 seasonal weather forecast information across all parameters in both locations (Figure 4.2-4.4). There are multiple factors that determine weather, within a specific agro-ecological zone. In contrast to atmosphere-land interaction, there are many oceanic-atmospheric based weather determinants that have not been accounted for by scientific research. Global climate models would therefore have to account for all determinants of weather for effective forecasting. There is therefore a greater daily variation in temperature and rainfall forecasts, leading to notable crop yield variation (Landman et al., 2012). There is reduced confidence to end-users especially farmers as there is no certainty to the predicted weather conditions. There is therefore need for greater financial and human resource investment in improving quality of seasonal forecasts.

The study realized notable variation in seasonal forecast as well as yield forecasts across all locations and crops. Most rainfall forecasts for Limpopo are within the historical range of measured weather data whereas most forecasts in the Eastern Cape were not within historical range (Figure 4.4). Previous research shows that there is higher skill in North eastern, western and central regions of South Africa (Landman et al., 2012). The higher skill increases the confidence in crop yield forecasts from seasonal forecasts based on the region. Farmers can therefore make use of seasonal forecast information for decision making purposes. There is limited forecasting skill in the South-eastern region, which is occupied by the Eastern Cape province of South Africa. The lower skill in regions bordering the oceans, such as the Eastern Cape, is therefore attributed to the inability of the models to account for most of the factors that determine weather, as well as the additional ocean-based climate determining factors. The lower skill reduces the confidence in crop yield forecasts from seasonal forecast. Farmers can therefore not use seasonal forecast information for decision making. In contrast to the Eastern Cape, crop yield forecasts and corresponding recommendations from Limpopo are therefore likely to be within historical range. This is attributed to the relatively higher forecasting skill in the Limpopo region. GCMs can account for several factors that determine future weather, in the region compared to the Eastern Cape. This increases the need for further research in developing skill that improves reliability of seasonal forecast information.

There was also notable crop yield variation from sowing periods towards the end of the season across all crops and locations. This was attributed to the increased rainfall variability towards the end of the cropping season. Increased rainfall variability leads to reduced planting opportunities which is associated with extreme rainfall variability biased towards low rainfall events. This therefore increases the chances of crop failure and increasing yield variability.

The highest yields were realized by sowing early in the season in the Eastern Cape. Early seeding increases the crop's chance of being exposed to solar radiation for a long time period and increased soil nitrogen mineralization earlier in the season (Nyagumbo et al., 2017). This therefore causes early vigorous crop growth. When the crop experiences mid-season dry spells, the crop would have already acquired tolerance due to initial vigorous growth. Delayed sowing would therefore cause low yields as this increases the crop's chances of sensitive phonological growth stages coincides with mid-season dry spells, leading to lower yields (Nyagumbo et al., 2017). A day's delay in planting leads to about 5 % yield loss in maize (Shumba et al., 1992). The major cause of yield loss as the season progresses is the increased rainfall and temperature variability as the season progresses. Farmers in the Eastern Cape or regions with agro-ecological conditions are therefore encouraged to plant earlier in the season to increase chances of attaining higher yields.

On the contrary early sowing did not lead to the highest yields in Limpopo, but the highest yields were realized from sowing in the middle of the cropping season. There is increased rainfall variability earlier in the season in Limpopo. In addition, the precipitation intensity is relatively lower. This therefore reduces the amount of water available for crop growth and development earlier in the season. This increases the chances of crop failure as well as low yields. Sowing in the middle of the season, will result in crop germination and development after the early season and mid-season droughts have passed. This therefore increases the chances of higher germination percentage as well as higher crop yields. There is therefore greater yield benefit for farmers to cultivate crops late in the season compared to early in the season. Given seasonal forecast information farmers in Limpopo are recommended to sow early to attain greater yield benefits.

4.5.2 Crop management practices

Most farm management practices leading to higher yields included organic residues such as maize, grass and compost, as well as long seasoned varieties, fertilizer and irrigation. This was consistent across most seasonal forecasts. The lowest yields were realized from a combination of practices with no fertilizer, short seasoned varieties and no irrigation.

Organic cover increases soil moisture through minimizing soil erosion and surface evaporation, which also reduces soil water loss. Soil water is critical in crop growth and development. Increased soil moisture enhances and prolongs crop growth and development leading to higher yields. The degree of yield increment differs with quantity and type of organic ground cover. Low quantities of mulch reduce moisture conservation leading to reduced yields. Mulch has proved to be effective in conserving soil moisture amongst farmers in Southern Africa. Past research shows that use of mulch leads to significant increase in yields under drier conditions as well as in soils of lower water holding capacity. Mulching increases crop yields by as high as 50 % (Thierfelder et al., 2014b). Farmers cannot be restricted to the use of grass, maize mulch and compost used in the study. Farmers can also make use of the diverse array of organic amendments such as leaf litter and residues from leguminous crops such as sunhmep, tephrosia and mucuna. Excessive use of mulch can however lead to waterlogging with consequences in leaching and ultimate crop yields loss (Wang et al., 2017). On the contrary, bare soil has a greater run-off potential which leads to reduced soil water infiltration and lower soil moisture. This therefore leads to lower crop yields (Thierfelder et al., 2014b). The combination of practices is potentially more reliable for use by farmers as about 51 % of the simulations included organic ground cover, fertilizer and irrigation.

There were some practices which led to contrasting yields under different forecasts. This was dominant in 40 % of the cases. Specifically, for peanut about 10 % of the forecasts had lower yields under organic residues, long seasoned varieties, fertilizer and irrigation. This may have been attributed to the relatively higher rainfall of up to 1100 mm. This therefore led to excess water available for crop growth and development. Thus causing; leaching and ultimately low yields. Farmers who have limited resources can therefore not use irrigation as there is sufficient soil moisture from the rainfall (Wang et al., 2017).

Most farmers prefer practices that conserve soil moisture or minimize soil moisture demand. Use of fertilizer does not increase or reduce soil moisture but however enhances the effectiveness of other practices to manage climate risk. Fertilizer increases nutrient availability to crops, therefore increasing efficient utilization of supplementary or conserved soil moisture. Benefits of fertilizer application are experienced under non-water limiting conditions as this leads to high yields. Application of fertilizer under water limited conditions cause fertilizer toxicity. On the contrary, under moisture limited conditions fertilizer can therefore not be applied as this leads to reduced yields and financial losses (Liu et al., 2016). Use of crop residues, potentially leads to nitrogen 'lock up' due to microbe activity. Application of minimal amounts of fertilizer therefore minimizes potential nitrogen 'lock up', thus improving crop yields.

Use of different crop varieties can be utilized in managing climate risk. Due to climate variability there has been irregular commencement and cessation of the rainfall season. Cultivation of short seasoned varieties enhances chances of increasing crop production in short seasons. Short seasons are characterized by delayed commencement of the rainy season or early cessation of rains. When forecasts predict longer rainfall season the farmer can cultivate long seasoned varieties. Long seasoned varieties have relatively slow growth and development, thus prolonging the growing period. They can therefore benefit from abundant rainfall, solar radiation and nutritional resources leading to higher yields (Seedco, 2018). This study therefore repeatedly realized high yields under higher yields under practices involving long seasoned varieties. This was due to increased soil moisture for crop growth and development due to irrigation as well as the mulching effect.

4.5.3 The decision-making process

When faced with a range of potential farm management decisions researchers and farmers face challenges on the identification of the most appropriate option. The study therefore assessed the pattern of interaction of a range of farm management practices and their corresponding potential under varying seasonal forecasts across all crops, farmer types and locations based on 2017/18 as the case study season. Assessing the pattern of interaction of a range of practices and the different forecasts leads to the development of a range of decision scenarios that enhances decision making. From the assessment of the patterns based on the case study season, the study realized the following decision scenarios: (1) *low decision capacity and low climate sensitivity*. (2) *high decision capacity and low climate sensitivity*. (3) *high decision capacity and high climate sensitivity*. The study did not however realize another potential decision scenario which could be (4) *low decision capacity and high climate sensitivity*.

Under the *low decision capacity and low climate sensitivity* scenario, there are challenges in decision making as all the management practices have uniform performance regardless of the varying climate conditions or different choice of farm practices. Given such a scenario, there is limited or no value arising from the choice of farm management practices as they all have a similar performance, including under varying seasonal forecast. The approach therefore does not provide valuable information for decision making. In such a scenario the end user, which is the farmer, is the most likely source of decision making. Such a scenario can also be characterizing potential future conditions where there is low climate variability corresponding to weak climate sensitivity. Under these conditions of low climate variability there is no need for alteration of farm management practices due to the non-significant changes in climate. Such conditions are however unlikely to be experienced as most climate predictions project increased climate variability. From the study such a scenario was identified in about 9 % of the cases hence the chances of experiencing such a scenario are relatively low.

The *high decision capacity and low climate sensitivity* scenario is highly valuable as there is a clear pattern and distinction of the performance of a range of farm management practices. The uniform performance of the practices occurs under conditions of limited sensitivity to forecast variation. The scenario can offer information on a clear subset of practices, which leads to high yield throughout the range of explored seasonal forecast. Decision making is therefore relatively easier under the *high decision capacity and low climate sensitivity* decision scenario. Such scenario is therefore valuable to the decision maker. Given that projections show potential increase in climate variability and change within the next 50-100 years (Niang et al., 2014). In this study, such a scenario occurs in about 51 % of the cases and therefore there is a higher chance of manifestation in the future.

There could also be valuable information for decision making, when both decision capacity and climate sensitivity are high. In such a scenario the performance of some practices is dependent on the climate. There is also better performance of some practices under certain specific forecasts relative to other forecasts. To a farmer distinguishing the management decision of choice is however challenging as there is need to separate and analyze the characteristics of the different climate forecasts. For climate and variability management analysis the scenario is useful as one can make farm management decisions that correspond to specific climate conditions. The scenario is very useful considering the projected increase in climate variability and change. The scenario mimics climate change and variability through varying seasonal forecasts. Such a scenario would therefore be beneficial under conditions of climate change. Such decision-making scenario was observed in about 40 % of the scenarios hence there is minor chance of occurring.

The case study did not however identify another potential decision scenario; *low decision capacity and high climate sensitivity*. Such scenario would be the most challenging of all the decision scenarios as it would offer a low decision capacity. There is therefore a limited impact of varying management practices and high sensitivity to seasonal forecast, which is challenging for decision making.

There is a chance that the *low decision capacity and high climate sensitivity* scenario which was not realized in the study as well as the *low decision capacity and low climate sensitivity* realized in low proportions can potentially be realized in the future. This could potentially arise from increased climate variability and change, which is also associated with the manifestation of climate phenomenon which previously occurred at low frequencies. Decision making under both scenarios is however challenging. The study can therefore project challenging future decision making with increasing climate change and variability. Non-identification of such a scenario could be attributed to the use of a limited sample size where this study used one season. Use of a larger sample can therefore improve the possibility of realizing such a scenario.

4.5.4 Sustainable use of seasonal forecast information

The research realized increased variation in seasonal forecast information from multiple forecasts for both rainfall and temperatures. There is a positive correlation between rainfall and crop yield (Drastig et al., 2016). Seasonal forecast variation therefore leads to crop yield variability. It is therefore challenging to make specific recommendations based on each specific seasonal forecast. The challenges associated with greater seasonal forecast variation can be counteracted using the decision capacity scenario identified in the study (Section 4.4.3). Such decision scenarios enable identification of a set of specific farm management practices that fit within the range of available forecasts. The effect of variation is therefore smothered by assessing the trend of the response of seasonal forecasts to sets of management practices.

The challenge can also be solved through, assessment of seasonal forecasts at a holistic level. Comparing parameters of seasonal forecast rainfall with historical rainfall extremes provides a measure of the seasonal forecast's relative to historical rainfall. Seasonal forecast information can also be used with short term weather forecasts, which have improved accuracy. Seasonal forecasts provide information of the general seasonal trends, which enhances determination of holistic farm management decisions, such as choice of crop. The study has shown that use decision scenarios such as the *high decision capacity and low climate sensitivity* enables decision making. This however does not solve the issue of variation in crop forecasts attributed to variation in seasonal forecasts. Despite differences in forecast accuracy practices including organic ground cover such as maize mulch, long seasoned varieties, increased fertility and irrigation consistently led to higher productivity across different farmers categories and location. Use of short-term weather forecast during the cropping season also complement use of seasonal forecasting where farm operations such as fertilizer application are sensitive to in-season weather, hence short-term weather forecasts can also be used to determine timing of fertilizer application.

Seasonal forecast information can also be used with indigenous knowledge (IK). IK is very diverse and is most IK holders are old-black African farmers. IK can also be used to determine short, medium to long term seasonal forecasts. IK uses the behavior and dynamics of natural and bio-physical phenomenon such as insects, animals, rivers, vegetation, trees etc. to determine weather. Certain specific changes in the behavior and dynamics has been found to be correlated with the occurrence of specific weather patterns. For instance, presence of locusts, mopane worms etc. usually correspond with very dry seasons. The presence and specific behavior of swallows is associated with immediate rainfall. Increase in the frequency of the birth of female animals such as cows or even humans, is a sign of an incoming high rainfall season. IK can therefore compliment the uncertainties associated with seasonal forecast information (Mapfumo et al., 2016).

4.6 Chapter conclusion

The research highlighted the potential feasibility of integrating seasonal forecast information and crop models in farm management decision making under South African small-scale farming conditions. The research however realized notable crop yield forecast variation across all crops, farmer types and locations due to inherent forecast variability. The crop yield forecasts from Limpopo are potentially more reliable compared to Eastern Cape as the forecasts are within range of measured historical weather. Greater crop yields can be realized with early planting in the Eastern Cape, whereas sowing mid-season leads to greater yields in Limpopo.

The benefits of integrating seasonal forecasts and crop models can be expanded to include the larger decision-making process to enhance farm management decision making. There was notable variation in the prescribed potential farm decision scenarios. In 9 % of the simulated management cases, the climate-crop model system does not provide any useful management decisions due to the uniformity of the performance of the recommendations. In 51 % of the cases, the climate-crop model system indicates consistent performance of the recommendations. Decision making is relatively easier when recommendations are uniform regardless of climate variation. In 40 % of the cases the performance of the recommendations is dependent with the climate conditions. Despite decision making being challenging to a certain extent, such a scenario is therefore effective for climate change and variability management. The potential usefulness is further highlighted by the projections of increased climate variability and change which increases the need for decision making. Most of these recommendations that lead to higher yields included organic ground cover, long seasoned varieties, fertilization and irrigation. The ability of farmers to use all these practices varies; hence farmers can select components of the combination of practices that lead to high yields, that correspond to their bio-physical and socio-economic conditions. Resource endowed, and literate farmers can utilize practices such as irrigation. Farmers that are unable to utilize such resource demanding practices can also utilize inexpensive practices such as organic amendments. Integrating seasonal forecast information and crop model can therefore be utilized as a tool to evaluate different management practices prior to commencement of the cropping season. To improve effectiveness, seasonal forecasts can be used with short term weather forecasts which are also relatively accurate or with indigenous knowledge. There is need for further research to assess the effectiveness of the decision-making process as well as the ensuing recommendations.

Chapter 5

5.0 Value of seasonal forecast-based recommendations in small-scale farming systems

5.1 Chapter summary

Fluctuation in crop productivity and food insecurity in small-scale farming systems, increases the need for improved decision making to counteract the impacts of climate variability in South Africa. An Integrated approach was proposed and utilized to improve farmer decision capacity (Chapter 4). There is limited knowledge on the effectiveness of the decision formulation process and the resulting recommendations. The current chapter study evaluated the effectiveness of the decision scenario formulation process and seasonal forecast-based recommendations under different seasons, crops, farm types and locations using 'integrated seasonal forecast and crop models' in South Africa. The study used seasonal forecast information from the CFSv2 model and measured historical weather data (2011-2017). The DSSAT 4.7 model was calibrated based on the biophysical data for different farmer types in Limpopo and Eastern Cape, South Africa (Chapter 4). The study evaluated different combinations of farm management practices: organic amendments, fertilizer, variety and irrigation. The DSSAT model simulated yields of different crops under different combinations of practices subjected to a range of historical seasonal forecasts and actual measured data. Placing the seasonal forecast-based recommendations within a scale based on response of the simulated practices to measured historical weather data enabled for an assessment of the reliability of the recommendations using percentile ranking. The study realized 2 decision scenarios which were *high decision capacity and low climate sensitivity* and *high decision capacity and high climate sensitivity*. The *high decision capacity and low climate sensitivity* scenario was predominant in the Eastern Cape. The *high decision capacity and high climate sensitivity* scenario was predominant in Limpopo. There were instances where, the scenarios were intermediate between the 2 major decision scenarios but biased towards *high decision capacity and low climate sensitivity* and this was predominant in the Eastern Cape. Most of the recommended farm management practices leading to higher yields included organic amendments, long seasoned varieties, fertilizer and irrigation. In most cases the highest yields

were from recommendations based on seasonal forecast information and from the optimal practices based on historical measured weather data. The lowest yields were farmer modelled yields. The percentile ranking was greater in Limpopo compared to the Eastern Cape. The percentile ranking was greater in cereal and vegetable crops compared to legume crops. Seasonal forecasts overestimate the size of the parameters compared to historical measured weather data, due to low skill. Consequently, there is greater confidence in the use of seasonal forecast-based recommendations in Limpopo where seasonal forecast skill is high.

5.2 Introduction

The 2030 Agenda for Sustainable Development aims to eradicate poverty, inequality and improve climate change management among other aspects. Achieving such a feat is proving to be challenging due to increased climate variability (Niang et al., 2014) and limited decision capacity especially in small-scale farming systems (UN, 2018). Farmer decision capacity in the context of climate variability is the mental, physical and socio-economic ability of a farmer to prepare and allocate resources in anticipation for manifestation of climate variability. Decision capacity is determined by multiple factors such as individual's mental, physical state, financial resources, institutional support, degree of climate change and variability and available climate variability management options (Palmer and Harmell, 2016). Climate variability is characterized by unpredictability in the manifestation of the parameters characterizing climate such as onset, cessation of the rainy season (New et al., 2006; Niang et al., 2014). This leads to extreme frequencies of crop yield variability and food insecurity in Southern Africa (Mkuhlani et al., 2019b). Increased climate variability limits the farmer's ability to make farm management decisions. Inability to make decisions potentially worsens the negative impacts of climate variability. This highlights the need for improved decision making to improve climate variability management in small-scale farming systems (Troccoli et al., 2008).

Small-scale farmers particularly in South Africa usually make farm decisions based on past experiences of climate variability. They normally use indigenous knowledge to enhance decision making in managing climate variability (Mapfumo et al., 2016). Observation of specific patterns in the behaviour of trees, animals and insect species would be interpreted as a sign of specific future weather or climate patterns. Increased climate variability and change, urbanization and cultural loss have however reduced the effectiveness of some aspects of indigenous knowledge. Specifically, behaviour of some trees, animals and insect species is no longer sufficiently observed due to deforestation, droughts, game reserves and extinction of some insect species. In addition, the rate of climate change has outpaced the rate at which indigenous knowledge is updated (Aswani et al., 2018).

This therefore increases the need for improved decision making that potentially integrates scientific knowledge, technological interventions and socio-economic organization to improve climate risk management (Taylor et al., 2014). Use of seasonal forecast information enhances decision making leading to improved climate variability management. Such decision support can be improved through integrating seasonal forecast information and crop models (Hansen, 2005; Hansen et al., 2009). Significant research has been undertaken on the integration of seasonal forecast information and crop models in evaluating farm management practices such as crop types, varieties, fertilizers and different planting dates on productivity (Cantelaube and Terres, 2005; Nelson et al., 2002; Roudier et al., 2012; Shafiee-Jood et al., 2014). Analysis of the farm management strategies resulting from such research can therefore be used to stream line farm management decision making (Chapter 4).

Potential farm management decision scenarios applicable for Southern African conditions were identified in Chapter 4. These decision scenarios are categorized into (1) *low decision capacity and low climate sensitivity*, where there is limited change crop yield in response to change of either management practice or seasonal forecast considered. (2) *High decision capacity and low climate sensitivity*, where there is noticeable change in crop yield resulting from a change of management practice but limited change in response to seasonal forecast considered (Chapter 4). (3) *High decision capacity and high climate sensitivity*, where there is noticeable change in crop yield response resulting from a change of management practice as well as noticeable change resulting from the seasonal forecast considered. Such decision scenarios have the potential to improve the decision-making capacity to enhance climate variability management. Decision scenarios however provide a holistic assessment of the decision-making process. The decision scenarios do not provide information of the corresponding specific recommended farm practices.

There are a wide range of management practices that can be recommended to farmers. Such practices include agro-forestry, conservation agriculture, different planting dates, organic ground cover, different season lengths and intercropping (Taylor et al., 2014). Some of these recommendations have been assessed for their effectiveness in managing climate variability in field and modeling based research (Mwansa et al., 2017). Assessment of the conditions under which these farm management practices are effective increases the adoption potential as well as benefit to farmers. Thierfelder et al., (2014) and Nyagumbo et al., (2015) evaluated performance of such practices e.g. conservation agriculture in different agro-ecologies using field trials. There is however need for further research using seasonal forecasts to assess the conditions under which such recommended practices are effective in the future. Most of the research was based on assessment of individual farm management practices such as different crop types and varieties (Haussmann et al., 2012), companion cropping (Midega et al., 2015) and agro-forestry (Mbow et al., 2014). Such research does not however fully mimic farmers utilizing different management practices on the farm. Farmers simultaneously use multiple different combinations of individual farm practices on a single field (Paudel, 2016). There is no known research that has been conducted to evaluate practices in combination. Research assessing farm management practices should therefore assess the practices in combination to mimic small-scale farming conditions.

This chapter study therefore sought to assess the effectiveness of the decision formulation process and the seasonal forecast based recommended farm management practices under varying conditions such as climate, crops, farmer types and locations. This was undertaken through comparative assessment of the seasonal forecast information based recommended farm management practices in the context of the response of such practices under historical measured weather data. This was undertaken by initially identifying ‘recommended’ practices under historical seasonal forecast, and then simulating and comparing productivity of these and other alternative combinations of farm management practices under measured actual weather data for Eastern Cape and Limpopo under different farmer types.

5.3 Materials and methods

5.3.1 Site characteristics

The study was based on Nkonkobe and Lambani communities in the Eastern Cape and Limpopo provinces in South Africa, respectively. The sites were described in detail in Chapter 3 and 4. To better understand the dynamics pertaining climate variability management in small-scale farming systems, farmers in both locations were categorized into different classes using the farm typology approach. In Lambani, Limpopo Province, farmers were classified into *mixed farming*, *horticultural farming* and *off farm income-dependent*. In the Nkonkobe, Eastern Cape, farmers were classified into *social welfare-dependent*, *enterprising pensioners*, *struggling subsistence*, *horticulture-dependent* and *cooperative crop* farmers. Climate variability management practices used by farmers in the different classes, were documented in Chapter 3. This study chapter compared practices recommended based on the seasonal forecast information, modeled current farmer practices and other alternative practices (Table 4.3) under historical weather data. The study utilized modelled farmer yields compared to measured farmer yields. Measured farmer yields cannot be accurately reproduced by the model due to the various conditions that affect yields which cannot be reproduced by the crop model. The attempt to reproduce yields is within acceptable limits as they fit within the acceptable RMSE (Sections 4.3.4). To avoid bias the study therefore compared model outputs together, rather than using measured farmer yields.

5.3.2 Integrating crop and climate models

Prior to undertaking the simulations, DSSAT 4.7 crop model was calibrated, for the different crops, farmers and locations (Chapter 4). The calibrations were based on the bio-physical and socio-economic characteristics for the different farmers types in Limpopo and Eastern Cape (Chapter 3).

The DSSAT crop model was coupled with historical seasonal forecast information from the CFSv2 model based on the global climate model (GCM) approach (Hansen and Indeje, 2004). The GCM approach was selected based on prior literature review (Chapter 2). Seasonal forecast data for Nkonkobe, Eastern Cape (32°47′ S, 26°38′ E) and Lambani, Limpopo (22°58’ S, 30°26’ E) was extracted from the GCM, CFSv2 (Yuan et al., 2011). The GCM data comprised of rainfall, solar radiation, minimum and maximum temperatures at a daily time step format and was therefore directly compatible with this crop model. The study used 6 sets of seasonal forecast data, from 1-6 October, each year (2011-2017) and each set of forecasts was for 9 months.

Historical measured weather data for the same period (2011-2017) was acquired from the South African Weather Service (SAWS). The data also comprised of temperature, rainfall and solar radiation at a daily time step. The data was measured from weather stations in the two communities.

5.3.3 Assessing effective farm management practices

Effectiveness of the seasonal forecast-based recommended practices was assessed through a series of steps. The seasonal forecast-based recommendations were derived from selecting the combination of farm management practices (Table 4.3) leading to the highest yields across the different seasons, crops, farmers and locations. Crop yields were derived from simulating the interaction between the different sets of seasonal forecast information and 48 different sets of combination of farm practices (Table 4.3) using the calibrated DSSAT crop model for different seasons, crops, farmer types and locations. The study used 6 season forecast data sets as it was relatively easy to manage. The 6 sets of seasonal forecasts were the minimum that could give a credible basis for recommendation. The study used 48 different combinations of farm management practices. The combinations of practices included multiple levels of major farm management practices: organic amendments, different varieties, fertilizer and irrigation (Table 4.3). The practices were selected for the study as they are commonly used by farmers (Cooper et al., 2008; Mkuhlani et al., 2019)

The simulation yield outputs of the different farm management practices and varying seasonal forecasts for each case were plotted in 'heat maps' with combination of farm practices against seasonal forecasts. Each case represented specific season, crop, farmer type and location. The different yield patterns were identified by the different colour codes, with 'red', 'yellow' and 'white' denoting 'low; 'high' and 'higher' yields. Heat maps highlighted the nature and pattern of the interaction effect of the farm management practices and forecasts which provided a platform for formulation of the decision scenarios. Decision scenarios were formulated based on assessing the pattern of yield response to the interaction between seasonal forecasts and the different combination of farm practices (Chapter 4). The decision scenarios were then compared to those realized in Chapter 4. The decision scenarios compared against were: (1) *low decision capacity* *and low climate sensitivity*. (2) *high decision capacity and low climate sensitivity*. (3) *high decision capacity and high climate sensitivity* (Chapter 4). The specific recommendations based on seasonal forecast information for each case were identified from each heat map. The recommended practices leading to high yields, were denoted by the 'white' and 'yellow' colour codes. The unrecommended set of practices with relatively low yields were denoted by the 'red' colour. The group of recommended farm management practices from each case were therefore selected and summarized in tables. The cells were colored differently, with each color denoting the different decision scenarios, the recommendations fall under. Each cell representing each case was highlighted by the different colours, where**: 1-***low decision capacity and low climate sensitivity*: **Black**; **2** *high decision capacity and low climate sensitivity*: **Yellow**. **3**-*high decision capacity and high climate sensitivity*: **Gree**n. **2/3** Intermediate between **2** and **3** but more biased towards **2**: **Orange**. **4**-*low decision capacity and high climate sensitivity*: **Red**. The recommendations for each specific case in each cell were further refined to highlight the key messages. This was undertaken by highlighting common components of the recommendations appearing across all the recommended practices in each case.

Assessment of the effectiveness of the seasonal forecast-based recommendations was measured using percentile ranking. Yields corresponding to the farm management practices (Table 4.3) based on historical measured weather data were plotted in line graphs in ascending order. Recommendations based on seasonal forecast information were superimposed within the line graphs (red columns) and current farmers practices (green columns). In this study, percentile ranking was referred to as the minimum or earliest appearance of seasonal forecast-based recommendation, within the line graphs displaying yield corresponding to farm management practices based on historical measured weather data in each case. The percentile ranking in the different seasons, crops, farmer types and locations was then assessed to determine the effectiveness of the seasonal forecast based recommended practices. High percentile ranking of the seasonal forecast recommended practices indicated effectiveness of the recommendations as well as the process. Low ranking of the seasonal forecast recommended practices was an indication of the ineffectiveness of the recommendations as well as the process.

5.4 Results

5.4.1 Seasonal forecast-based recommendations

The study realized 2 major decision scenarios for the period 2011-17, as highlighted by 2 predominant colours (Table 5). The most predominant decision scenario for the Eastern cape was the *high decision capacity and low climate sensitivity* (yellow colored cells), whereas *high decision capacity and high climate sensitivity* was predominant in Limpopo (green colored cells). The *high decision capacity and low climate sensitivity* in the Eastern cape was more pronounced for cabbage, maize and green bean crops (Table 5.1a, b and f) (Yellow colored cells). In Limpopo, the *high decision capacity and high climate sensitivity* was predominant across all crops and farmer types. There were however several cases which were intermediate between the 2 major decision scenarios, but these were mostly biased towards the *high decision capacity and low climate sensitivity* scenario (Orange colored cells). The pattern was more notable for tomato, peanut and dry bean in the Eastern cape and a few cases in peanut and dry bean in Limpopo (Table 5.1c). The few cases in Limpopo were amongst the mixed farmers in 2015-16 for peanut (Table 5.1d) and for dry beans in the 2011-12 and 2012-13 seasons for mixed farming (Table 5.1e). The quantity of seasonal forecast-based farm management recommended practices differed in each of the different cases. Generally, there were fewer seasonal forecast based recommended farm management practices from the *higher decision capacity and low climate sensitivity* scenario, compared to the *high decision capacity and high climate sensitivity* scenario. The highest number of recommended farm management practices was realized in the cases which were intermediate between the 2 main decision scenarios. This was more predominant in the Eastern cape in the tomato and dry bean crops (Table 5.1a-f).

In most cases the recommended practices included long seasoned varieties, fertilizer and irrigation in both locations (Table 5.1). This pattern was specific for cabbage in the Eastern cape but did not apply in Limpopo as the recommendations included medium seasoned varieties with no irrigation (Table 5.1a). For maize, in the Eastern cape, most of the practices included long seasoned varieties, fertilizer and irrigation. There were however instances where recommended practices included medium seasoned varieties and no irrigation. In Limpopo most of the strategies included long seasoned varieties, fertilizer and irrigation (Table 5.1b). For tomato, in both Eastern Cape and Limpopo most of the recommended practices included long seasoned varieties, fertilizer and irrigation. there were however few instances where the practices did not include irrigation (Table 5.1c).

For peanut, most of the recommended practices did not include fertilizer but included irrigation (Table 5.1d). In dry beans there were some instances where recommended practices did not include fertilizer but included irrigation. The pattern was more noticeable in the Eastern Cape compared to Limpopo (Table 5.1e). In green bean, most of the recommended practices included fertilizers and irrigation and a lesser proportion included no fertilizer and irrigation (Table 5.1f).

Table 5.1: Common farm management practices within the different combinations of seasonal forecast-based recommendations in cabbage amongst small-scale farmers in South Africa. **NB: 1**-low decision capacity and low climate sensitivity: **Black**; **2**-high decision capacity and low climate sensitivity: **Yellow**. **3**-high decision capacity and high climate sensitivity: **Gree**n. **2/3** Intermediate between **2** and **3** but more biased towards **2**: **Orange**. **4**-low decision capacity and high climate sensitivity: **Red.**

	Eastern Cape			Limpopo
Year	enterprising pensioners	horticulture dependent	cooperative crop	horticultural
2011-12	-- -- LO FE IR	-- -- LO FE IR	-- -- LO FE IR	-- -- FE --
2012-13	-- -- LO FE IR	-- -- LO FE IR	-- -- LO FE IR	-- -- -- IR
2013-14	-- -- LO FE IR	-- -- LO FE IR	-- -- LO FE IR	-- LO FE IR
2014-15	-- -- LO FE IR	-- -- LO FE IR	-- -- LO FE IR	-- ME FE IR -- LO FE NR MMLOFEIR COMENFIR
2015-16	-- -- LO FE IR	-- -- LO FE IR	-- -- LO FE IR	-- -- FE IR -- -- NF IR

Table 5.1 a: Common farm management practices within the different combinations of seasonal forecast-based recommendations in maize amongst small-scale farmers in South Africa. **NB: 1**-low decision capacity and low climate sensitivity: **Black**; **2**-high decision capacity and low climate sensitivity: **Yellow**. **3**-high decision capacity and high climate sensitivity: **Green**. **2/3** Intermediate between **2** and **3** but more biased towards **2**: **Orange**. **4**-low decision capacity and high climate sensitivity: **Red.**

	Eastern Cape				Limpopo		
Year	social welfare dependent	enterprising pensioners	struggling subsistence	horticulture dependent	mixed farming	horticultural	off farm income
2011-12	-- LO FE IR -- LOFENR	-- LO FE IR -- LO FE NR	-- LO FE IR -- LO FE NR	-- LO FE IR GRMEFENR GRLOFENR	-- LO FE IR	-- LO FE IR	-- LO FE IR
2012-13	-- LO FE IR --ME FE IR GRLOFENR	-- LO FE IR -- LO FE NR GRMEFENR	-- LO FE IR -- LO FE NR	-- -- FE NR -- LO FE IR	-- LO FE IR	-- LO FE IR	-- LO FE IR
2013-14	-- LO FE IR MMLOFENR GRLONFIR	-- LO FE IR -- LO FE NR	-- LO FE IR -- LO FE NR	-- LO FE IR -- LO FE NR	-- LO FE IR	-- LO FE IR	-- LO FE IR
2014-15	-- LO FE IR GRLOFENR GRLONFIR	-- LO FE IR -- LO FE NR	-- LO FE IR -- LO FE NR	-- LO FE IR -- LO FE NR	-- LO FE IR	-- LO FE IR	-- LO FE IR
2015-16	-- LO FE IR -- LO FE NR -- LO FENIR	-- LO FE IR -- LO FE NR	-- LO FE IR -- LO FE NR	-- LO FE IR -- LO FE NR	-- LO FE IR	-- LO FE IR	-- LO FE IR

Table 5.1 b: Common farm management practices within the different combinations of seasonal forecast-based recommendations in tomato amongst small-scale farmers in South Africa. **NB: 1**-low decision capacity and low climate sensitivity: **Black**; **2**-high decision capacity and low climate sensitivity: **Yellow**. **3**-high decision capacity and high climate sensitivity: **Green**. **2/3** Intermediate between **2** and **3** but more biased towards **2**: **Orange**. **4**-low decision capacity and high climate sensitivity: **Red.**

	Eastern Cape			Limpopo		
Year	enterprising pensioners	horticulture dependent	cooperative crop	mixed farming	horticultural	off farm income
2011-12	-- LO FE IR -- LO FE NR	-- LO FE IR -- LO NF IR -- LO FE NR	-- LO FE IR NOLOFENR	-- LO FE IR	-- LO FE IR -- LO FE NR GRMEFEIR	-- LO FE IR -- LO FE NR NOLONFIR
2012-13	-- LO FE IR -- LO FE NR -- LO NF IR	-- LO FE IR -- LO NF IR	-- LO FE IR NOLOFENR	-- LO FE IR	-- LO FE IR -- LO FE NR NOLONFIR	-- LO FE IR -- LO FE NR
2013-14	-- LO FE IR -- LO FE NR	-- LO FE IR -- LO FE NR	-- LO FE IR NOLOFENR	-- LO FE IR -- ME FE IR	-- LO FE IR COMEFEIR NOLOFENR	-- LO FE IR -- LO FE NR NOLONFIR
2014-15	-- LO FE IR -- LO FE NR	-- LO FE IR -- LO FE NR	-- LO FE IR NOLOFENR	-- LO FE IR	-- LO FE IR -- -- FE IR	-- LO FE IR NOLOFENR
2015-16	-- LO FE IR -- LO FE NR	-- LO FE IR -- LO FE NR	-- LO FE IR NOLOFENR	-- LO FE IR -- ME FE IR	-- LO FE IR -- ME FE IR NOLOFEIR	-- LO FE IR NOLOFENR

Table 5.1 c: Common farm management practices within the different combinations of seasonal forecast-based recommendations in peanut amongst small-scale farmers in South Africa. **NB: 1**-low decision capacity and low climate sensitivity: **Black**; **2**-high decision capacity and low climate sensitivity: **Yellow**. **3**-high decision capacity and high climate sensitivity: **Gree**n. **2/3** Intermediate between **2** and **3** but more biased towards **2**: **Orange**. **4**-low decision capacity and high climate sensitivity: **Red.**

Year	Eastern Cape struggling subsistence	Limpopo mixed farming
2011-12	-- -- -- IR	-- -- FE IR -- -- NF IR
2012-13	-- LO FE IR -- LO NF IR	-- -- FE IR -- -- NF IR
2013-14	-- LO FE IR MMLONFIR	-- -- FE IR -- -- NF IR
2014-15	-- LO FE IR MMLONFIR	-- -- FE IR -- -- NF IR
2015-16	-- LO FE IR MMLONFIR	-- -- FE IR -- -- NF IR

Table 5.1 d: Common farm management practices within the different combinations of seasonal forecast-based recommendations in dry bean amongst small-scale farmers in South Africa. **NB: 1**-low decision capacity and low climate sensitivity: **Black**; **2**-high decision capacity and low climate sensitivity: **Yellow**. **3**-high decision capacity and high climate sensitivity: **Gree**n. **2/3** Intermediate between **2** and **3** but more biased towards **2**: **Orange**. **4**-low decision capacity and high climate sensitivity: **Red.**

Year	Eastern Cape social welfare dependent	Limpopo mixed farming
2011-12	-- -- FE IR -- -- NF IR	-- -- FE IR GRLONFIR
2012-13	MMLOFIER MMLONFIR	-- -- FE IR -- -- -- IR
2013-14	-- -- FE IR -- -- NF IR	-- -- FE IR -- -- -- IR
2014-15	-- -- FE IR -- -- NF IR	-- -- FEIR -- -- -- IR
2015-16	-- -- FE IR -- -- NF IR	-- -- FE IR -- -- -- IR

Table 5.1 e: Common farm management practices within the different combinations of seasonal forecast-based recommendations in green bean amongst small-scale farmers in South Africa. **NB: 1**-low decision capacity and low climate sensitivity: **Black**; **2**-high decision capacity and low climate sensitivity: **Yellow**. **3**-greater decision capacity and high climate sensitivity: **Green**. **2/3** Intermediate between **2** and **3** but more biased towards **2**: **Orange**. **4**-low decision capacity and high climate sensitivity: **Red**.

	Eastern Cape
Year	horticulture dependent
2011-12	-- -- FE IR
2012-13	-- -- FE IR CO LO NF IR
2013-14	-- -- FE IR
2014-15	-- -- FE IR
2015-16	-- -- FE IR

5.4.2 Assessment of potential for crop yield improvement

This involved comparing the productivity of seasonal forecast-based recommendations and current farming practices referred to as modelled farmer management practices that were simulated under historical weather data (2011-2017).

Farmer modelled yields were lower in the Eastern cape compared to Limpopo. The pattern was more noticeable in dry bean, green bean and peanut compared to other crops (Annexure 5.109-Annexure 5.222). In addition, yield improvements attributed to the seasonal forecast-based recommendations and optimal practices under historical measured weather data relative to farmer modelled yields were greater in the Eastern cape compared to Limpopo. In most cases the highest yields were derived from seasonal forecast-based recommendations and optimal practices under historical measured weather data. On the contrary, farmer modelled yields were the lowest in most cases (Figure 5.1 and 5.2). Farmer modelled yields were the lowest especially for legumes crops such as peanuts amongst resource constrained farmers in the Eastern cape (Figure 5.1). The magnitude of the yield improvements varied between those from seasonal forecast-based recommendations and those derived from optimal practices under historical measured data (Annexure 5.109-Annexure 5.222).

Seasonal forecast-based recommendations and those derived from optimal practices under historical measured data led to crop yield improvements of more than 100 % in legume crops such as peanut, dry bean and green bean. Specifically, for green beans, the farmer modelled yields were 250 kg ha^{-1} compared to about 5000 kg ha^{-1} and at least 10000 kg ha^{-1} derived from optimal practices under historical measured data and seasonal forecast-based recommendations respectively (2011-2015). This represented at least a 100 % increase in green bean yields from the modelled farmer yields. There was a 50 % further increase in green bean yields from yields based on optimal practices under historical measured data and those from seasonal forecast-based recommendations (Annexure 5.215-5.219).

Seasonal forecast-based recommendations Vs similar practices simulated yield under historical measured weather data

Seasonal forecast-based recommendations were compared to current modelled farmer practices and practices under historical measured weather data for different seasons, crops, farmers and locations (2011-2017). Yields corresponding to the different practices under historical data was illustrated in line graphs, with the farm management practices arranged in ascending order based on the yield size. Seasonal forecast-based recommendations identified in Section 5.4.1 were superimposed (Red columns) on the line graphs displaying the response of the practices to historical measured weather data. Current farmer practices and corresponding yields referred to as farmer modelled yields (green columns) were also superimposed on the graphs.

Assessment of all the cases shows that most of the seasonal forecast-based recommendations (red columns) were above the 50th percentile. About 12 % of the recommendations were below the 50th percentile, 66 % were above the 88th percentile and 22 % were between the 50th and 88th percentiles. Most of the recommended practices led to higher productivity compared to the current farmer practices in about 86 % of the cases. Most of the recommended practices were above the 95th percentile and mostly included the practices fertilizer and irrigation. The pattern was more pronounced during the 2012-2015 period, across all crops, farmer types and in both locations (Annexure 5.111-Annexure 5.219).

The pattern was however more specific in the 2014/15 season, amongst social welfare dependent farmers for the peanut crop in the Eastern Cape, South Africa where most of the recommended practices were above the 88th percentile, highlighting the effectiveness of the recommendations. The farmer practices were in the lower 25th percentile. Above the 95th percentile, most practices included organic amendments such as irrigation, fertilizer and long seasoned varieties. There were also instances where above the 95th percentile there were practices with no organic amendments but with irrigation and fertilizer (Figure 5.1). Practices within the 25th percentile, which included current farmer practices had lower yields and included no organic amendments, short seasoned varieties, no fertilizer and no irrigation (Figure 5.1).

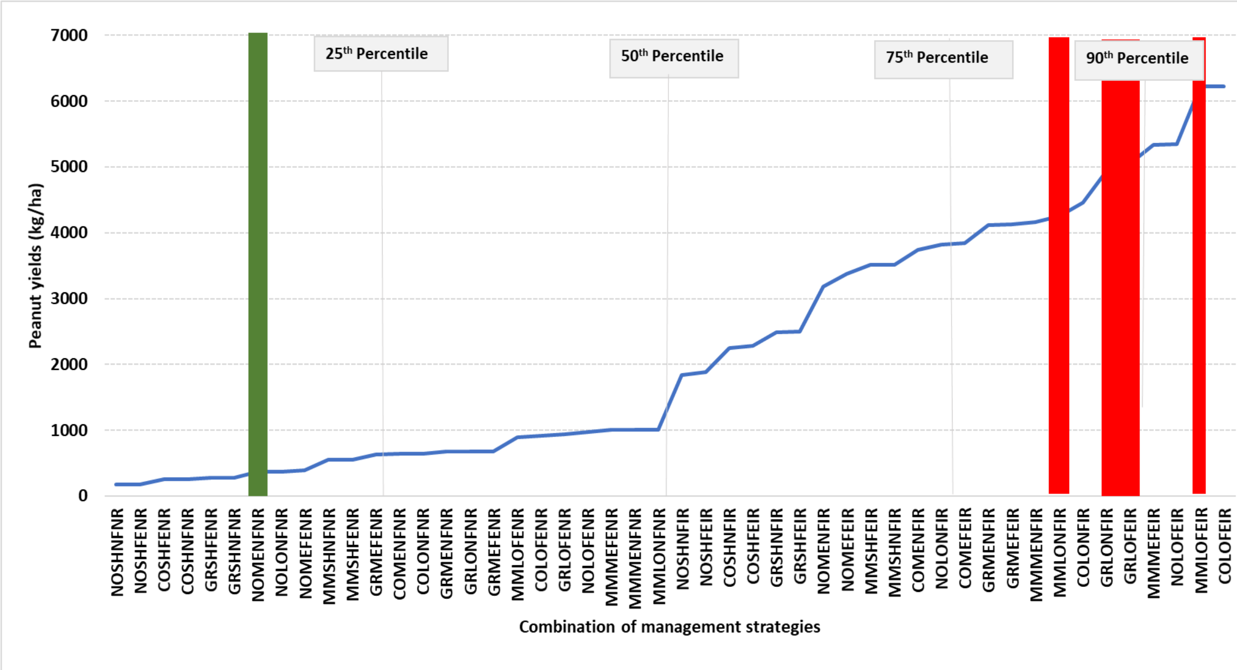

Figure 5.1: Seasonal forecast based recommended practices (red bars) and modelled farmer yields (green bars) in the context of the performance of the same practices under historical measured data (Blue line) for peanut yields amongst social welfare dependent farmers in Eastern Cape, South Africa (2014/15). **NB: Green Bars: Current modelled farm management practices and corresponding yields. Red Bars: Seasonal forecast based recommended farm management practices. Blue line: Crop yields based on measured historical weather data.**

There was however a slight difference from the other seasons where above the 95th percentile there were practices with no irrigation for the 2011 and 2015 seasons. Most of the practices within the 25th percentile, which also led to lower yields included short seasoned varieties, no seasonal forecast fertilizer and no irrigation. The pattern was specific for green beans under, social welfare dependent farmers in Eastern Cape, South Africa, where in 2015/16 cropping season, most practices above the 95th percentile did not include irrigation (Figure 5.2)**.** Despite the differences most of the recommendations were above the 88th percentile, highlighting the effectiveness of the approach. The farmer practices were below the 25th percentile.

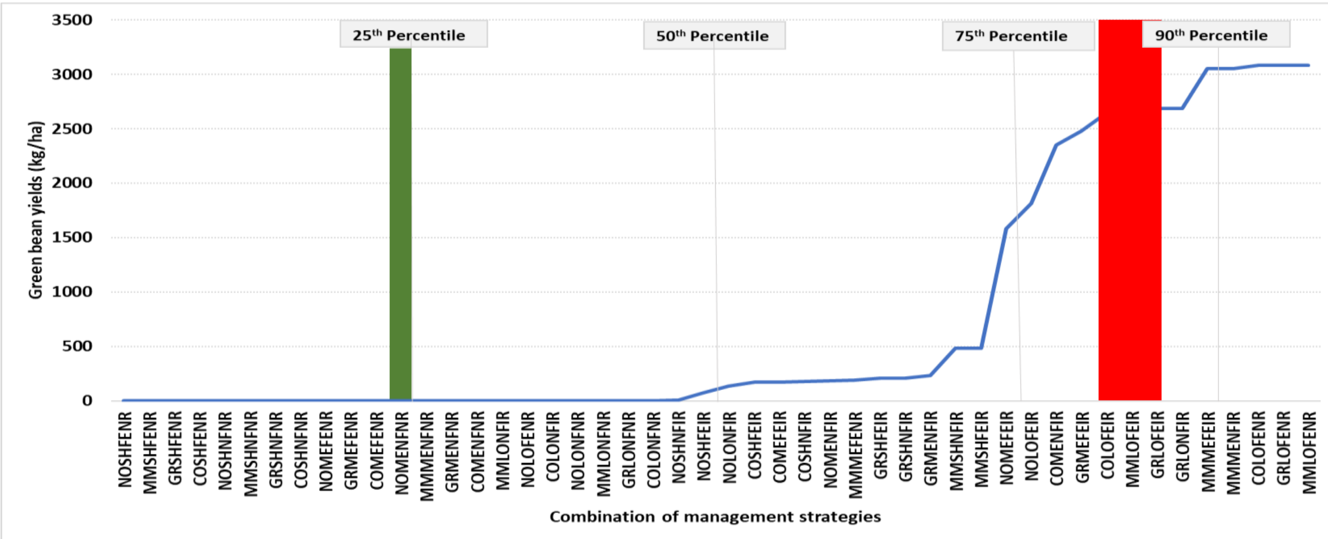

Figure 5.2: Seasonal forecast based recommended practices (red bars) and modelled farmer yields (green bars) in the context of the performance of the same practices under historical measured data (Blue line) for green bean yields amongst social welfare dependent farmers in Eastern Cape, South Africa (2015/16). **NB: Green Bars: Current modelled farm management practices and corresponding yields. Red Bars: Seasonal forecast based recommended farm management practices. Blue line: Crop yields based on measured historical weather data.**

There were some instances where the current farmer practices refered to as modelled farmer yields performed better than the seasonal forecast-based recommendations. This was specific for cabbages under horticultural farmers in Limpopo, South Africa for the 2014/15 season. Farmer modelled practices led to higher yields compared to those being recommended by forecasts. Farmer modelled yields were above the 95th percentile, whereas the recommended practices were above the 80th percentile. Despite the difference, the relatively high percentile ranking of at least 75 highlighted the effectiveness of the approach (Figure 5.3).

There were however some instances where the recommended practices were above the 88th percentile whereas the modelled farmer yields were lower in the 70th percentile. The differences in yields were however relatively low despite in the different percentile range. Fertilizer and irrigation were the common practices from the decisions (Figure 5.4).

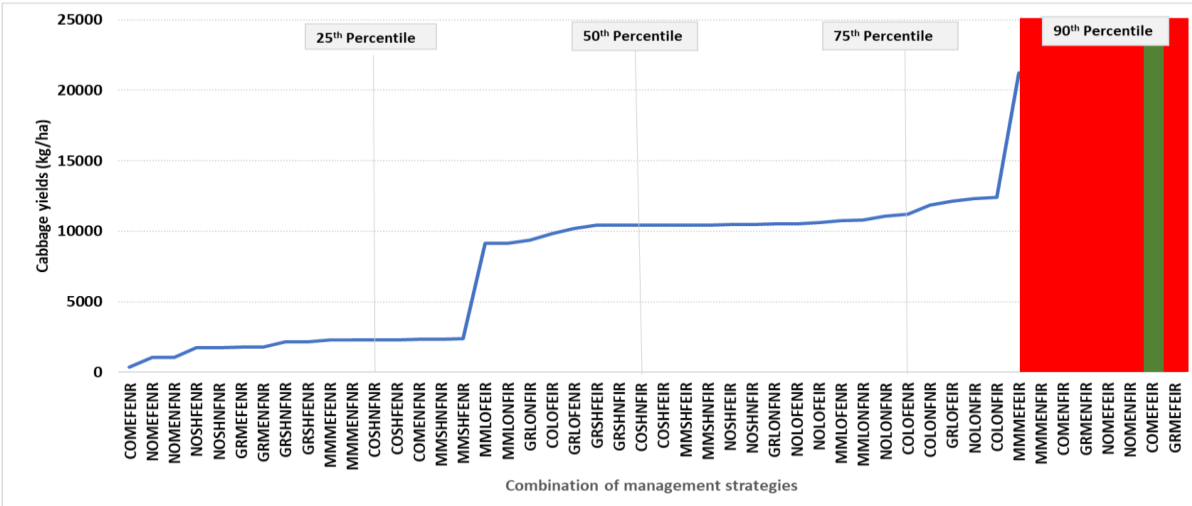

Figure 5.3: Seasonal forecast based recommended practices (red bars) and modelled farmer yields (green bars) in the context of the performance of the same practices under historical measured data (Blue line) for cabbage yields amongst horticultural farmers in Limpopo South Africa (2014/15). **NB: Green Bars: Current modelled farm management practices and corresponding yields. Red Bars: Seasonal forecast based recommended farm management practices. Blue line: Crop yields based on measured historical weather data.**

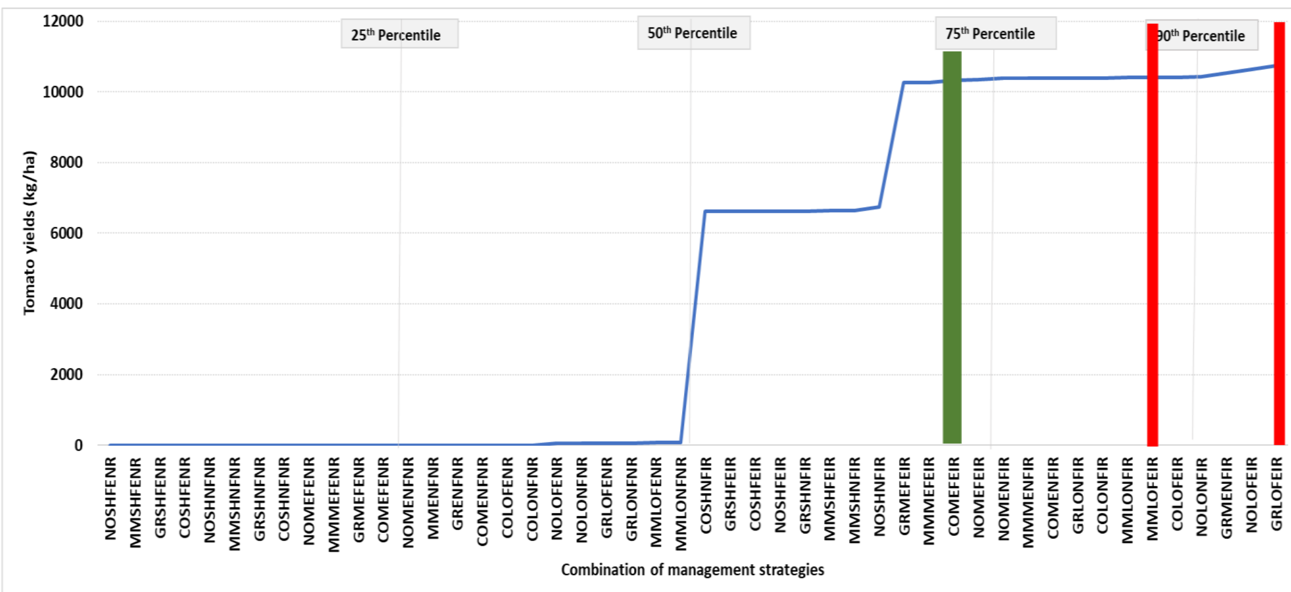

Figure 5.4: Seasonal forecast based recommended practices (red bars) and modelled farmer yields (green bars) in the context of the performance of the same practices under historical measured data (Blue line) for tomato yields amongst mixed farming farmers in Limpopo, South Africa (2015/16). **NB: Green Bars: Current modelled farm management practices and corresponding yields. Red Bars: Seasonal forecast based recommended farm management practices. Blue line: Crop yields based on measured historical weather data.**

5.4.3 Comparative decision making under different climate conditions

This section evaluates the seasonal forecast-based recommendations in the context of the response of these and other practices under historical measured data (2011-2017). This was undertaken by assessing the performance of seasonal forecast-based recommended practices within the context of the performances under actual measured historical weather data using the percentile ranking value (Annexure 5.111-Annexure 5.219). A greater percentile ranking value corresponds to effectiveness of the seasonal forecast recommendations, whereas a low percentile ranking value corresponds to ineffectiveness of the seasonal forecast-based recommendations (Annexure 5.111-Annexure 5.219).

Overall, there were no notable differences of the percentile ranking between the different farmer groups in both locations. The study however showed a generally higher percentile ranking in Limpopo compared to the Eastern Cape (Table 5.2-5.7). This was manifested through a relatively higher percentile ranking of at least 70 across all seasons in Limpopo. In contrast, in the Eastern Cape, there was relatively lower percentile of as low as 29 (Table 5.2-5.7).

The percentile ranking differed with crops within the specific locations. The percentile ranking ranged from 60-96 in Limpopo for cereal and vegetable (maize, cabbage, tomato). For legume crops, such as peanut and dry bean, the percentile ranking value fluctuated from 60-94. The fluctuations were greater for Eastern Cape compared to Limpopo.

The percentile ranking value was relatively constant across all seasons in Limpopo. On the contrary, the percentile ranking value fluctuated between the different seasons in the Easter Cape. The percentile ranking value was generally lower up to 30 for the 2011/12, 2014/15 and 2015/16 seasons for the cereal and vegetable crops. The percentile ranking value was generally higher in the 2012/13 and 2013/14 seasons (Table 5.2-5.7).

Table 5.2: Percentile ranking values of the seasonal forecast-based recommendations in the context of the response of the practices under historical measured weather data for cabbage in South Africa (2011-2017). **NB: 0-25: Blue; 25-50: Green; 50-75: yellow; 75-100: Orange.**

	Eastern Cape			Limpopo
Year	enterprising pensioners	horticulture dependent	cooperative crop	horticultural
2011-12	29	58	48	71
2012-13	37	28	63	85
2013-14	40	85	85	85
2014-15	90	38	69	83
2015-16	35	54	41	83

Table 5.3: Percentile ranking values of the seasonal forecast-based recommendations in the context of the response of the practices under historical measured weather data for tomato in South Africa (2011-2017). **NB: 0-25: Blue; 25-50: Green; 50-75: yellow; 75-100: Orange**

	Eastern Cape			Limpopo		
Year	enterprising pensioners	horticulture dependent	cooperative crop	mixed farming	horticultural	off farm income
2011-12	48	68	44	98	94	94
2012-13	63	56	68	96	98	94
2013-14	79	73	96	90	90	80
2014-15	51	57	65	94	94	94
2015-16	38	73	81	88	98	92

Table 5.4: Percentile ranking values of the seasonal forecast-based recommendations in the context of the response of the practices under historical measured weather data for maize in South Africa (2011-2017). **NB: 0-25: Blue; 25-50: Green; 50-75: yellow; 75-100: Orange**

	Eastern Cape				Limpopo		
Year	social welfare dependent	enterprising pensioners	struggling subsistence	horticulture dependent	mixed farming	horticultural	off farm income
2011-12	57	44	55	36	94	90	94
2012-13	63	54	63	96	92	94	94
2013-14	67	60	85	88	96	94	96
2014-15	59	65	92	45	94	94	94
2015-16	33	48	46	50	96	96	96

Table 5.5: Percentile ranking values of the seasonal forecast-based recommendations in the context of the response of the practices under historical measured weather data for dry bean in South Africa (2011-2017). **NB: 0-25: Blue; 25-50: Green; 50-75: yellow; 75-100: Orange**

	Eastern Cape	Limpopo
Year	social welfare dependent	mixed farming
2011-12	59	75
2012-13	85	85
2013-14	74	94
2014-15	38	90
2015-16	88	88

Table 5.6: Percentile ranking values of the seasonal forecast-based recommendations in the context of the response of the practices under historical measured weather data for Peanut in South Africa (2011-2017). **NB: 0-25: Blue; 25-50: Green; 50-75: yellow; 75-100: Orange**

	Eastern Cape	Limpopo
Year	social welfare dependent	social welfare dependent
2011-12	63	81
2012-13	73	94
2013-14	61	88
2014-15	67	83
2015-16	65	88

Table 5.7: Percentile ranking values of the seasonal forecast-based recommendations in the context of the response of the practices under historical measured weather data for green bean in South Africa (2011-2017). **NB: 0-25: Blue; 25-50: Green; 50-75: yellow; 75-100: Orange**

	Eastern Cape
Year	horticulture dependent
2011-12	60
2012-13	94
2013-14	83
2014-15	88
2015-16	81

5.5 Discussion

5.5.1 Effectiveness of the decision scenarios

The decision-making process used for the 2017/18 season conditions was also used for the 2011-17 season. The process identified decision scenarios for the 2011-17 season conditions which matched the decision scenarios identified for the 2017/18 season conditions in about 50 % of the cases (Chapter 4). This therefore highlighted the potential effectiveness of the decision-making process for potential future use. Future climate change adaption policies and farm management planning can therefore be made based on these decisions scenarios.

Most often the seasonal forecast-based recommendations identified resulted from 2 decision scenarios: *high decision capacity and low climate sensitivity*; and *high decision capacity and high climate sensitivity*, with both occurring in almost equal proportions. About 26 % of the cases were intermediate between the 2 scenarios but being more biased towards *high decision capacity and low climate sensitivity*. Decision capacity is therefore relatively higher under the 2 scenarios as there is a notable pattern of the ideal decisions. Decision making capacity is however very high in the *high decision capacity and low climate sensitivity* scenario as the decision pattern is much more notable across a range of variable seasonal forecasts. Such a scenario is predominant for the Eastern Cape region of South Africa. There is therefore greater decision capacity in the Eastern Cape. The effectiveness of the decision scenario may however be affected by the poor skill in the region (Lazenby et al., 2014).

Decision capacity is also high under the scenario *high decision capacity and high climate sensitivity* compared to other scenarios, but the decision capacity is however not uniform across all climate predictions. This therefore complicates decision making to a certain extent as the ideal decisions are not uniform across all the climate forecasts but are seasonal forecast specific. Such scenario is however more beneficial in climate change and variability management as decision making can be tailored to climate conditions. Stronger decision capacity under greater climate sensitivity requires assessment of the specific conditions under which the decisions are ideal. Decision making corresponding to specific climate conditions therefore enhances climate change and variability management. Such scenario is predominant in Limpopo where there is also higher forecast skill (Lazenby et al., 2014). High forecasting skill improves confidence in the seasonal predictions. Decision making scenarios are therefore more reliable for Limpopo compared to the Eastern cape.

Decision making is also challenging in the scenarios that were intermediate between the 2 main scenarios even though they were more aligned to the *higher decision capacity and low climate sensitivity scenario*. This therefore further complicates decision making as there are a range of recommended contrasting decisions. This is worsened by the low skill which characterizes the

Eastern Cape where such scenarios are predominant. On the other hand, the presence of a significant proportion of undefined decision scenarios potentially casts doubt on the effectiveness of the decision formulation process for the Eastern Cape. The absence of intermediate scenarios in Limpopo potentially highlights the improved value of the decision formulation process as well as the decisions scenarios in Limpopo, compared to the Eastern cape.

Realization of both scenarios during the period 2011-2017 based on measured data and under seasonal forecasts for the 2017/18 season highlights the likelihood of experiencing such decision scenarios in the future compared to other decision scenarios. Policy makers and farmers can therefore prepare specific recommendations suited to such decision scenarios. There can however be challenges in the decision-making process as some of the decisions are contrasting. Decision making would therefore be easier under *high decision capacity and low climate sensitivity* scenario as the decisions are uniform across the range of climate conditions with the *high decision capacity and high climate sensitivity* scenario being the most valuable in climate variability management.

The study did not however match all the previously identified scenarios where the scenarios such as '*low decision capacity and low climate sensitivity*' and '*low decision capacity and high climate sensitivity*' were not identified in 2011-17 conditions despite having been identified in 2017/18 conditions. The absence of such decision scenarios in the period 2011-2017 is however not surprising as such a scenario only appeared in less than 10 % or none of the cases under the 2017/18 conditions which was used to formulate the decision scenarios (Chapter 4). Such scenarios were therefore considered to be of low frequency with lower chances of being experienced in similar research and in future, hence they did not appear under the 2011-17 conditions (Chapter 4). This was also attributed to the design of the study which utilized a single season (2017/18) hence such phenomena would be of extreme variability in a small sample. There would have been a chance of not experiencing such phenomena in future had the sample size been larger. Climate variability and change have been increasing with time since mid-1950s and is projected to increase in future (Bathiany et al., 2018). Such scenarios may therefore portray conditions to be experienced in the future under cases of increased climate variability and change. Increased climate variability and climate change may therefore lead to the increased occurrence of phenomena that were previously rare or occurred in low frequencies. There is therefore a chance that such decision-scenarios may occur in the future due to increased climate change and variability. Despite the potential of manifestation of such decision scenarios, there are challenges due to the weak decision capacity associated with weak sensitivity to climate. Specifically, this is attributed to lack of clear decision amongst the multiple choices. Such decision scenarios would still be of lesser value as it presents more challenges due to the weak decision capacity.

5.5.2 Potential impact of seasonal forecast-based recommendations on crop yield improvement

Seasonal forecast-based recommendations led to higher yields compared to modelled farmer yields. Yield improvements attributed to seasonal forecast-based recommendations were greater in the Eastern Cape compared to Limpopo. The differences were largely attributed to the difference in the predominant farmer types between the 2 locations, where there were more underperforming farmers in the Eastern Cape compared to Limpopo. Recommendations would therefore lead to greater increase in crop yields in the Eastern Cape. Most farmers in Limpopo had relatively well managed farming systems. This was attributed to abundance of resources, farming knowledge and experience (Mkuhlani et al., 2019a). As a result, the current farming systems in Limpopo led to higher yields and recommendations would lead to minimal increase in yields.

Specifically, extent of crop yield improvement differed with the different farmer types. Current farmer yields were generally low amongst such resource constrained farmers, and this was predominant in the Eastern cape. The poor productivity was attributed to the poor management conditions which characterized most of these farmer types. The conditions were not conducive for crop growth and development. This was specific for cereal and legume crops, such as maize and peanuts. In maize, the farmers used low fertilizer rates of about 11 kg ha^{-1} for basal dressing in maize. They also did not apply top dressing and were heavily dependent on rain fed agriculture. These farmers also used short and medium seasoned varieties and mulch. This ultimately led to lower maize grain yields of less than 400 kg ha^{-1} amongst social welfare dependent farmers. Under the ‘same conditions’, use of seasonal forecasts-based recommendations improved farmer improved modelled yields at least as 100 % to 5000 kg ha^{-1}

for maize in the 2012/13 season. These practices provide a conducive environment for crop growth and development (Seed Co, 2018). Such practices included practices such as organic amendments, long seasoned varieties, fertilizer and irrigation.

On the contrary, in most farmers in Limpopo, seasonal forecast-based recommendations and optimum practices from historical measured data led to minor maize crop yield improvements of as low as 20 %. This was predominant in mixed and horticultural farmers. These farmers to a certain extent already use some of the recommended practices such as fertilizer and irrigation but with medium season varieties hence the current yields are relatively high. Additional use of some practices such as long seasoned varieties will increase maize yields by minor margins. These practices mostly included long seasoned maize varieties, higher fertilizer rates such as 75 kg ha^{-1} N, irrigation and organic ground cover. This therefore led to high maize crop yields. The change in farm management amongst the small-scale farmers therefore led to increased crop yields (Seedco, 2018).

The largest yield improvements between the modelled farmer yields and seasonal forecast-based recommendations were from the resource constrained farmers cultivating legume crops such as dry bean and peanut, where there were yield increases of at least 100 %. Legume crops fix nitrogen in the soil hence they do not require additional nitrogen. There are however conditions required to effectively fix nitrogen. Most of the soils in communal areas in Eastern cape and Limpopo are acidic or lime. This therefore does not create the ideal pH conditions for the rhizobium bacteria which is needed to fix nitrogen, thus there is limited nitrogen available for crop growth and development. In addition, legumes are usually planted late in the season as they do not require greater amount of rainfall compared to other crops such as cabbages. They then usually face late season droughts whose effect is combined by poor soil conditions, hence the modelled farmer realized yields were very low. The increased yield in seasonal forecast recommendations and optimization was based on the use of fertilizer where it provides additional nutrients which are difficult to acquire due to the unconducive soil conditions. Irrigation therefore increases the amount of water available. Water which would have been limiting due to late season droughts.

Seasonal forecast-based recommendations did not always lead to the highest productivity yields as there were some instances where the farmer yields led to high yields. This may have been attributed to the inability of the crop model to accurately account for all factors contributing to crop growth and development. This therefore limits the reliability of yield prediction. In addition, data used in model set up was collected under non-conducive conditions hence some of the input data may have been inaccurate, leading to erroneous simulations. On the other hand, seasonal forecast based recommended practices and those derived from optimization are ideal conditions for crop growth and development, whereas the modelled farmer yields are usually under unconducive environments. Modelled farmer yields should therefore at least be equal or higher than seasonal forecast based recommended practices and those derived from optimization. The differences can be attributed to clerical, transcribing and translation errors. This may also have resulted from over-estimation of crop yields by the farmers during the study.

5.5.3 Value of alternate farm management decision making in small-scale farming

Prior farm management decision making minimizes the potential impacts of climate risk in small-scale farming systems. This is achieved through recommendation of specific management practices. Evaluation of seasonal forecast based recommended farm management practices in the context of the response of the practices under historical weather data was essential to build confidence in seasonal forecast-based recommendations.

The farm management decision making process was reliable for Limpopo compared to the Eastern Cape as realized by the higher percentile ranking. Such decision support is therefore of greater potential benefit for farmers in Limpopo. Such decision support can also be beneficial to farmers in the Eastern Cape but with limited reliability attributed to the poor forecasting skill in the region. In Limpopo, the greater reliability in the recommendations is attributed to the greater skill in forecasts in Limpopo compared to the Eastern Cape (Lazenby et al., 2014).

The study also highlights the value of the decision-making process and seasonal forecast-based recommendations in the different crops. There was greater reliability in cereals and vegetable crops and less reliability for legumes. This is attributed to the sensitivity of legume crops, where rainfall and temperature variability may affect nitrogen fixation (Paramasivan et al., 2016). Nitrogen fixation is key as it improves in fertility thus increasing productivity of legume crops.

Since rainfall and temperature have a direct effect on crop growth and development, temperature and climate variability can therefore lead to fluctuation in productivity. This also affects the ideal farm management strategy, leading to contrasting management decisions. Cereals are the staple food crops in South Africa, hence such recommendations are of high value in cereal cropping in small-scale farming systems. The low percentile ranking in legumes denoting the ineffectiveness of the seasonal forecast-based recommendations has notable consequences in decision making as legumes are a key cash crop as well contributing to nutrition security.

The value would be greater for resource constrained farmers, where the yield improvements are greater compared to the resource endowed farmers. Most of the resource constrained farmers were identified in the Eastern Cape, hence they can therefore benefit more from such recommendations leading to greater increase in yields. On the contrary in Limpopo, the recommendations are useful as they lead to yield improvements, but the improvements are minor compared to the Eastern Cape. Despite the potential benefits from yield increments for the Eastern Cape farmers, there is limited forecasting skill such that there is lower reliability in the forecast reducing the value such seasonal forecast-based recommendations in Eastern cape. On the contrary despite the recommendations being of lesser value in Limpopo since farmers are relatively resilient, the greater forecasting skill increases the value the recommendations in Limpopo.

Previous research by Mkuhlani et al., (2019) highlighted that choice of farm management practices vary with farmers socio-economic conditions. The study therefore expected the recommended farm management practices to be farmer dependent (Chapter 3). In contrast the current Chapter, however showed that the ideal farm management practices leading to the highest yields were not farmer dependent and were generally similar across the different crops as well as farmer types. The non-sensitivity is potentially due to the process of deriving the recommended farm management practices. They were determined based on selection of the combination of farm practices leading to the highest yields. The seasonal forecast recommended practices that lead to the highest yields were uniform across all farmers and locations. Not all farmers can manage to utilize these recommended combinations of practices due to the differences in the implementation capacity attributed to varying socio-economic characteristics. Some farmers therefore prefer some strategies, with resource endowed farmers preferring irrigation and constrained farmers utilizing mulch. Farmers can therefore utilize specific practices that are compatible with their socio-economic status from the combination of recommended practices. Resource constrained farmers can therefore utilize organic amendments or even some form of flood irrigation where there is abundant water and labor.

5.6 Chapter conclusion

The chapter assessed the effectiveness of seasonal forecast-based recommendations in the context of the response of such to historical weather data. The differences in farmer socio-economic status has no effect on the effectiveness of the seasonal forecast-based recommendations. Seasonal forecast information-based recommendations lead to higher crop productivity compared to current farmer practices. The high percentile ranking value in the different crops and locations highlights the reliability of some seasonal forecast-based recommendations. Such reliability and the realization of previously identified decision scenarios highlights the effectiveness of the decision-making process. Effectiveness is however not uniform due to the differences in crops and agro-ecological conditions. There is greater effectiveness of recommendations in areas such as Limpopo and less so in the Eastern Cape as realized by the higher percentile index. Recommendations are potentially less beneficial in legume crops compared to vegetables and cereals which are relatively stable. The uptake of such recommendations by farmers is however potentially affected by the difference in forecasting skill. Greater forecasting skill increase the reliability and potential adoption of the recommendations. Seasonal forecast-based recommendations are therefore more useful in agro-ecologies with greater forecasting skill. Seasonal forecast-based recommendations cause notable improved productivity, which can be of beneficial to constrained small-scale farmers, but they should be utilized with caution due to low skill in some regions.

Chapter 6

6.0 Conclusions

6.1 Main findings

Small-scale farmers currently utilize a range of different farm management practices to manage climate variability. These practices are specific to each category of farmers as they correspond to the farmer's socio-economic characteristics. The categories are based on the different socio-economic characteristics such as education, farming experience and resource endowment. These small-scale farmers face multiple challenges in managing climate variability. Most of the challenges are related to insufficient water, poor climate information and financial resources to manage and acquire irrigation equipment.

There are challenges in integrating seasonal forecast information and crop models due to the spatial and temporal incompatibility between seasonal forecast information format and crop model input data requirements. The GCM approach was the most appropriate technique to integrate seasonal forecast and crop models as they are readily accessible and less technologically demanding in managing and processing. Analogue and stochastic disaggregation techniques require high computation capacity and the products have greater prediction errors. Statistical yield prediction was incompatible with the main aims of the study and does not allow for assessment of the different farm management practices. Process based crop models such as DSSAT and APSIM are more ideal for the research as they can mimic farm management practices that can be utilized in climate variability management.

In the formulation of the decision process and the decision-scenarios using the 2017/18 year as a case study, the study realized variable success through location, crops and farm types. Variation was more pronounced for rainfall compared to temperature and in areas with high forecasting skill compared with areas with low forecasting skill. Seasonal forecasts also over estimated rainfall in the Eastern Cape compared to Limpopo which are areas with low and high skill respectively. Such variation directly translated to crop yield variation. Early planting led to higher yields in the Eastern Cape, whereas sowing in the middle of the season led to higher yields in Limpopo. The decision formulation process developed decision scenarios (1) *low decision capacity and low climate sensitivity,* with reduced value and limited ability to make decisions due to the uniform performance of the different farm management practices. (2) *high decision capacity and low climate sensitivity,* with value due to realization of clear-cut practices leading to high productivity. (3) *high decision capacity and high climate sensitivity* with high value due to realization of clear-cut ideal practices. Additional value is realized from the realization of ideal practices which correspond to the different climate conditions. Under these conditions, another potential decision scenario, the (4) *low decision capacity and high climate sensitivity,* was not realized.

The study then assessed the effectiveness of the process of formulating decision scenarios. under different conditions (2011-17). Realization of some decision scenarios previously identified highlighted the effectiveness and repeatability of the process.

In most cases seasonal forecast-based recommendations led to greater productivity compared to current farmer practices across all seasons, crops, farmer types and locations. Such yield improvements were greater in the Eastern Cape compared to Limpopo. This is attributed to the current farmer practices being similar to the recommended practices in Limpopo whereas they are different in the Eastern Cape. Seasonal forecast-based recommendations were more effective in Limpopo compared to the Eastern Cape, especially amongst cereal and vegetables crops. Effectiveness was realized as the seasonal forecast-based recommendations were similar to those that would have been realized under measured historical weather data.

6.2 Implications of the research

The study developed a decision-making approach that is based on processing outputs of integration of seasonal forecast information and crop models. This led to the formulation of a range of decision scenarios that can be utilized in climate variability management. The scenarios describe the capacity for making decisions under a set of climate conditions of varying sensitivity. On assessing the benefits and applicability of the decision-making approach and the corresponding formulated decision scenarios under different conditions the study realized most of the decision-making scenarios, that had been realized under the initial conditions. Such realization provides confidence in the decision formulation process as well as the corresponding decision scenarios. This highlights the repeatability of the approach for use in different conditions. Though minor, failure to completely mimic the decision scenarios realized in the initial conditions highlights the significant effect of changing climate on potential decision scenarios as well as decision making to the farmer. The value and importance of some decision scenarios my therefore vary with increasing climate change and variability.

The specific seasonal forecast information-based recommendations resulting from the range of decision scenarios were uniform across almost all farmer categories, crops and locations. The study realized uniform cross-cutting recommendations which may however not be compatible with all farmers. This is attributed to the variation in socio-economic status of the different farmer types. The study in Chapter 3 realized that farmers have high farmer diversity owing to the different socio-economic characteristics. As a result, different types of farmers are compatible with different farm management practices as well as climate variability management strategies. Compatibility is determined by education, financial resources and availability of water resources among other factors. From the combination of practices making the seasonal forecast-based recommendations, farmers can therefore select practices compatible with their socio-economic characteristics from the different recommended combination of practices. Seasonal forecast-based adaptation initiatives should therefore be tailor made to suit the different farmer's socio-economic characteristics. Recommendation of adaptation options should also be flexible to enable effectiveness and maximize the benefits from the recommendations corresponding to suitable farmers. The benefits of such an approach span across all small-scale farmers as each farmer type can therefore focus on seasonal forecast recommendations that are effective for their conditions as opposed to using recommendations not compatible with their socio-economic conditions.

Integration of seasonal forecasts and crop models has immediate benefits in making specific recommendations to decision makers. Such recommendations on the choice of practices and crops minimizes the impact of climate risks which is high in small-scale farmers. As a result, farmers can either sustain or increase production as most recommendations ultimately lead to high yields in comparison with current farmer practices. The consistently high potential productivity under seasonal forecast-based recommendations makes them more attractive to farmers compared to the current practices. There is improved confidence in the recommendations as such recommendations are mostly consistent across the different crops. The certainty of the recommendations is however reduced for some agro-ecologies resembling the Eastern Cape of South Africa, with low forecasting skill. Despite the low skill in some areas such recommendations provide a general view of the direction which can be undertaken by farmers to improve farm productivity. In environments with good forecast skill such as Limpopo, the confidence in such recommendations is greater. Such recommendations have greater value in agro-ecologies with greater forecasting skill not only within South Africa but in the whole of Africa. Despite such potential benefits to small-scale farmers the benefits may not be realized in agro-ecological environments with limited forecasting skill. The effectiveness of such recommendation for cereal crops such as maize is commendable as the crop is staple food crop in South Africa and the sub Saharan region at large. Ineffectiveness of the recommendations in legumes production has notable negative implications to small-scale farmers who use such crops as alternate sources of protein as they usually lack resources to acquire other protein rich foods. This may therefore contribute to nutritional insecurity hence alternate household plans should be in place to minimize the negative impacts of nutritional insecurity.

6.3 Contribution to the body of knowledge

The research opens up new frontiers in climate variability management for South Africa as well as the African continent at large. Such frontiers are opened up through streamlining the decision process leading to improved climate variability management. This solves the challenges in decision making, that can be attributed to the availability of multiple potential farm management strategies and further complicated by climate variability. There is limited value in the decision making from a few practices and recommendations. Opening such frontiers adds value to the combined set of decisions whilst concurrently enhancing climate variability management. Such novel decision approach has the capacity to enhance decision making in small-scale systems. Such an approach leaves small-scale farmers with more adaption capacity and at par with their commercial farmer colleagues, with higher decision capacity due to the socio-economic characteristics and resources.

Improvement of farmer’s decision capacity has more positive consequences for farming. Such capacity potentially leads to high crop productivity and resilience to climate variability. Use of an approach can have consequences to improve food security in small-scale farmers. Despite being applicable across the whole farming sector, small-scale farmers are likely the biggest beneficiaries. The research realizes such benefits to south Africa and such benefits can be extrapolated for the whole sub Saharan region and the whole of Africa. Ideally extrapolation would be challenging due to a wide farmer diversity. Farming systems are however similar across the African continent; hence the benefits can potentially be realized in small-scale farmers across all the different African countries. All farmers can benefit from such initiatives as the recommendations are cross cutting.

Addressing climate variability is critical for agricultural transformation. Improvement of crop productivity under climate variability conditions will therefore improve farmer's food security and income. This provides a platform for enhancing the sector's capacity to be more efficient and more productivity for broader economic and social development. Such benefits can go a long way in improving food security as well as livelihoods for South Africa and the African continent which is characterized by recurrent food insecurity and poverty.

Despite the potential benefits of the study outputs, their reliability is however not accurate due to inherent model deficiencies. This provides an opportunity for further assessment of the recommendations through undertaking on farm research under the different climate analogues.

The study outputs places the country and region at par with other countries on advanced application of integration of seasonal forecasts and crop models. With the increased use of information and technology products, smart phones and other associated applications, the methodology of the research on decision making and determination of recommendations can be further developed into a cell phone application. Such a product would be of use to farmers, agricultural practitioner and policy makers. Such a tool potentially brings decision making to the farmer's finger tips. This eliminates delays associated with dissemination of forecasts as well as adding value in decision making.

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6.4 Limitations of the study

- Compound errors: Seasonal forecasts are a probabilistic estimation of future weather. They have limited accuracy as observed by the greater seasonal forecast and crop variability. Similarly, crop models are a crude estimation of reality. Integrating seasonal forecasts with crop models potentially compounds errors from both components. The outputs may therefore need moderation.
- Input data for crop models: There were challenges in accessing input data for calibration of crop models. Most farmers had challenges in recalling the exact crop management systems as well yields. The study relied on secondary data for calibration.
- Validation of outputs: Effectiveness of the recommendations were supposed to be evaluated in on farm and on station field trials. The study was however limited by funds and time. There was therefore no opportunity for verification and validation of the outputs.

6.5 Recommendations

In future, the study therefore recommends:

- There is need for investment in on farm and on station experiments that can be used in calibration of crop models for use in future modelling studies.
- The outputs from this study should not be treated as the exact state of the future. They however give a general idea of the recommendations.
- The study used the CFSv2 model whose reliability over southern Africa is in doubt. Prior to similar studies, there is therefore need for further research on seasonal forecasting models that are suitable for the southern African region.
- There is need for research to improve the forecasting skill. This increases reliability and clarity of the research outputs.
- Future research should utilise multiple seasonal forecasts sets as well as multiple sources if seasonal forecasts i.e. more than what have been used in the current study. This improves the reliability of the research outputs.

- There is need for verification of the research outputs through undertaking on farm research. This could be similar to research by Thierfelder et al., (2013), who undertook farm management component experiments, to ascertain the actual on farm experiments.
- There is need to automate the decision formulation process to improve effectiveness of the process and increase the ability to assess a plethora of climate and management scenarios.
- There is need to consider use of seasonal forecast information with indigenous knowledge as a tool to enhance climate risk management in small-scale farming systems.

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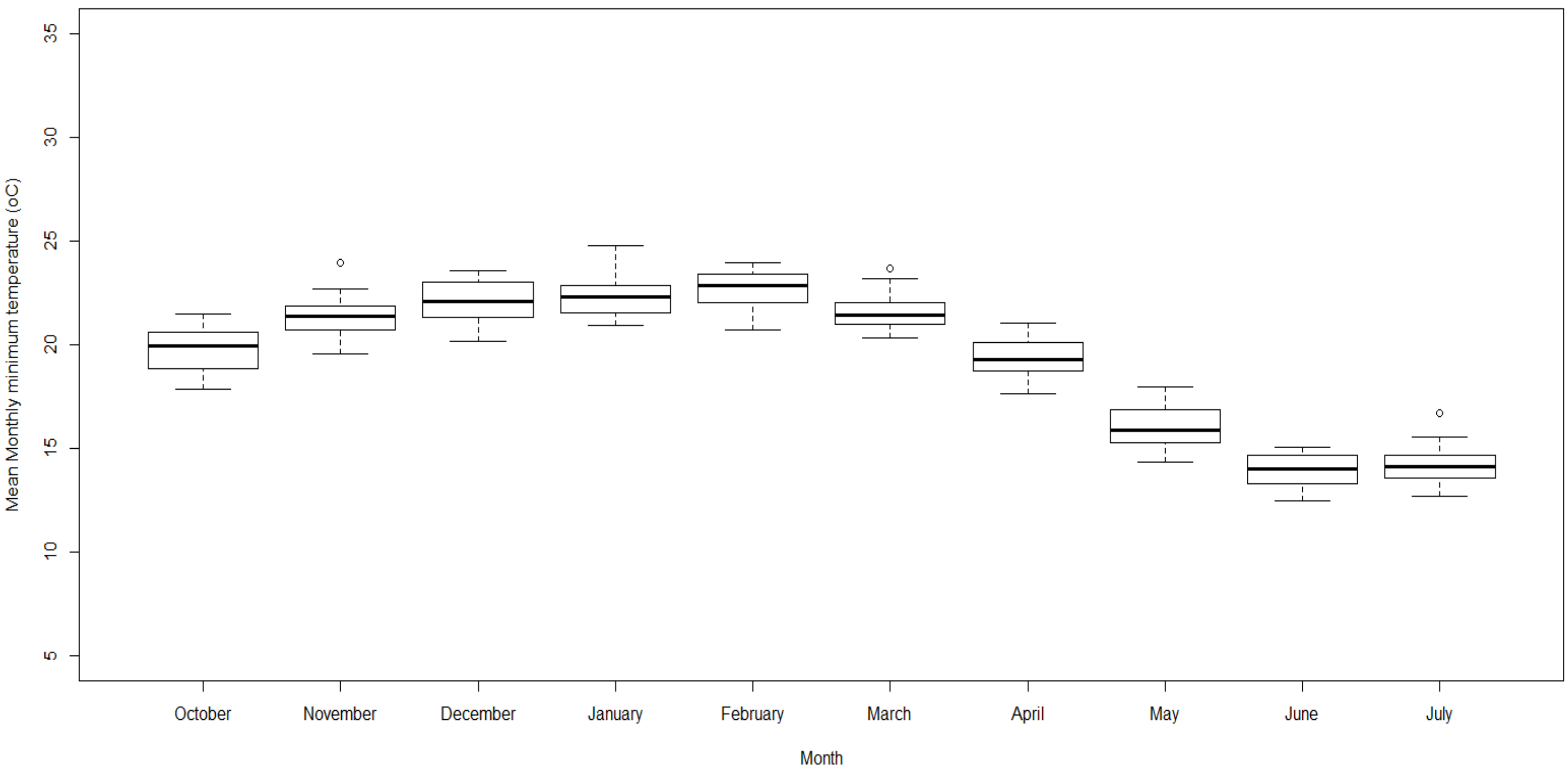
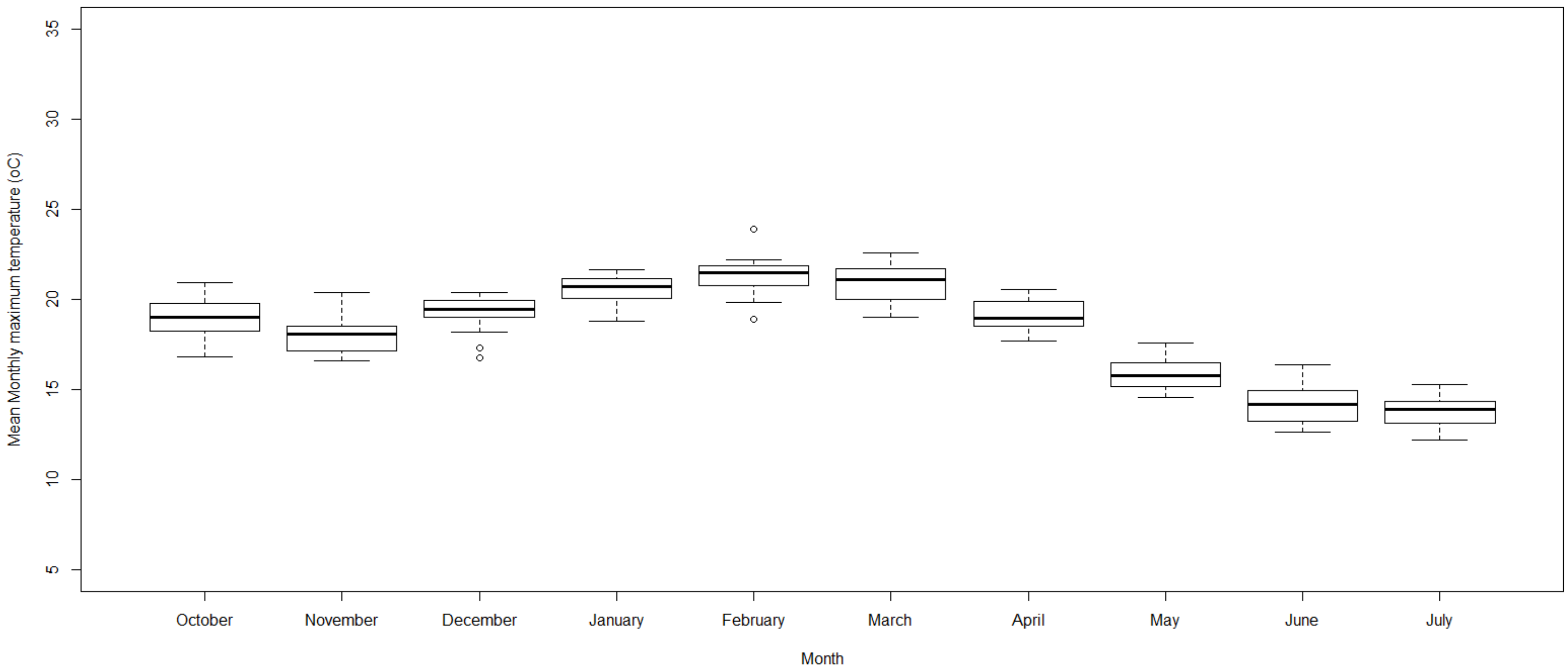
Annexures

Annexure 4.1: Mean minimum monthly temperatures from 23 seasonal forecasts for the 2017/18 cropping season in Lambani, Limpopo, South Africa

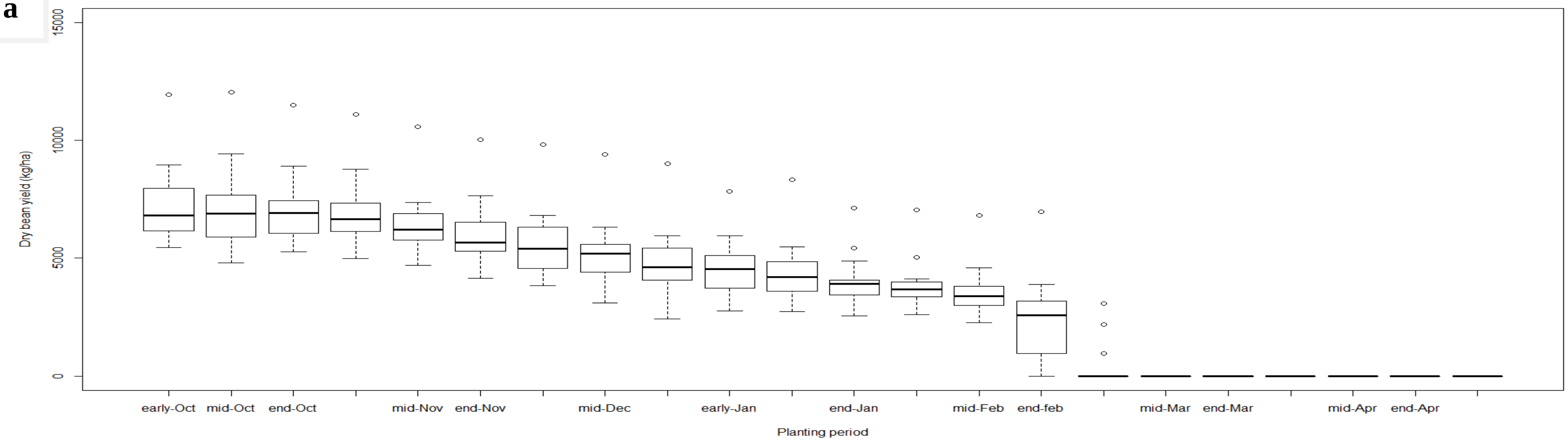


Annexure 4.2: Mean maximum monthly temperatures from 23 seasonal forecasts for the 2017/18 cropping season in Eastern Cape, South Africa.

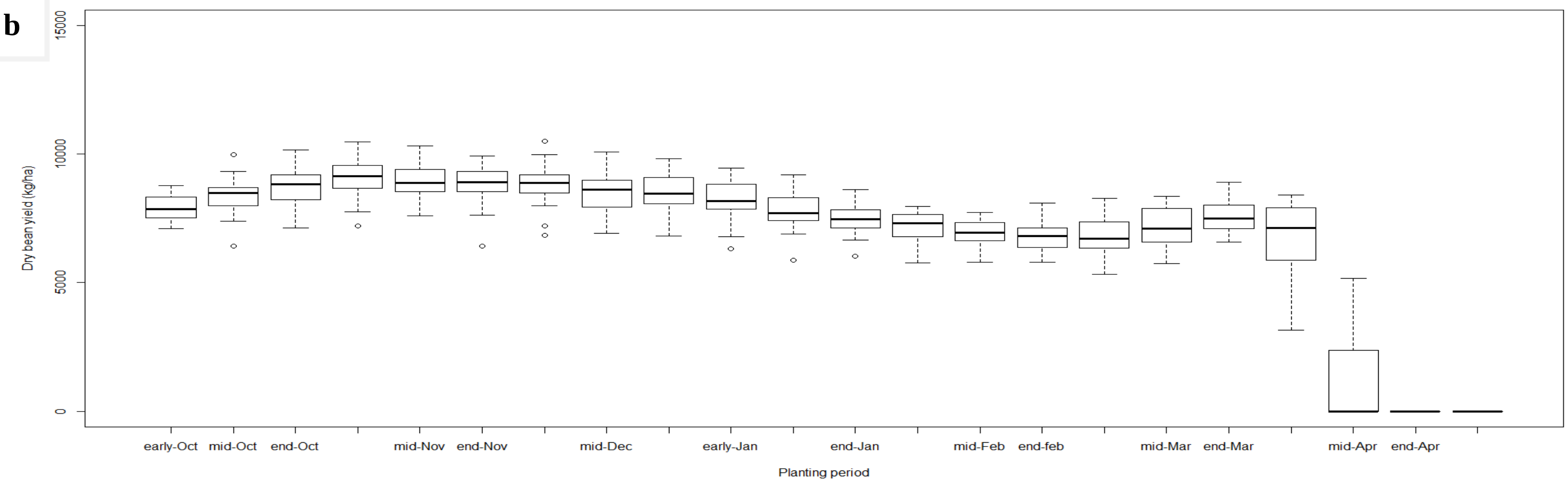


Annexure 4.3: Distribution of dry bean grain yields from the different seasonal forecasts within each planting period for the 2017/18 season in the Eastern Cape, (b) Limpopo provinces, South Africa.

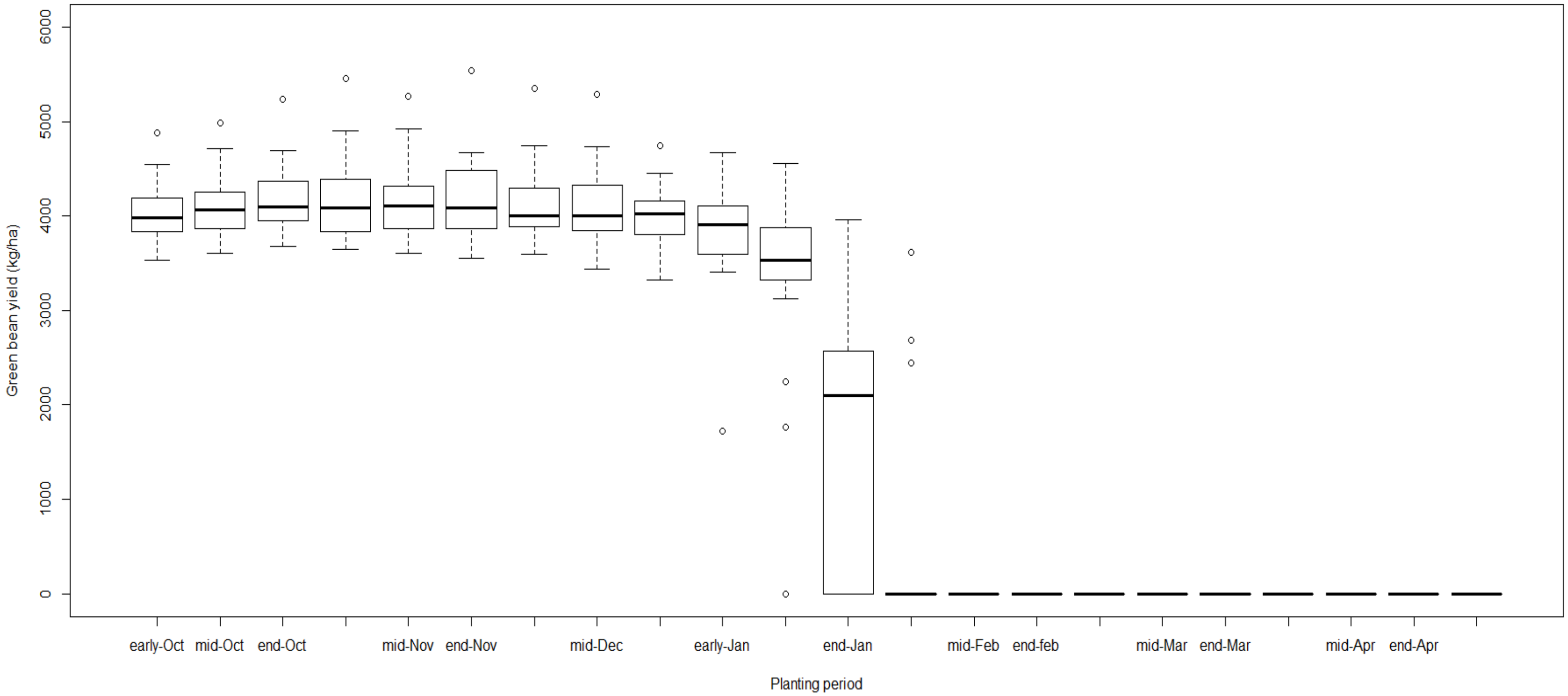
a



b

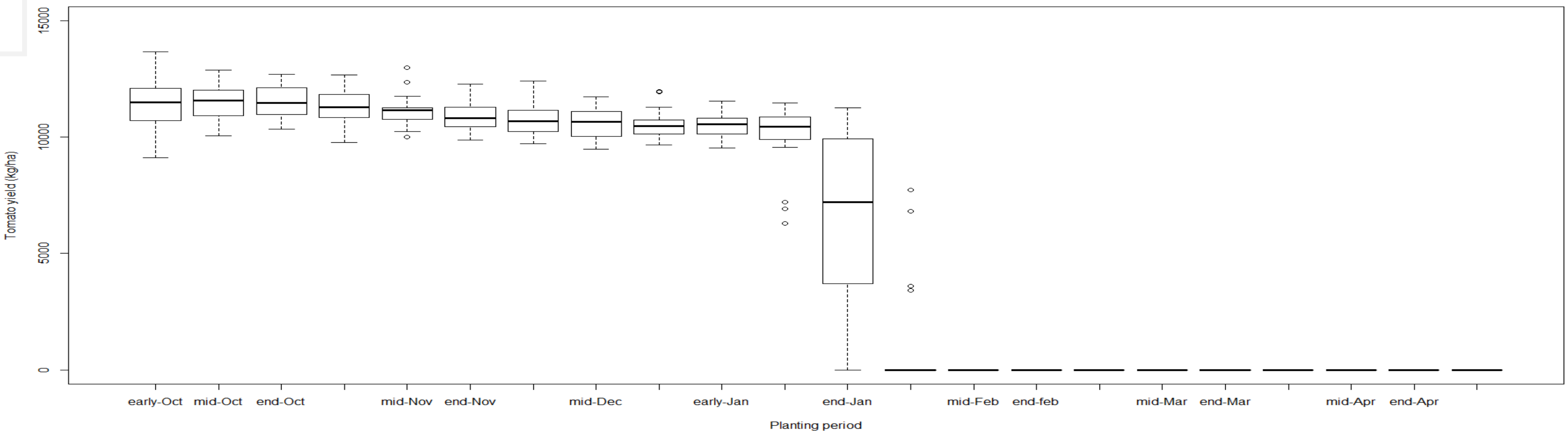


Annexure 4.4: Distribution of green bean grain yields from the different seasonal forecasts within each planting period for the 2017/18 season in the Eastern Cape, province, South Africa.

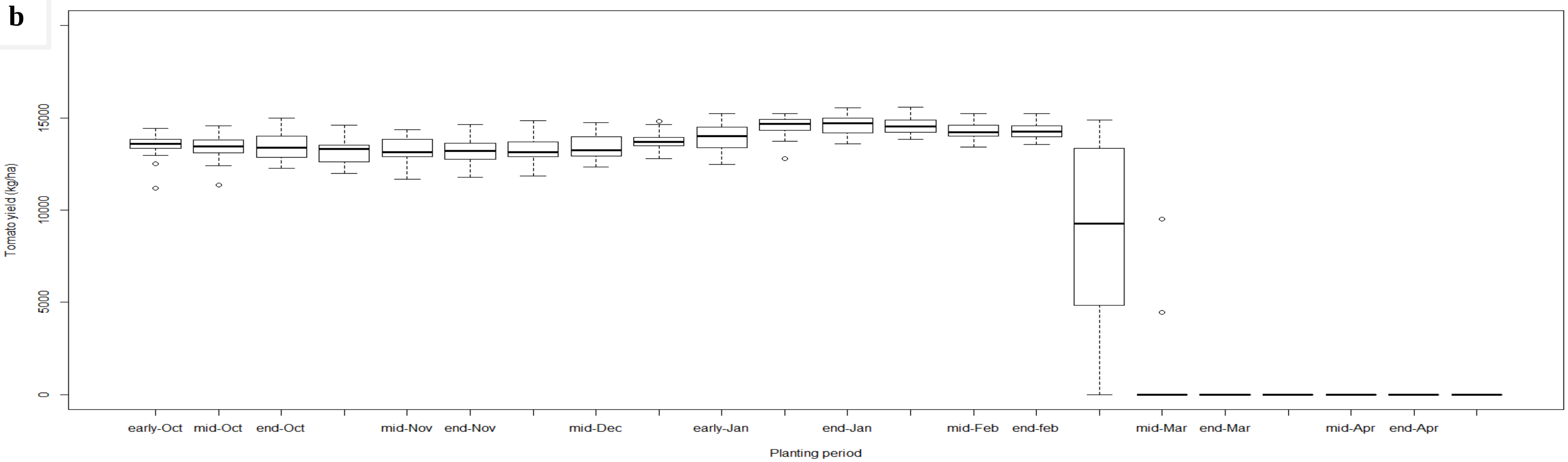


Annexure 4.5: Distribution of tomato yields from the different seasonal forecasts within each planting period for the 2017/18 season in the (a) Eastern Cape, (b) Limpopo provinces.

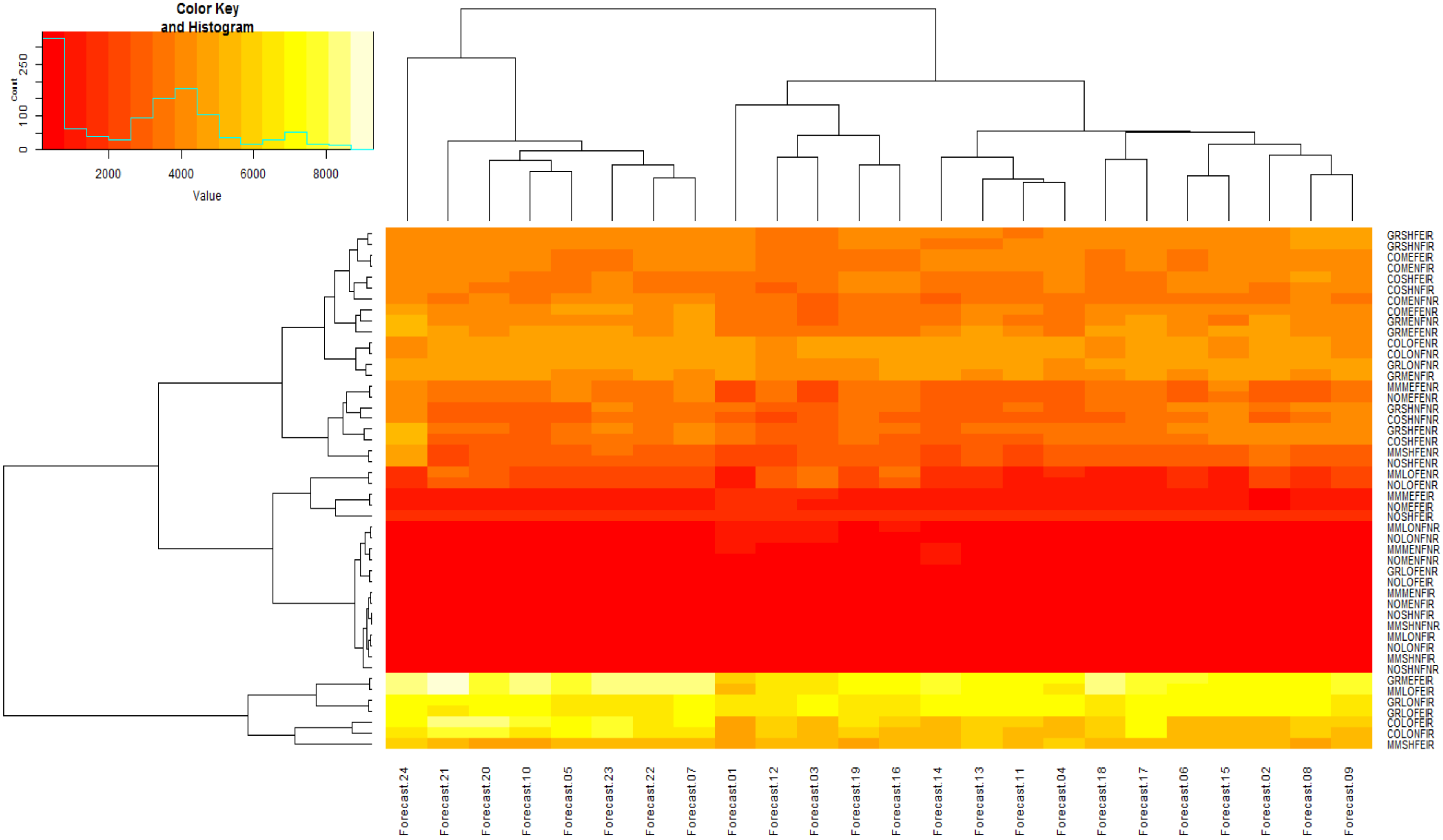
a



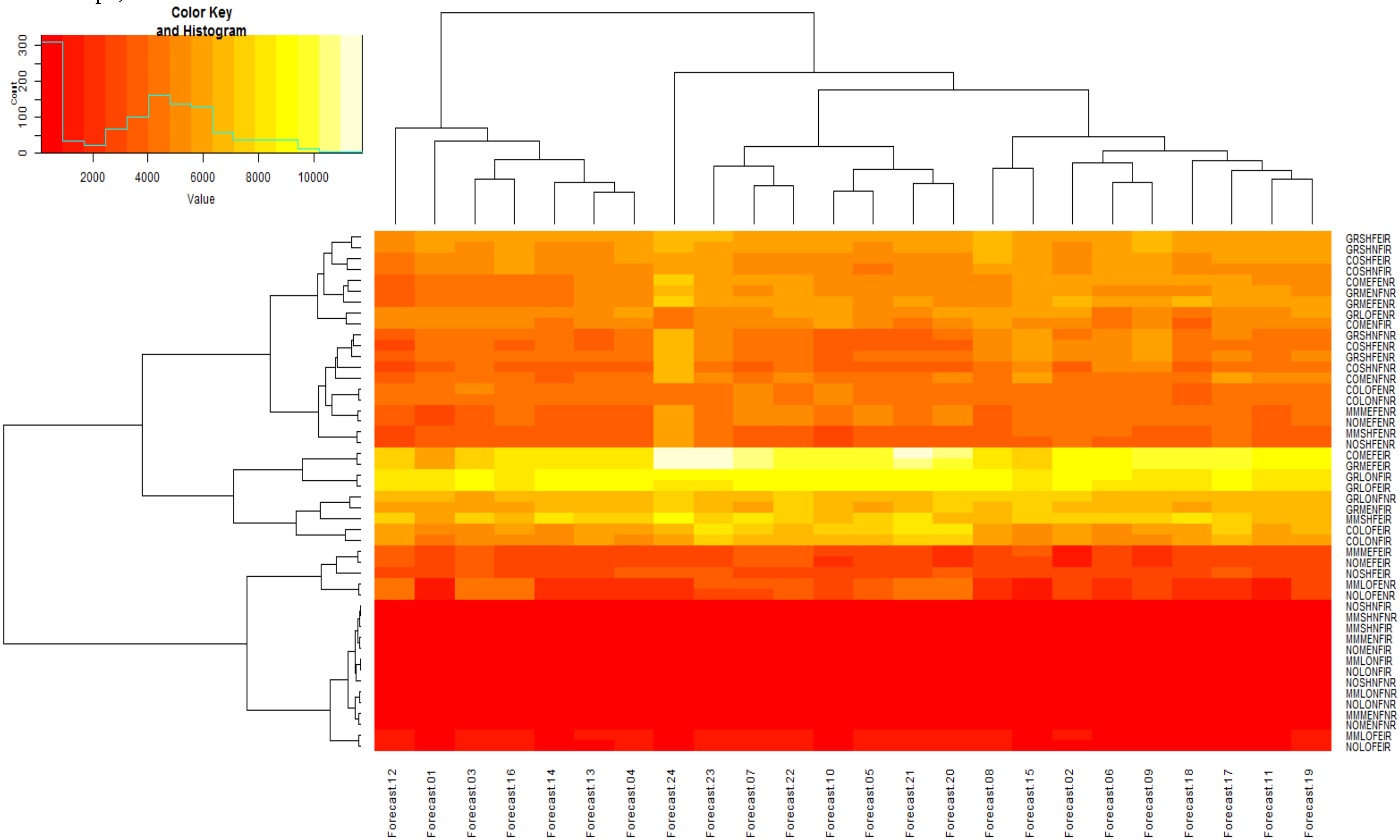
b



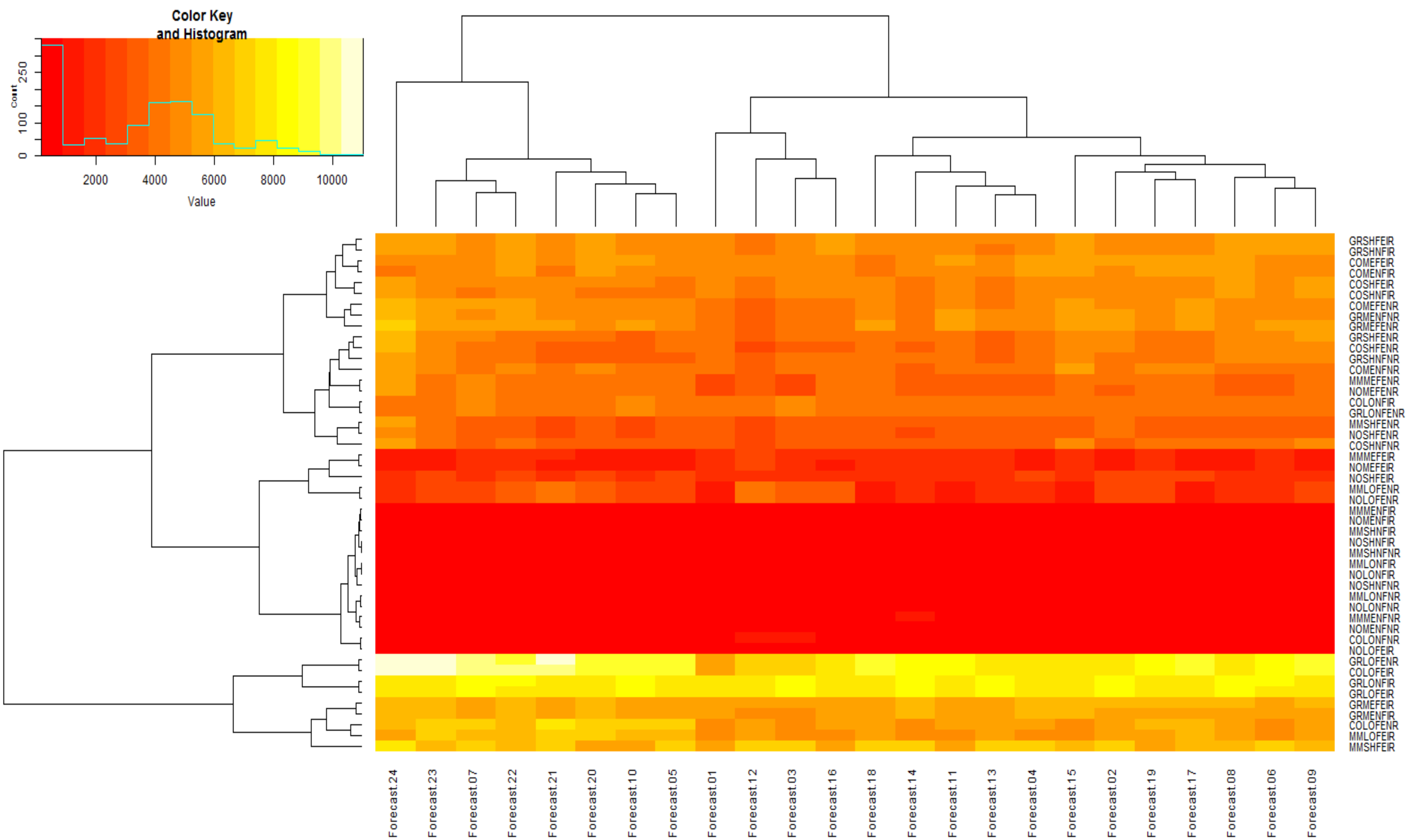
Annexure 4.6: Maize production under different seasonal forecasts and farm management decisions amongst social welfare dependant farmers in the Eastern Cape, South Africa.



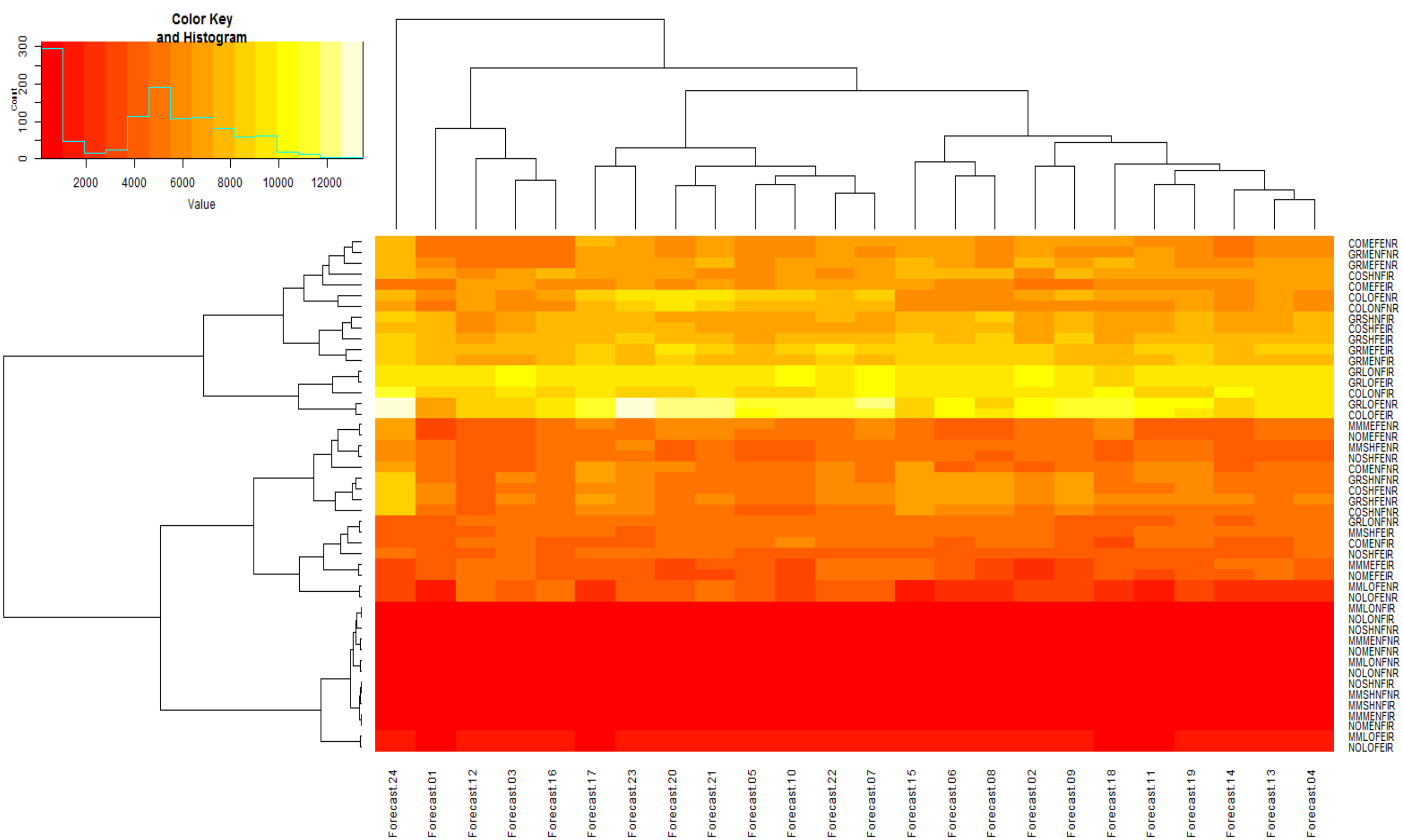
Annexure 4.7: Maize production under different seasonal forecasts and farm management decisions amongst enterprising farmers in the Eastern Cape, South Africa.



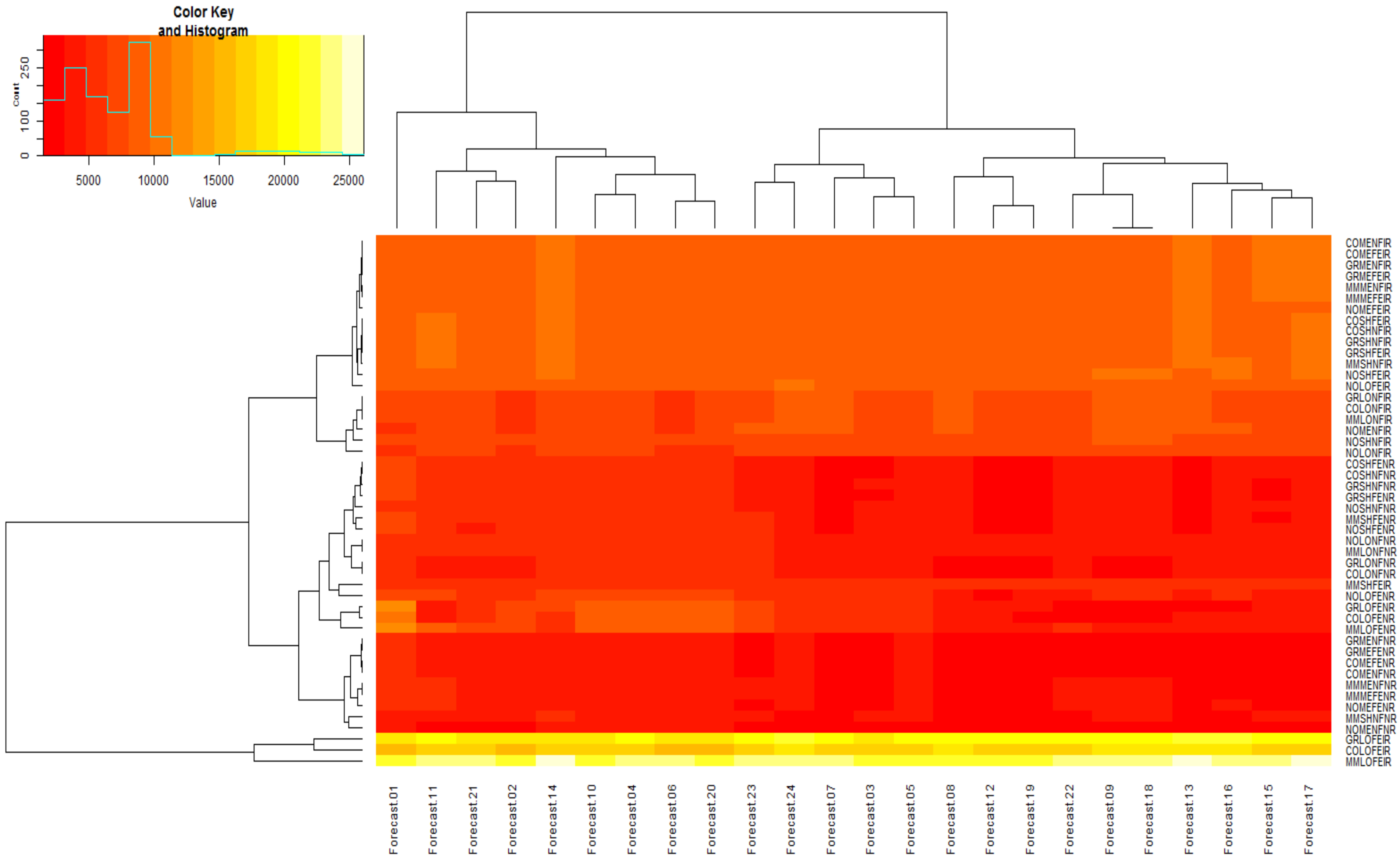
Annexure 4.8: Maize production under different seasonal forecasts and farm management decisions amongst struggling subsistence farmers in the Eastern Cape, South Africa.



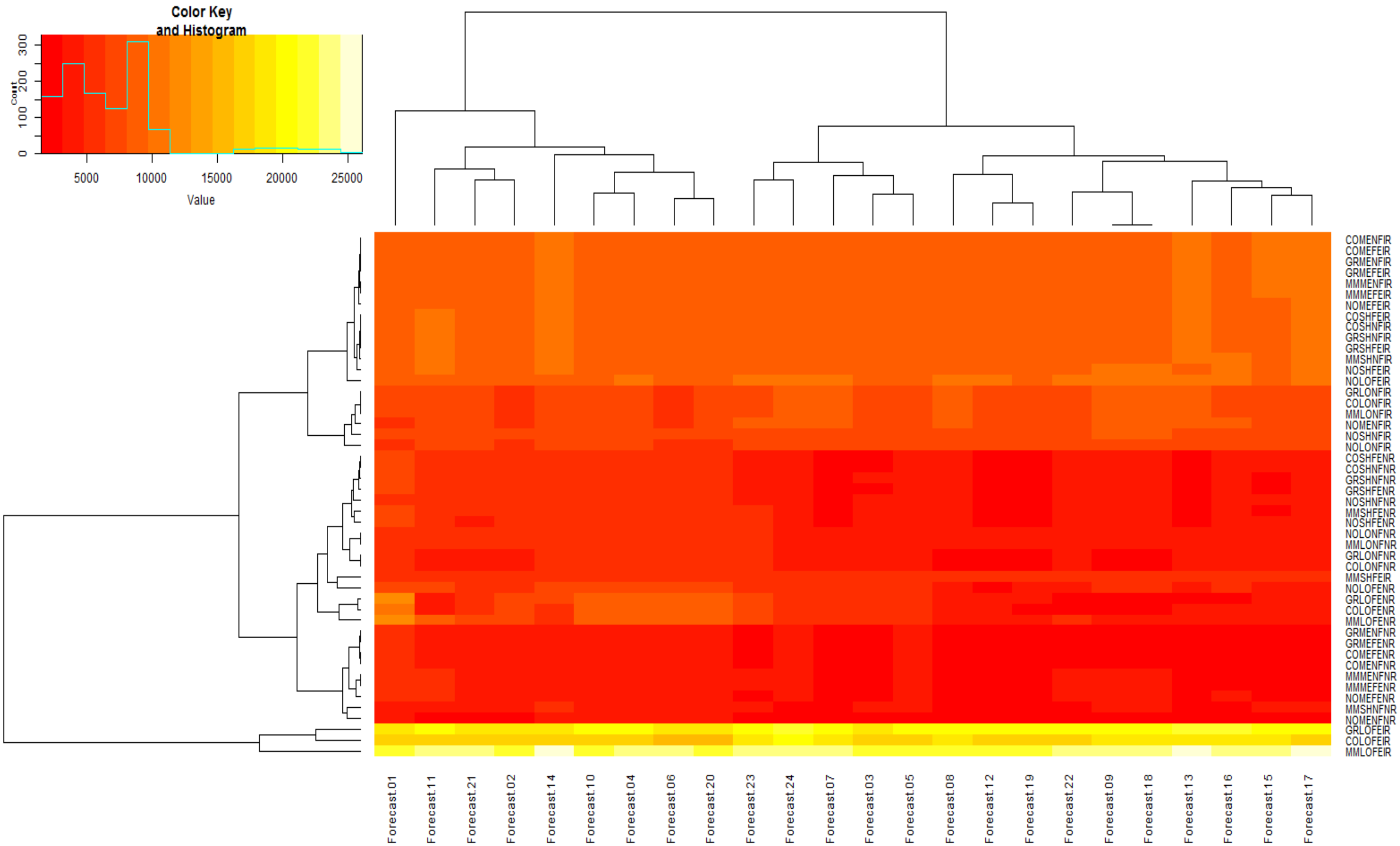
Annexure 4.9: Maize production under different seasonal forecasts and farm management decisions amongst horticultural dependant farmers in the Eastern Cape, South Africa.



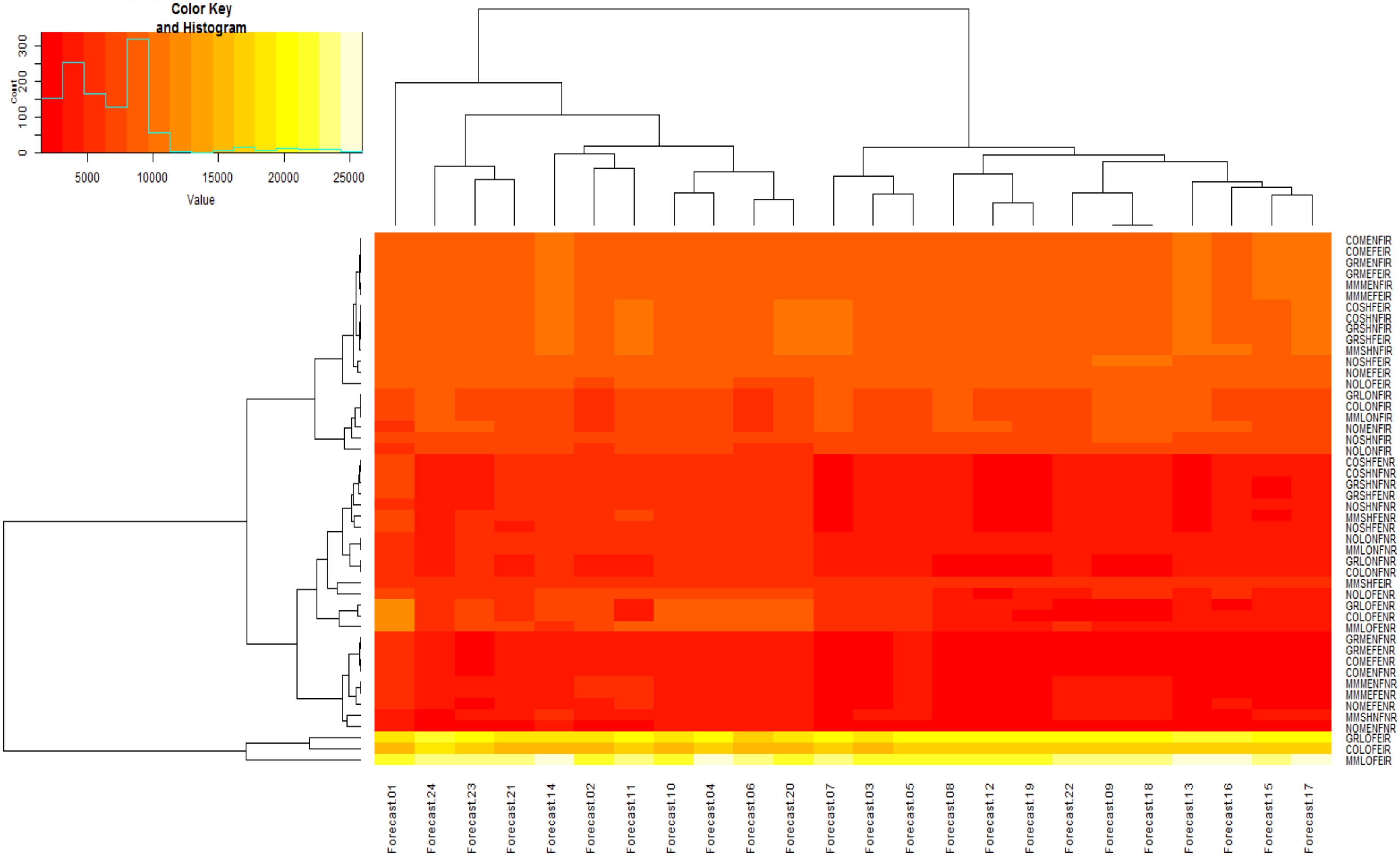
Annexure 4.10: Maize production under different seasonal forecasts and farm management decisions amongst mixed farmers in Limpopo, South Africa.



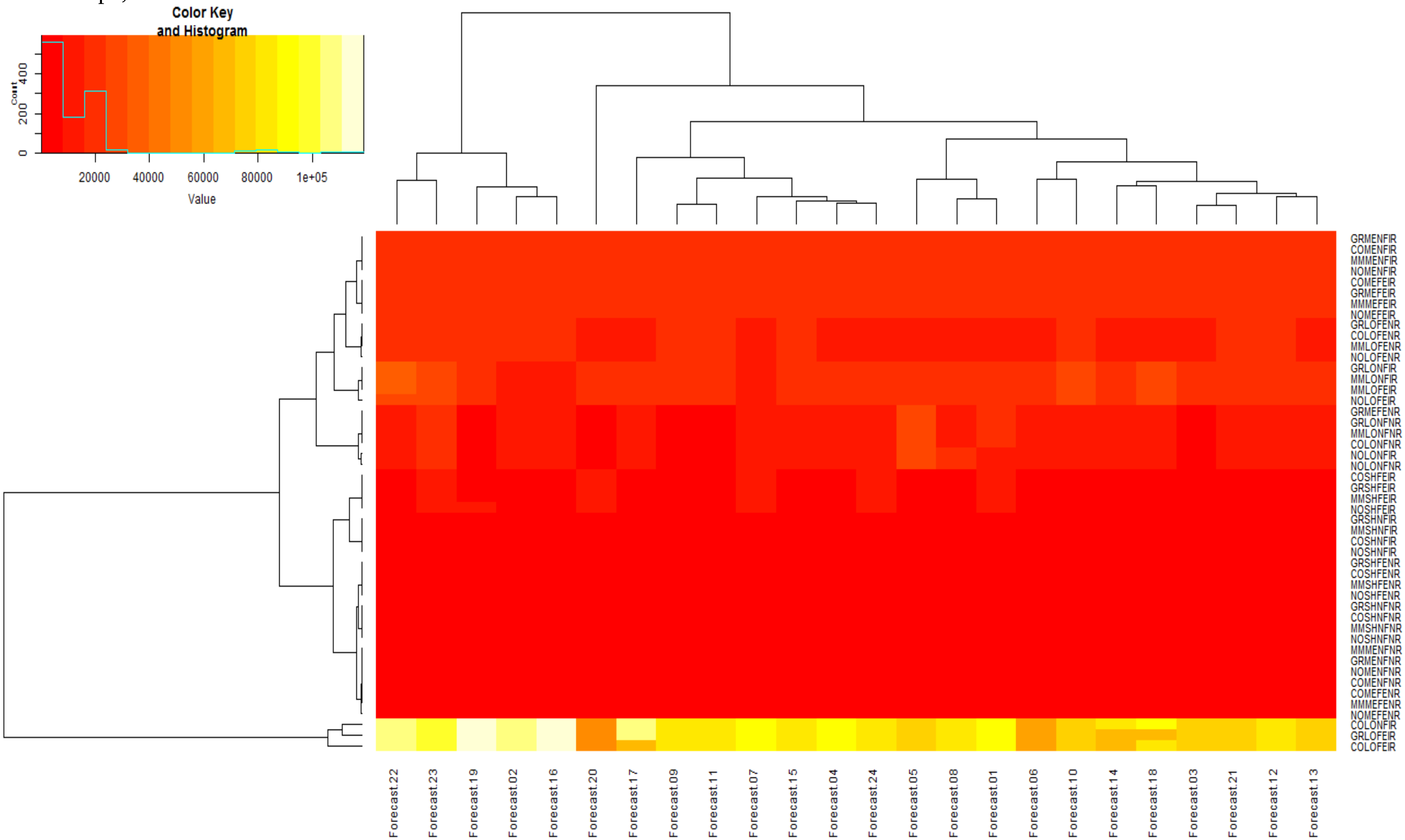
Annexure 4.11: Maize production under different seasonal forecasts and farm management decisions amongst Horticultural dependant farmers in Limpopo, South Africa.



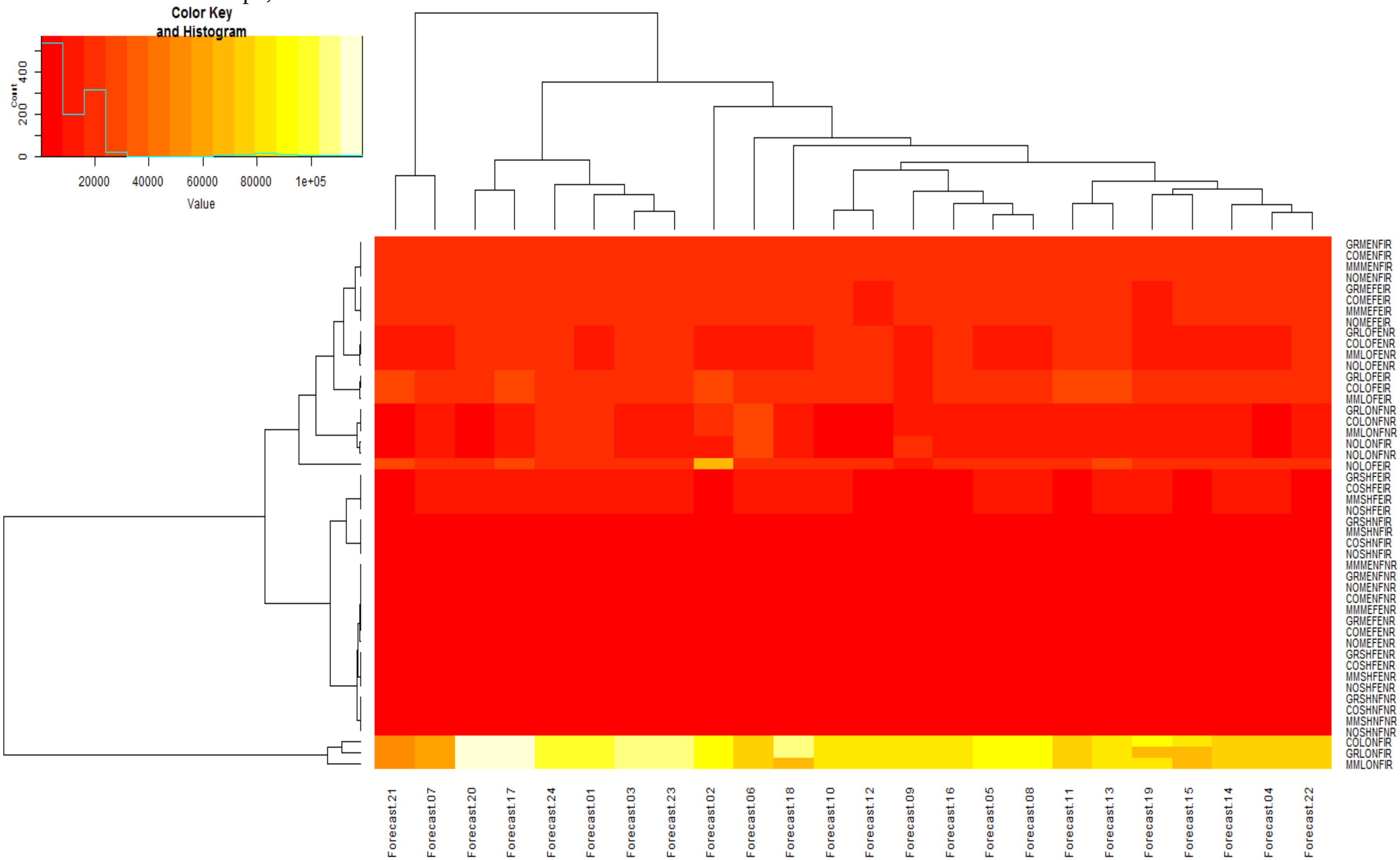
Annexure 4.12: Maize production under different seasonal forecasts and farm management decisions amongst Off farm income dependant farmers in Limpopo, South Africa



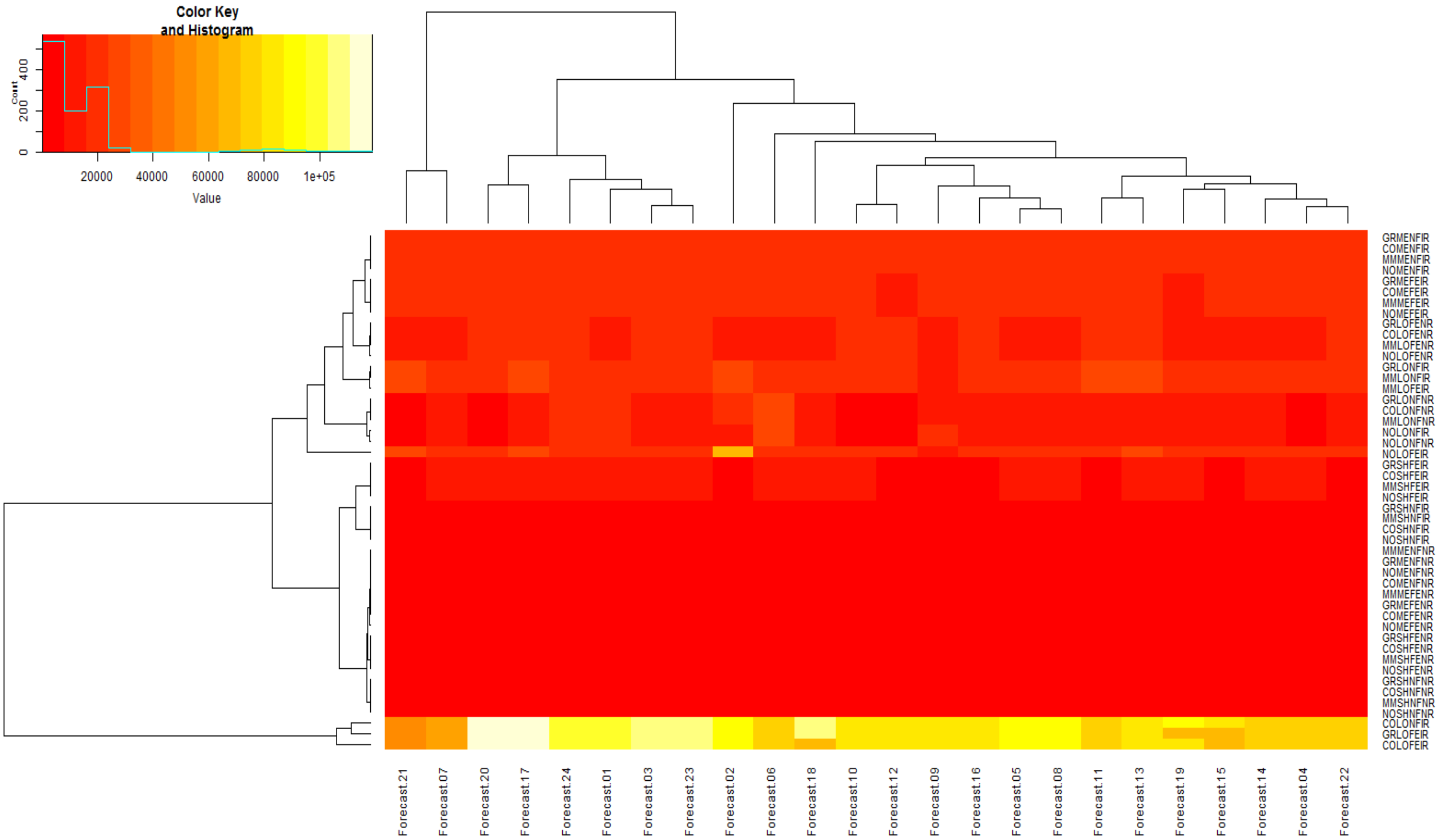
Annexure 4.13: Cabbage production under different seasonal forecasts and farm management decisions amongst enterprising farmers in the Eastern Cape, South Africa.



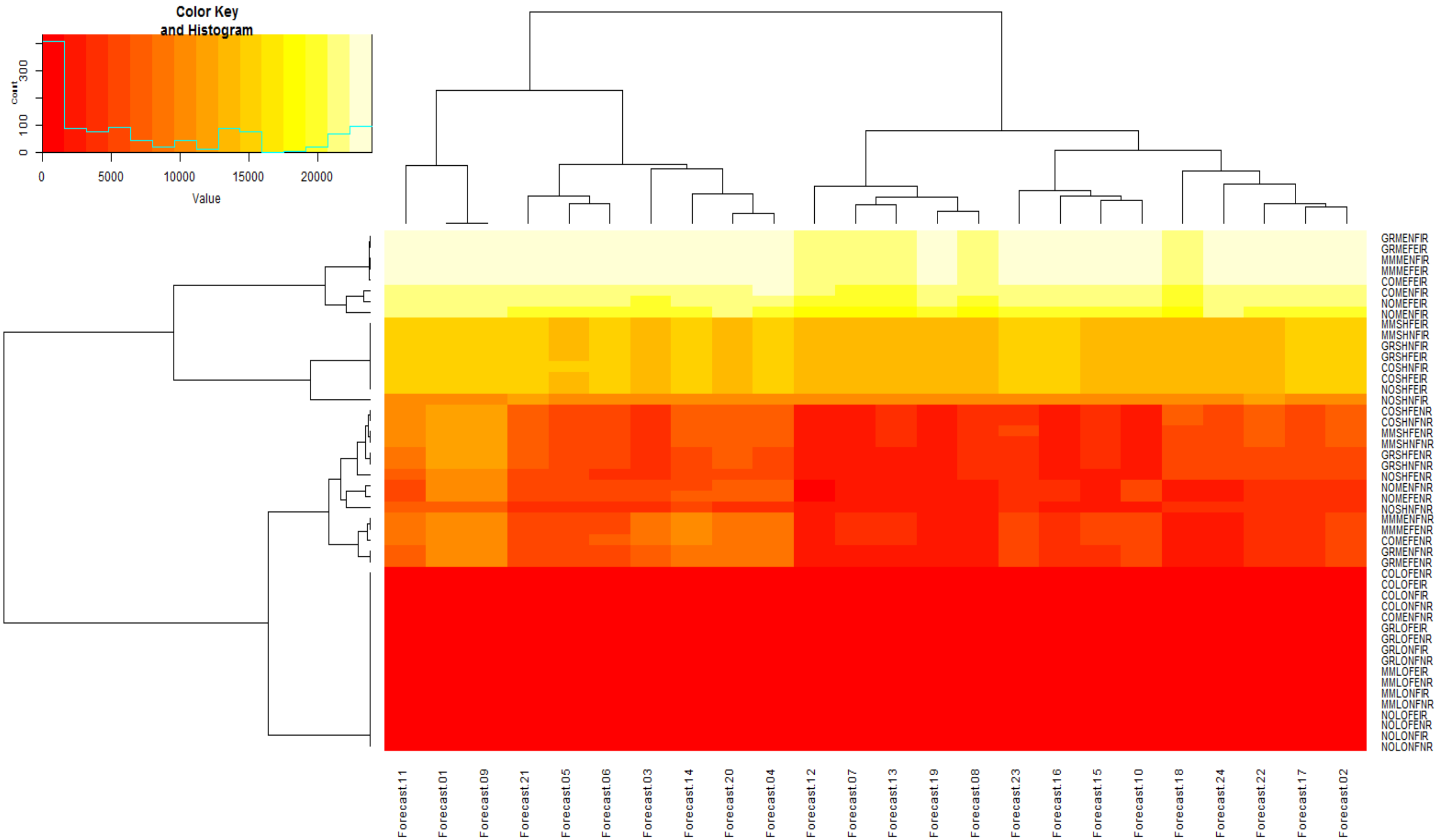
Annexure 4.14: Cabbage production under different seasonal forecasts and farm management decisions amongst horticultural dependant farmers in the Eastern Cape, South Africa.



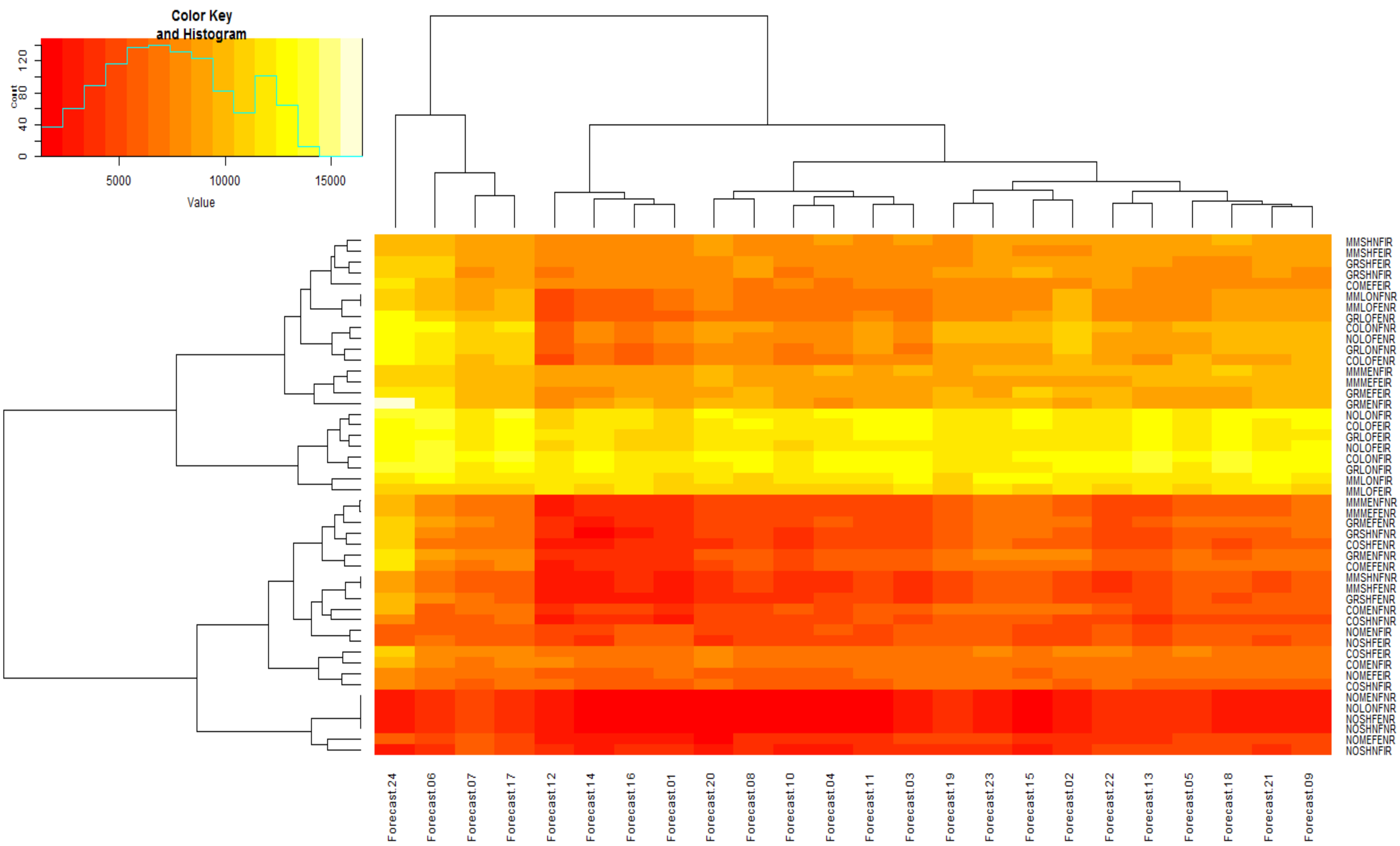
Annexure 4.15: Cabbage production under different seasonal forecasts and farm management decisions amongst cooperative crop farmers in the Eastern Cape, South Africa



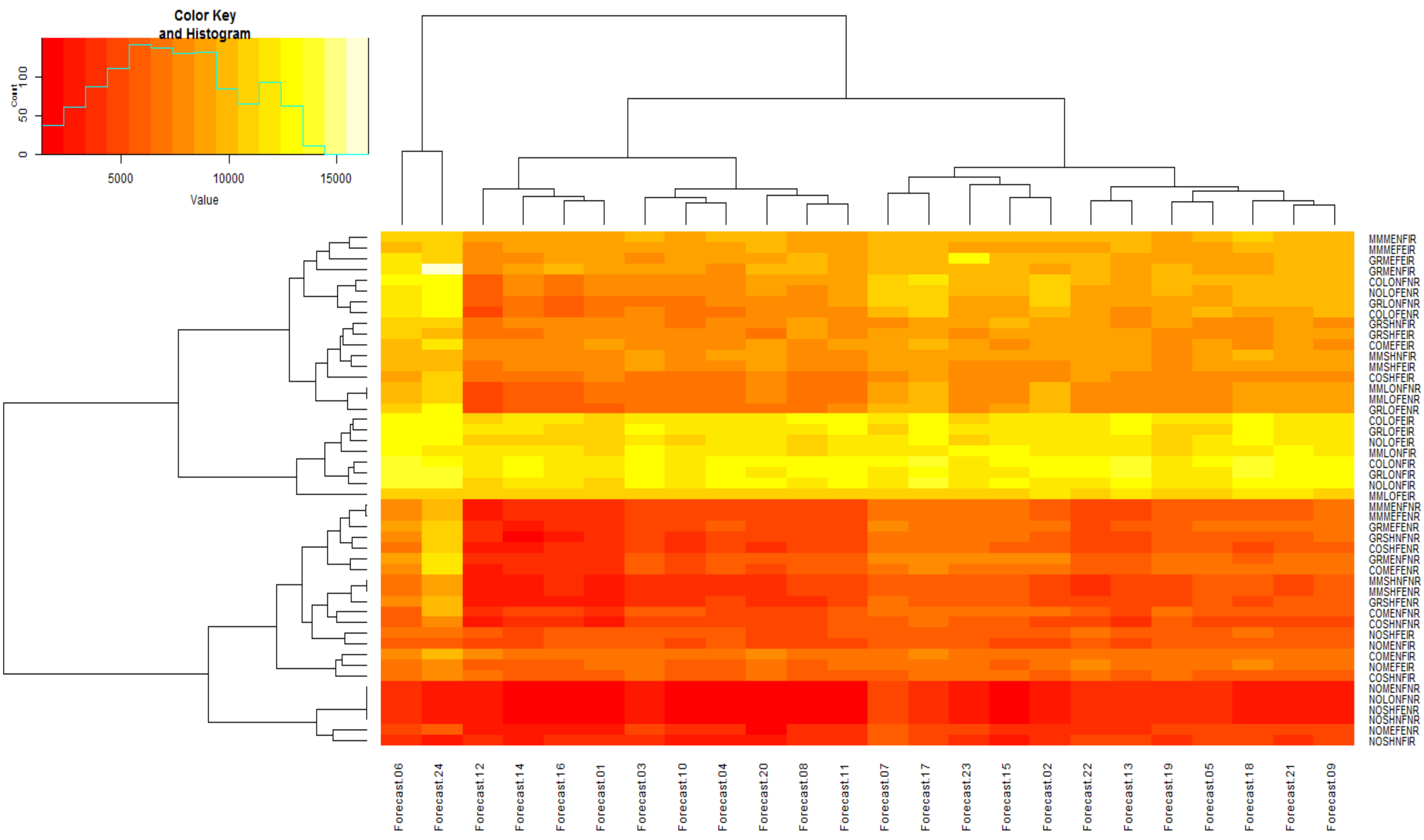
Annexure 4.16: Cabbage production under different seasonal forecasts and farm management decisions amongst horticultural dependant farmers in Limpopo, South Africa.



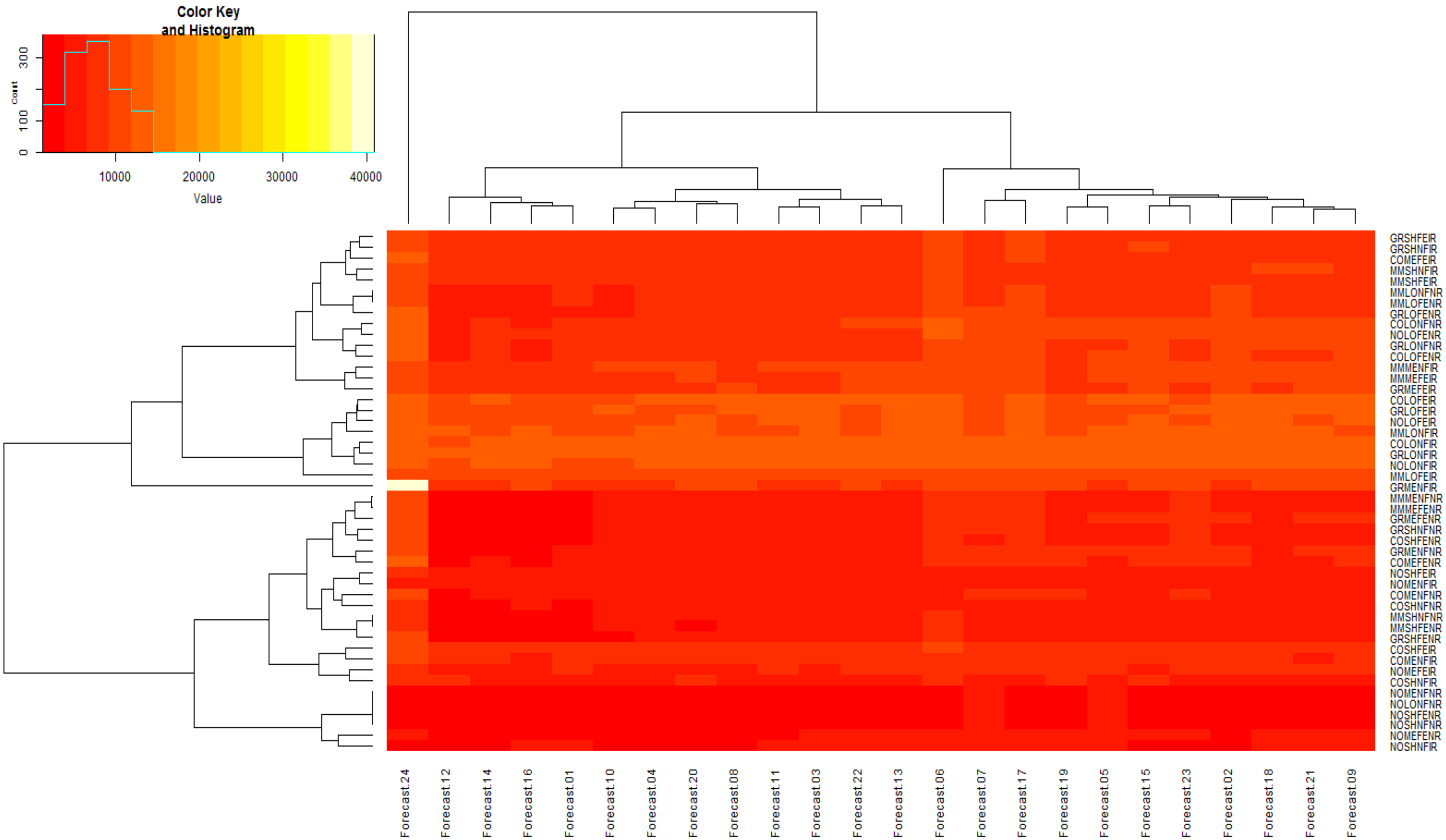
Annexure 4.17: Tomato production under different seasonal forecasts and farm management decisions amongst enterprising farmers in the Eastern Cape, South Africa



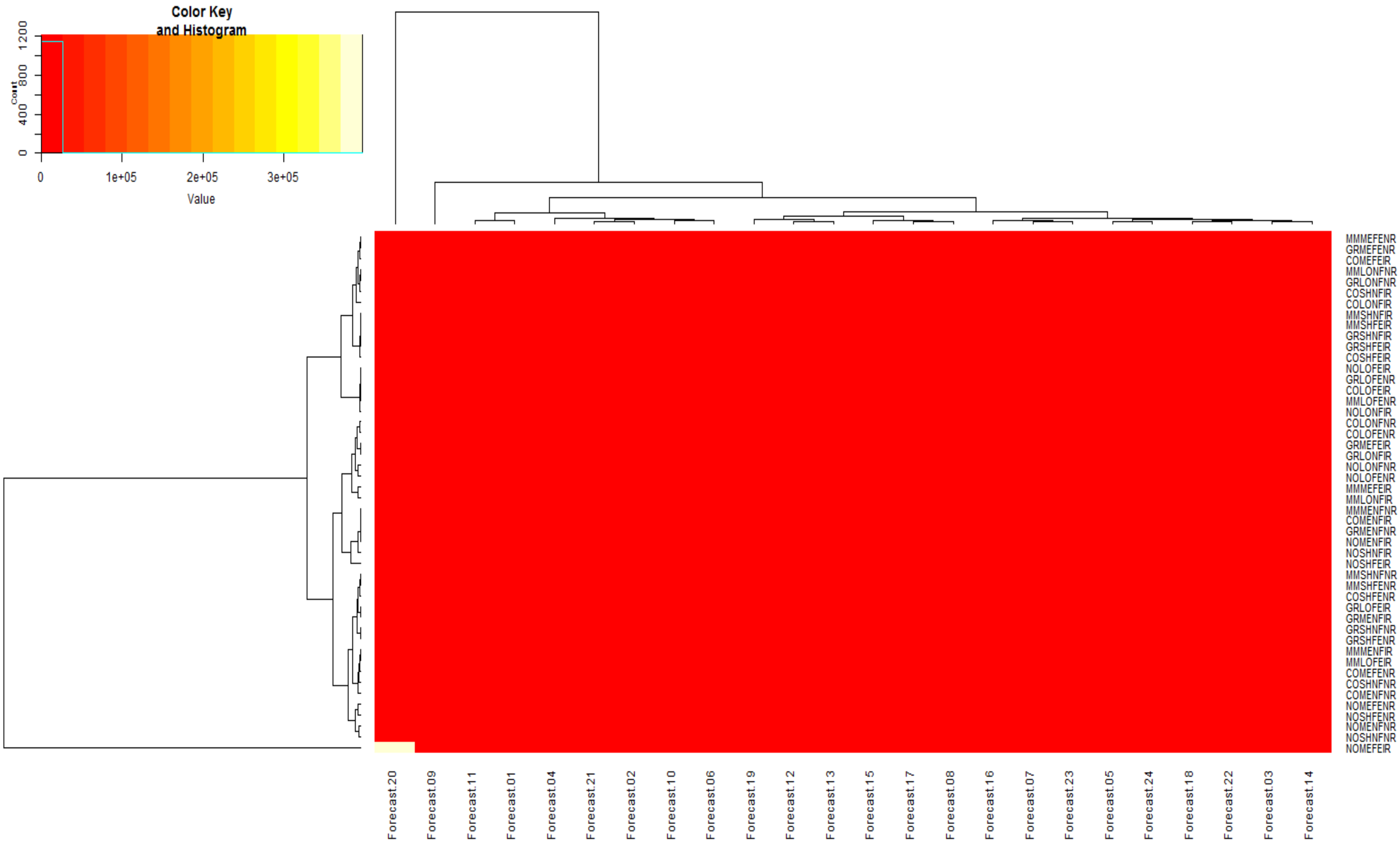
Annexure 4.18: Tomato production under different seasonal forecasts and farm management decisions amongst horticultural dependant farmers in the Eastern Cape, South Africa



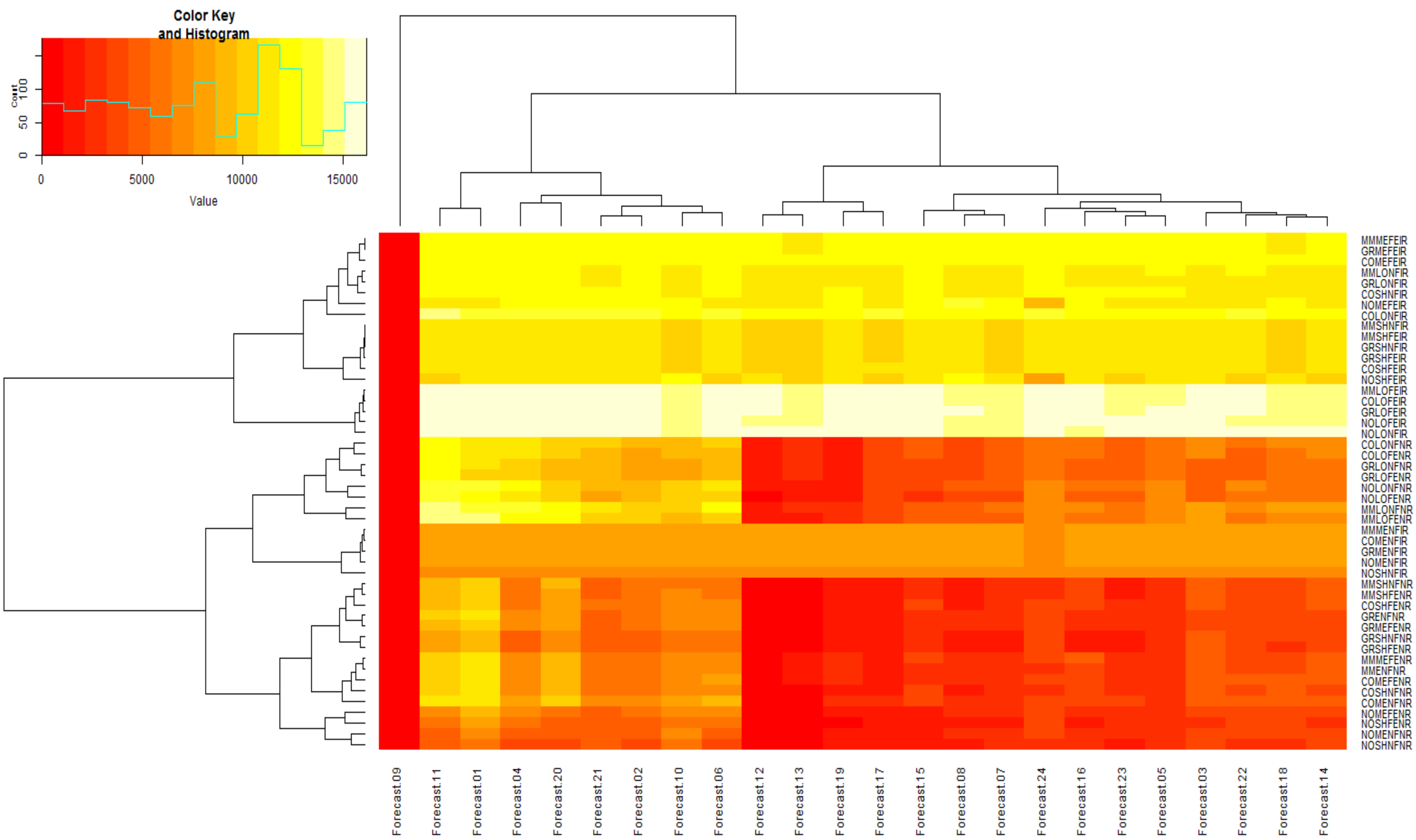
Annexure 4.19: Tomato production under different seasonal forecasts and farm management decisions amongst cooperative crop farmers in the Eastern Cape, South Africa.



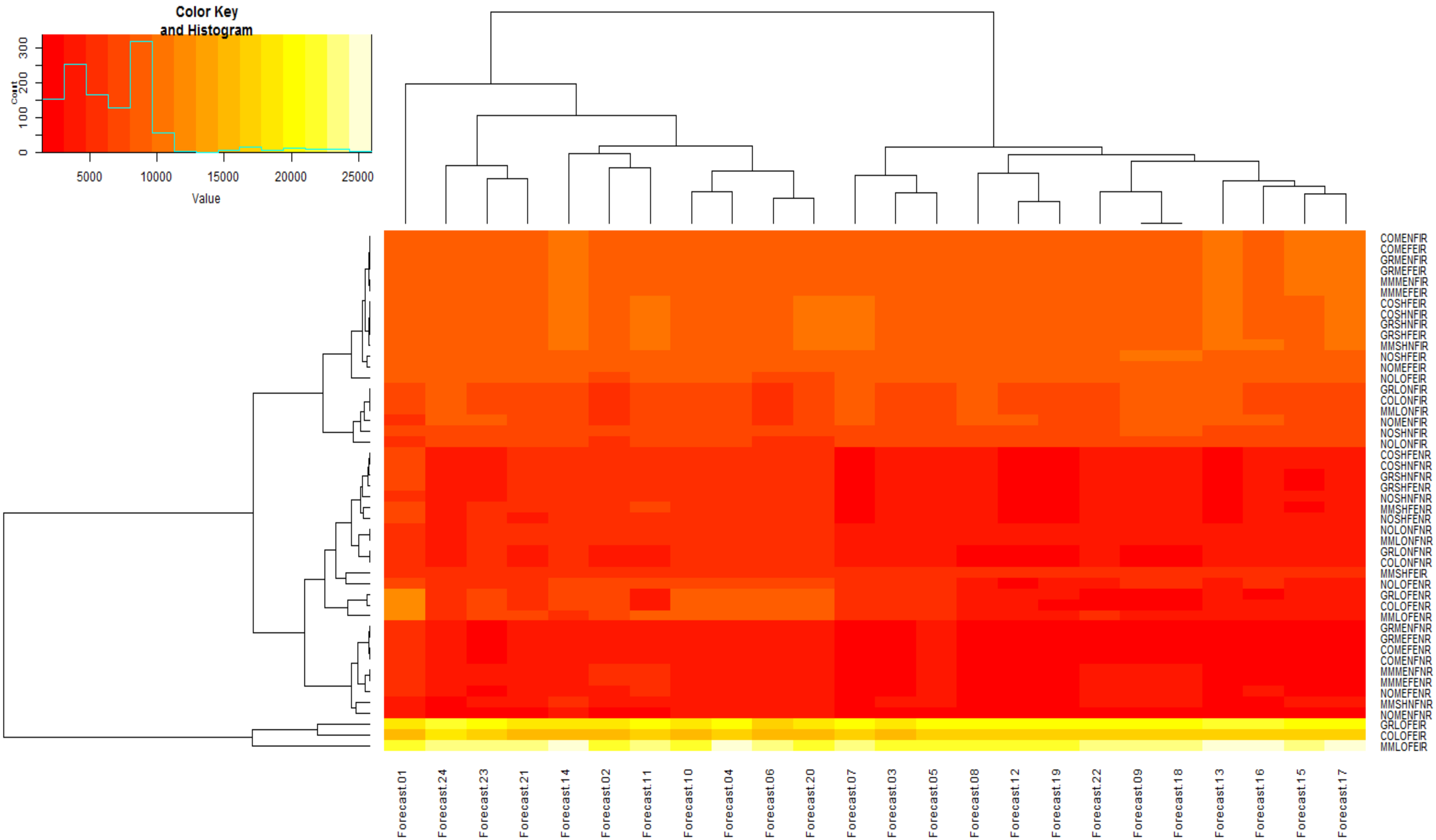
Annexure 4.20: Tomato production under different seasonal forecasts and farm management decisions amongst mixed farmers in Limpopo, South Africa.



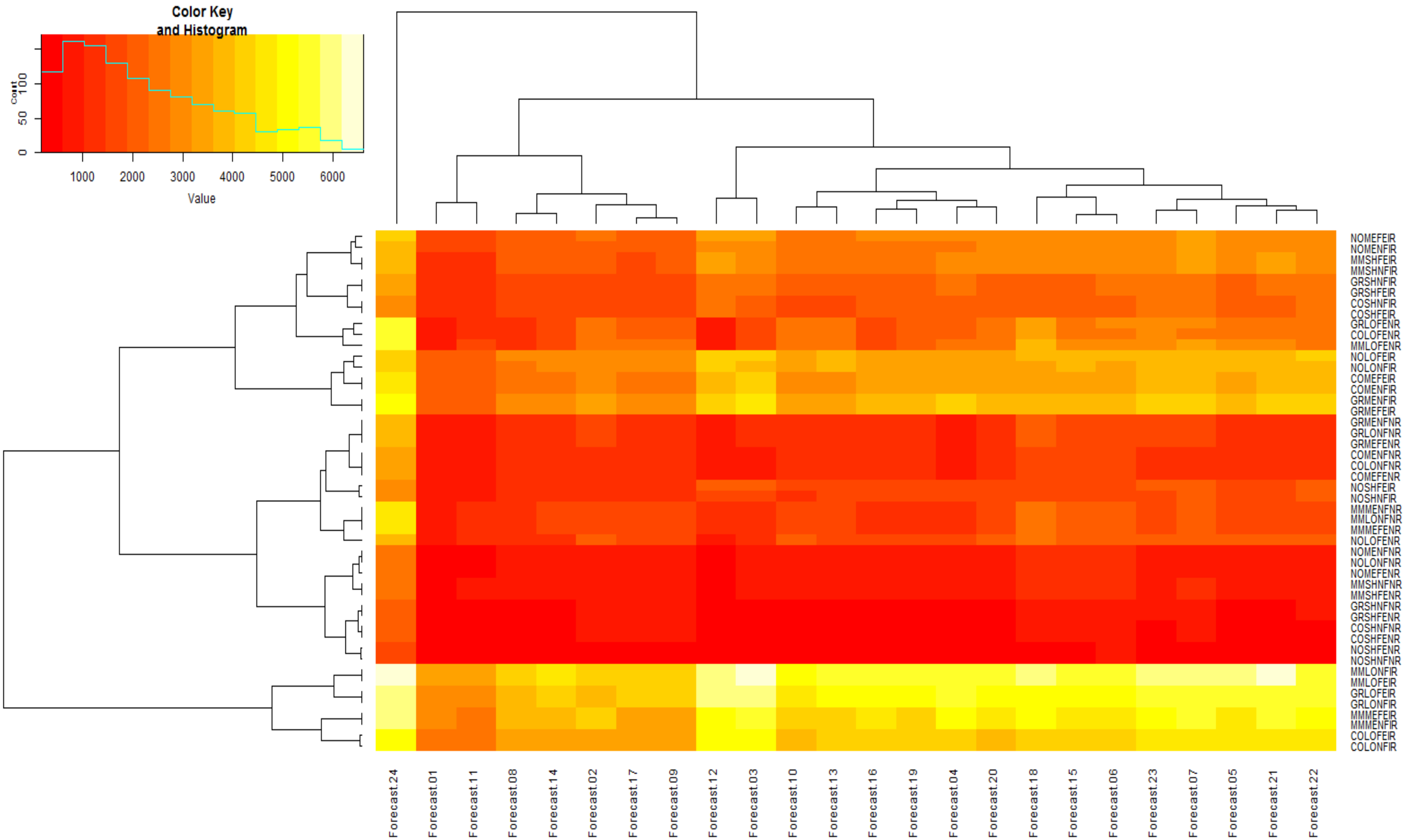
Annexure 4.21: Tomato production under different seasonal forecasts and farm management decisions amongst horticultural dependant farmers in Limpopo, South Africa.



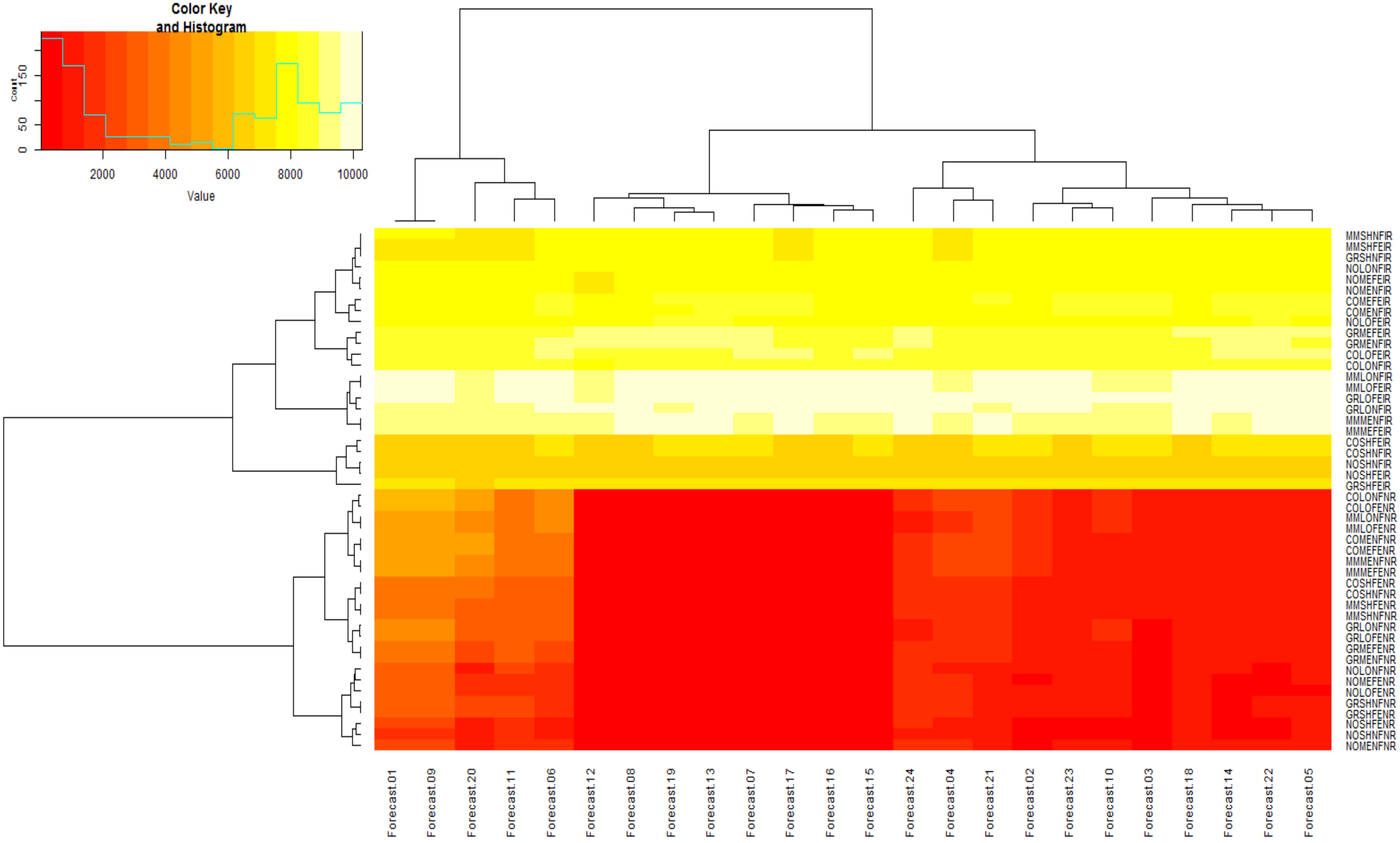
Annexure 4.22: Tomato production under different seasonal forecasts and farm management decisions amongst off farm income farmers in Limpopo, South Africa.



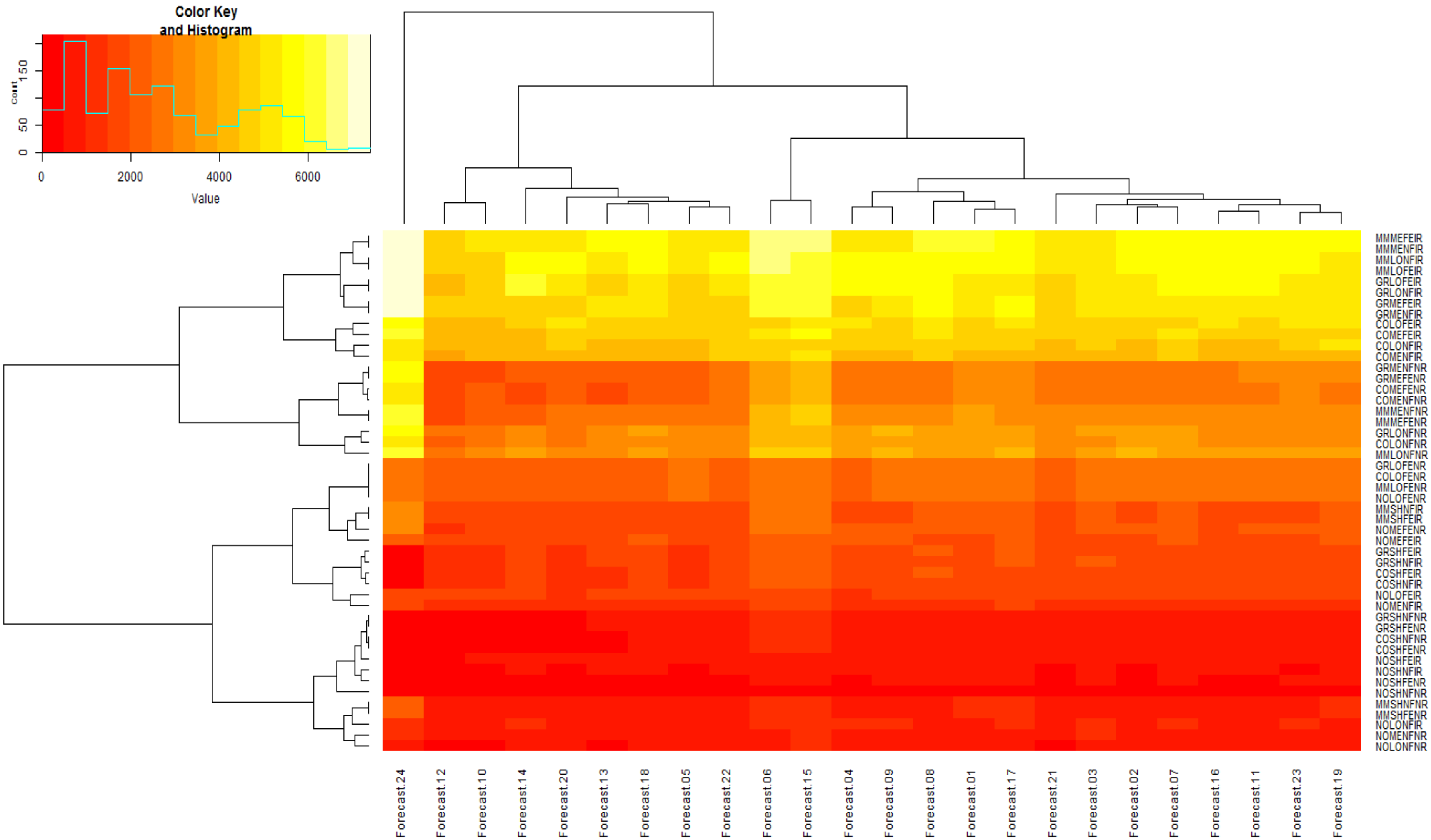
Annexure 4.23: Peanut production under different seasonal forecasts and farm management decisions amongst off farm income farmers in the Eastern Cape, South Africa.



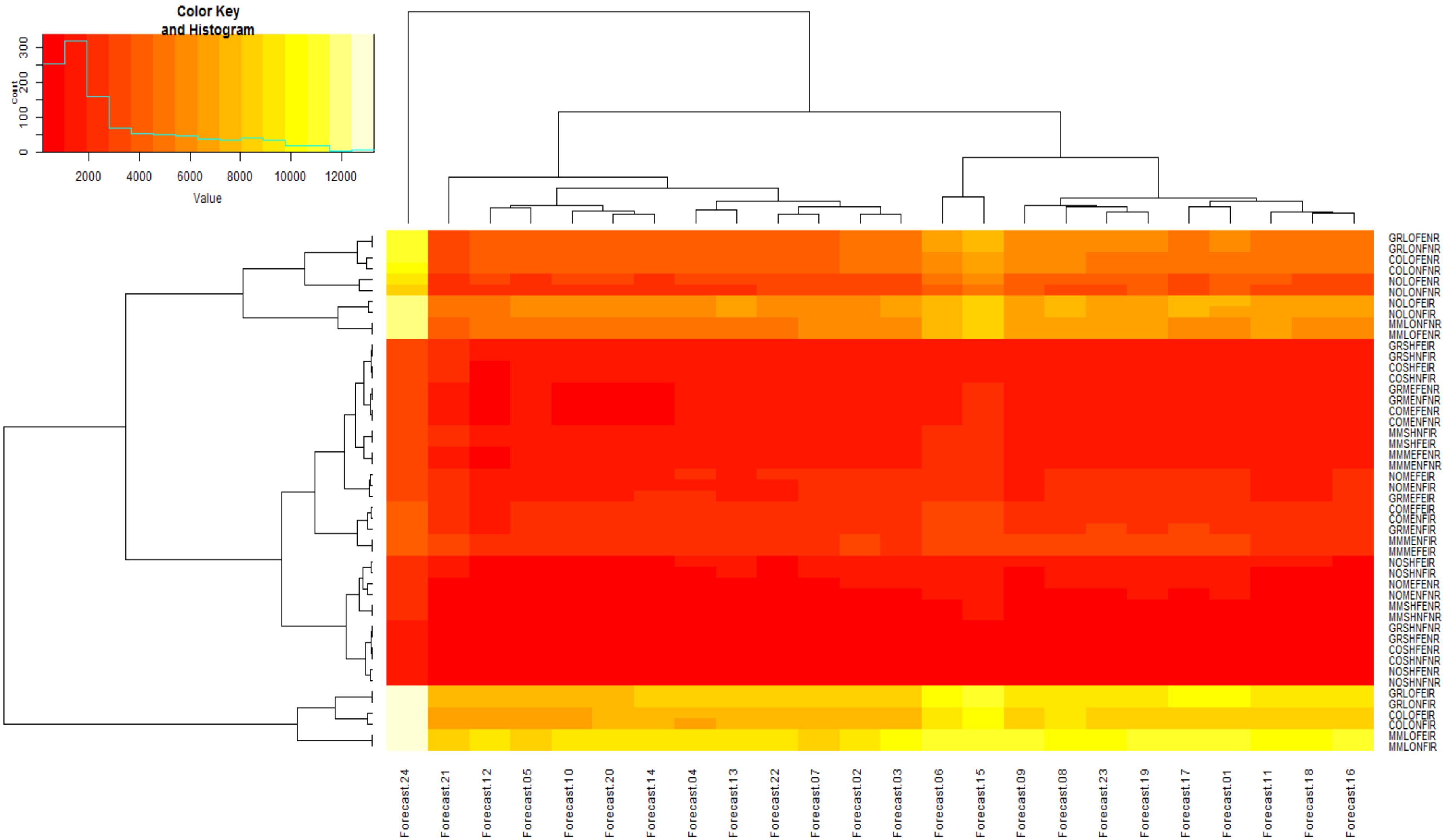
Annexure 4.24: Peanut production under different seasonal forecasts and farm management decisions amongst mixed farmers in Limpopo, South Africa



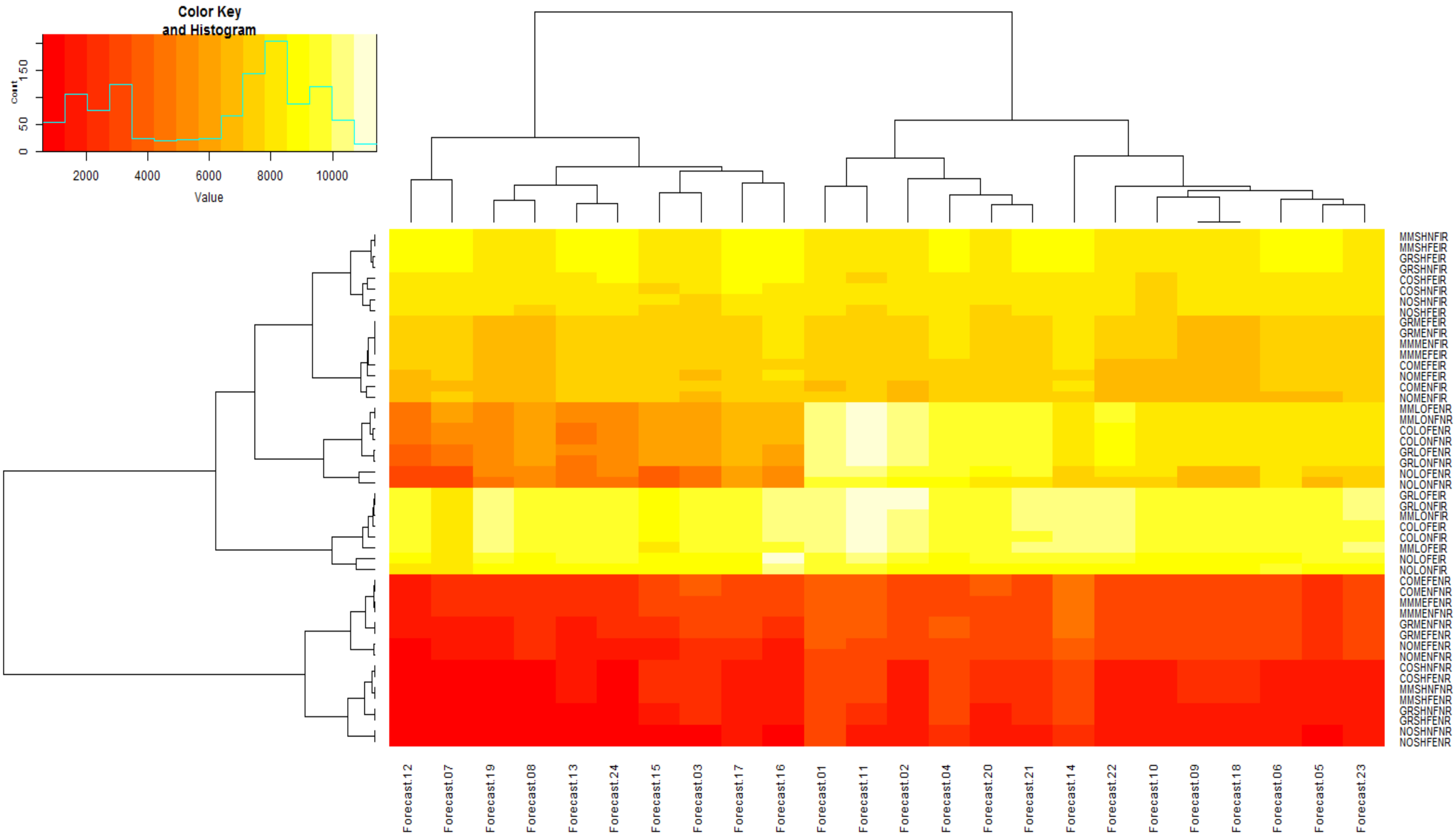
Annexure 4.25: Green bean production under different seasonal forecasts and farm management decisions amongst social welfare dependant farmers in the Eastern Cape, South Africa



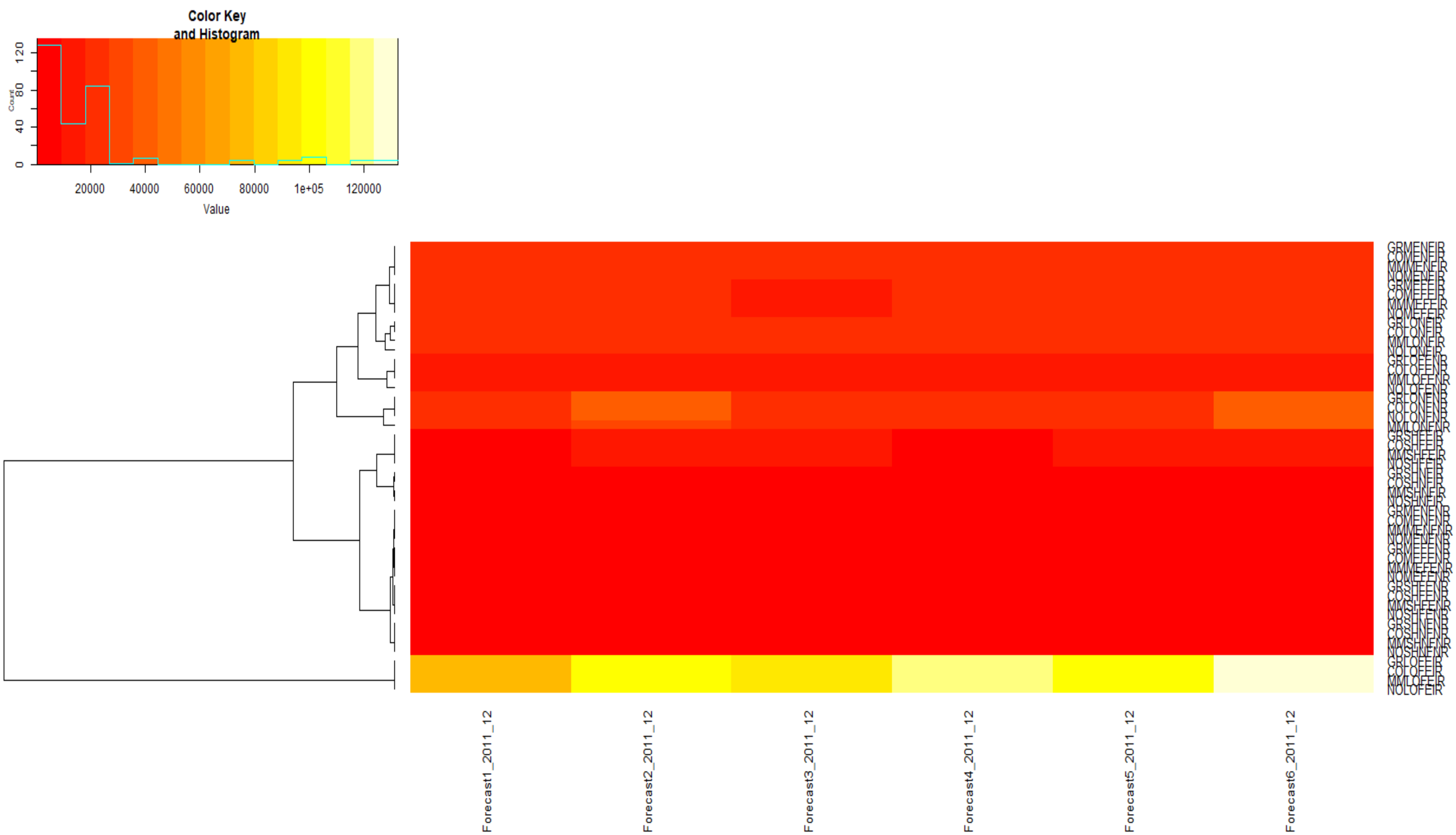
Annexure 4.26: Green bean production under different seasonal forecasts and farm management decisions amongst mixed farmers in the Eastern Cape, South Africa



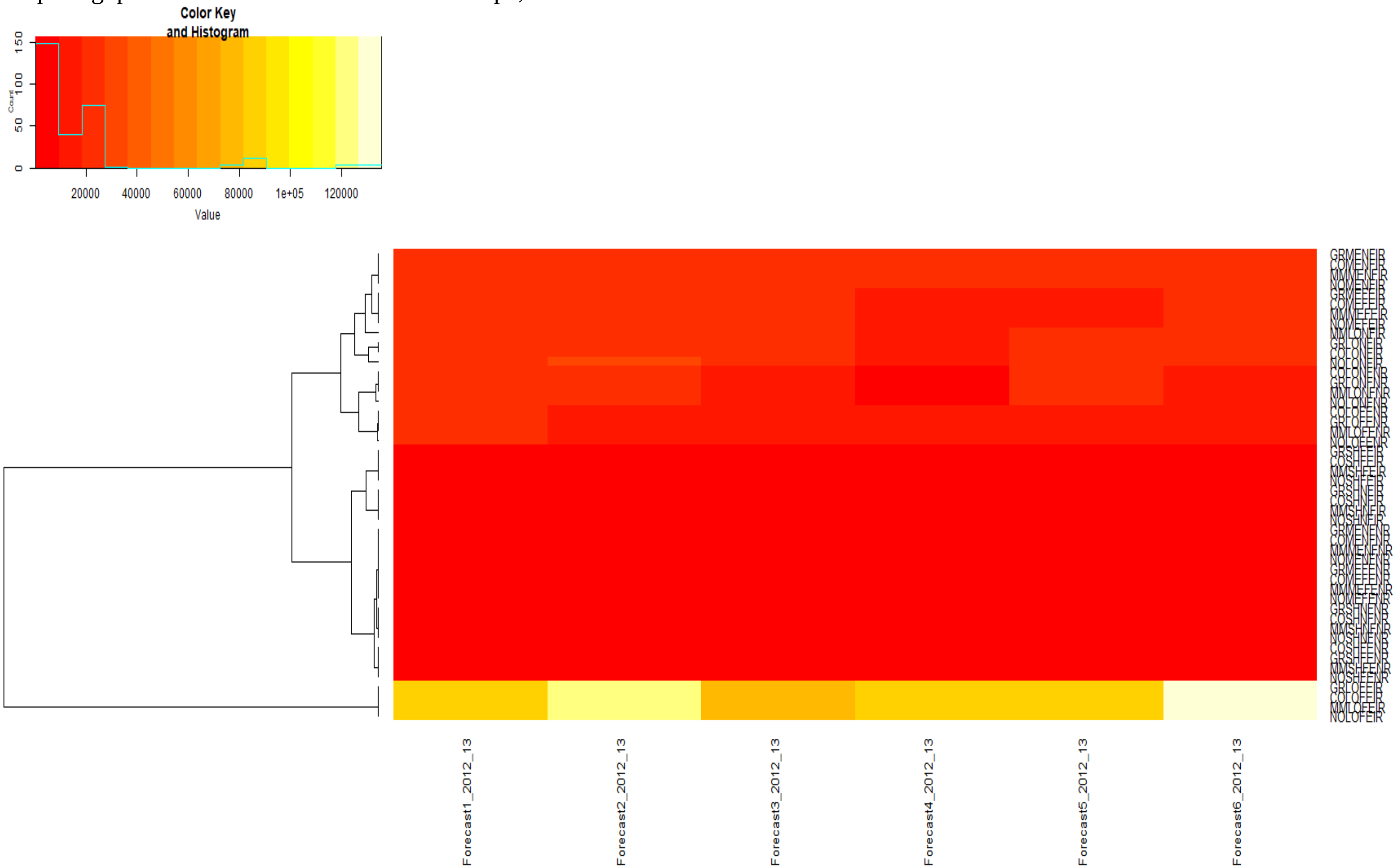
Annexure 4.27: Green bean production under different seasonal forecasts and farm management decisions amongst mixed farmers in Limpopo, South Africa.



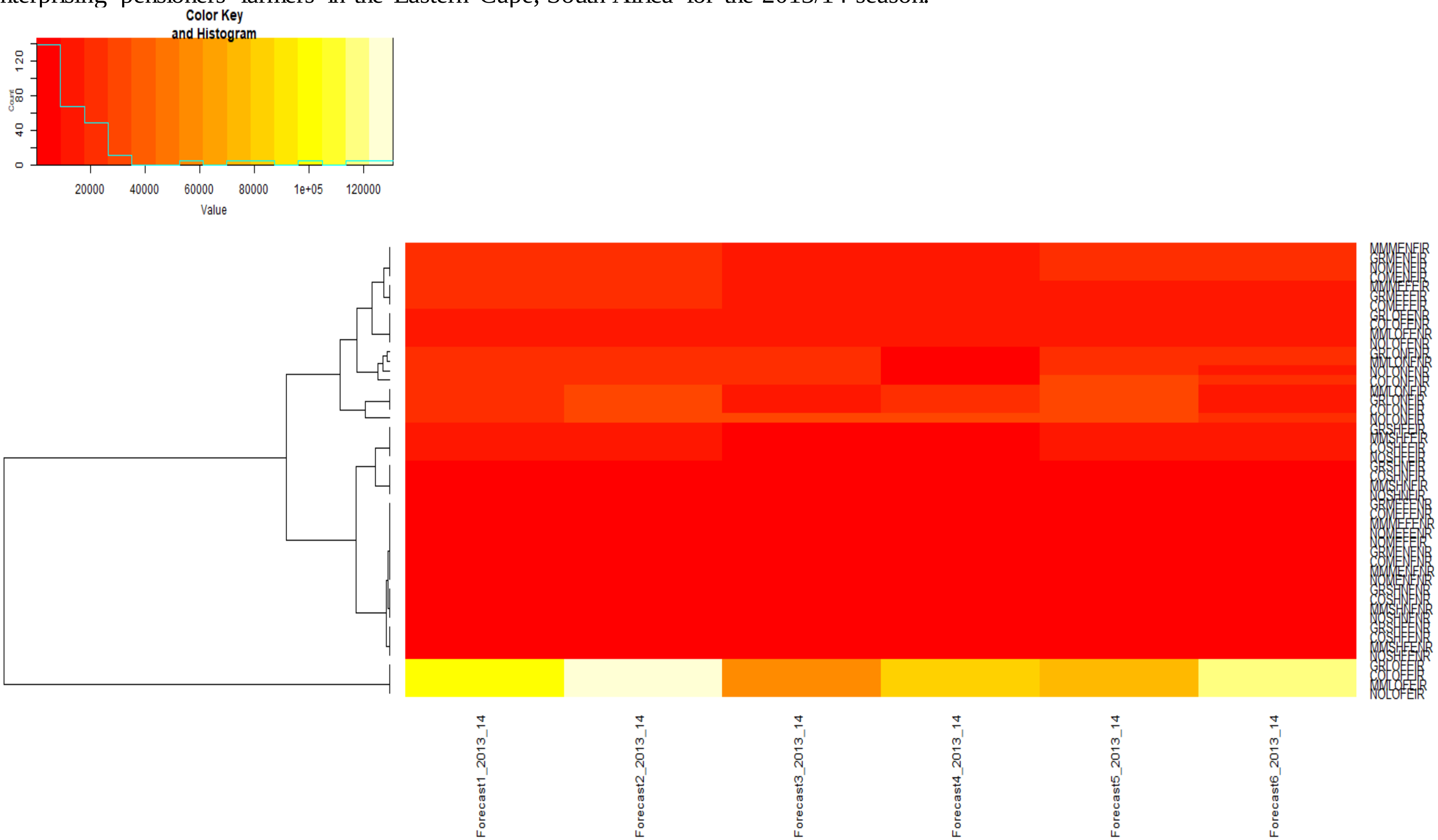
Annexure 5.1: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for enterprising pensioners farmers in the Eastern Cape, South Africa for the 2011/12 season.



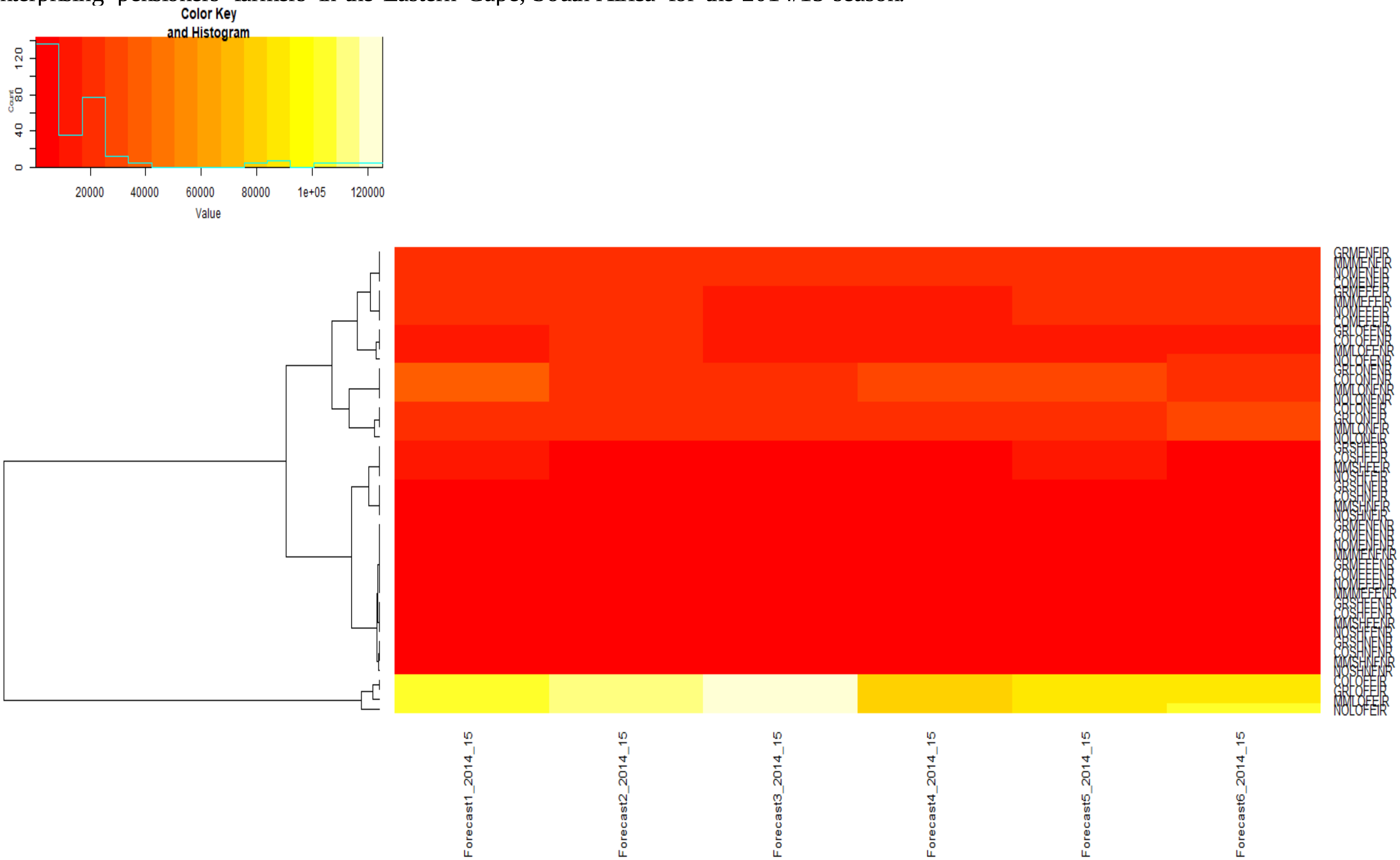
Annexure 5.2: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for enterprising pensioners farmers in the Eastern Cape, South Africa for the 2012/13 season.



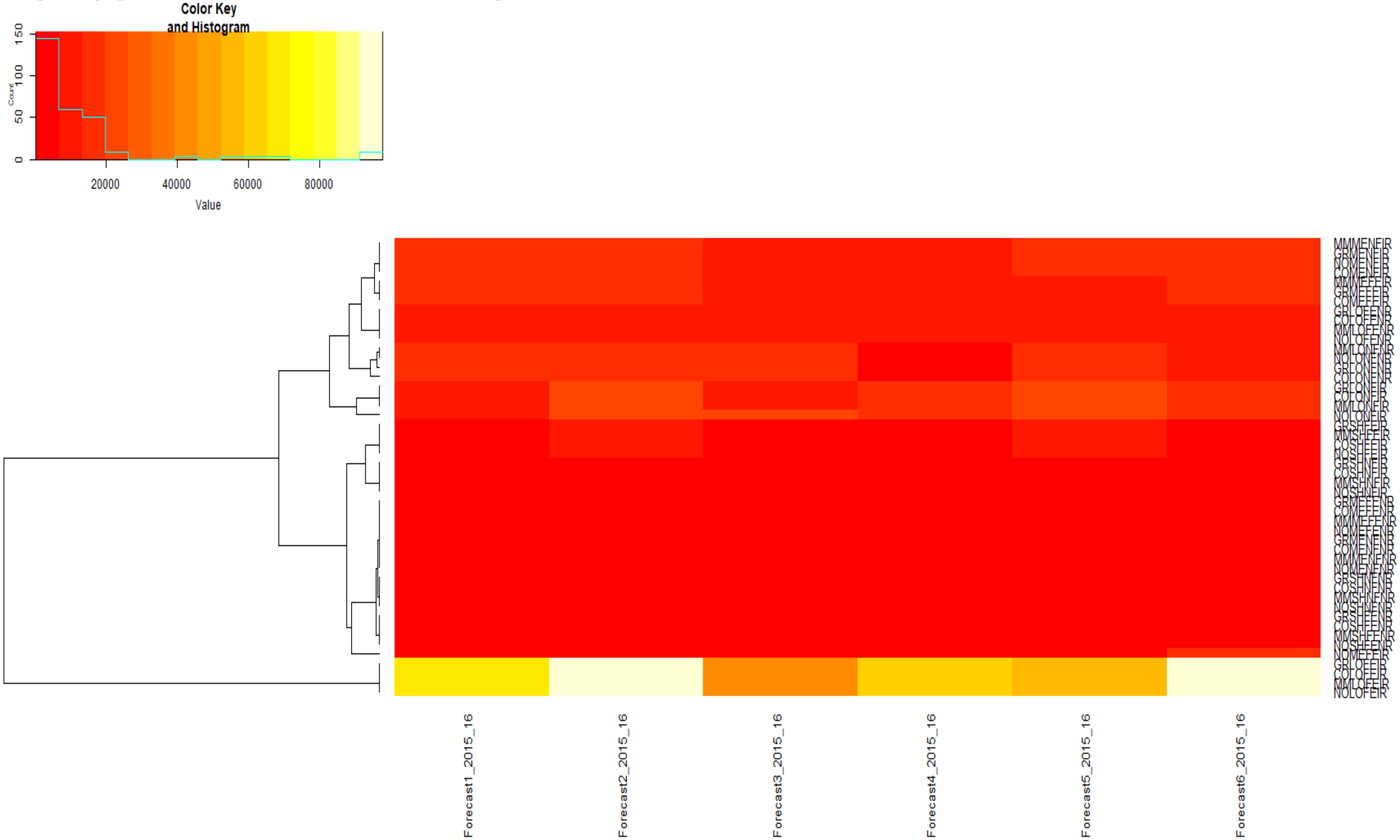
Annexure 5.3: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for enterprising pensioners farmers in the Eastern Cape, South Africa for the 2013/14 season.



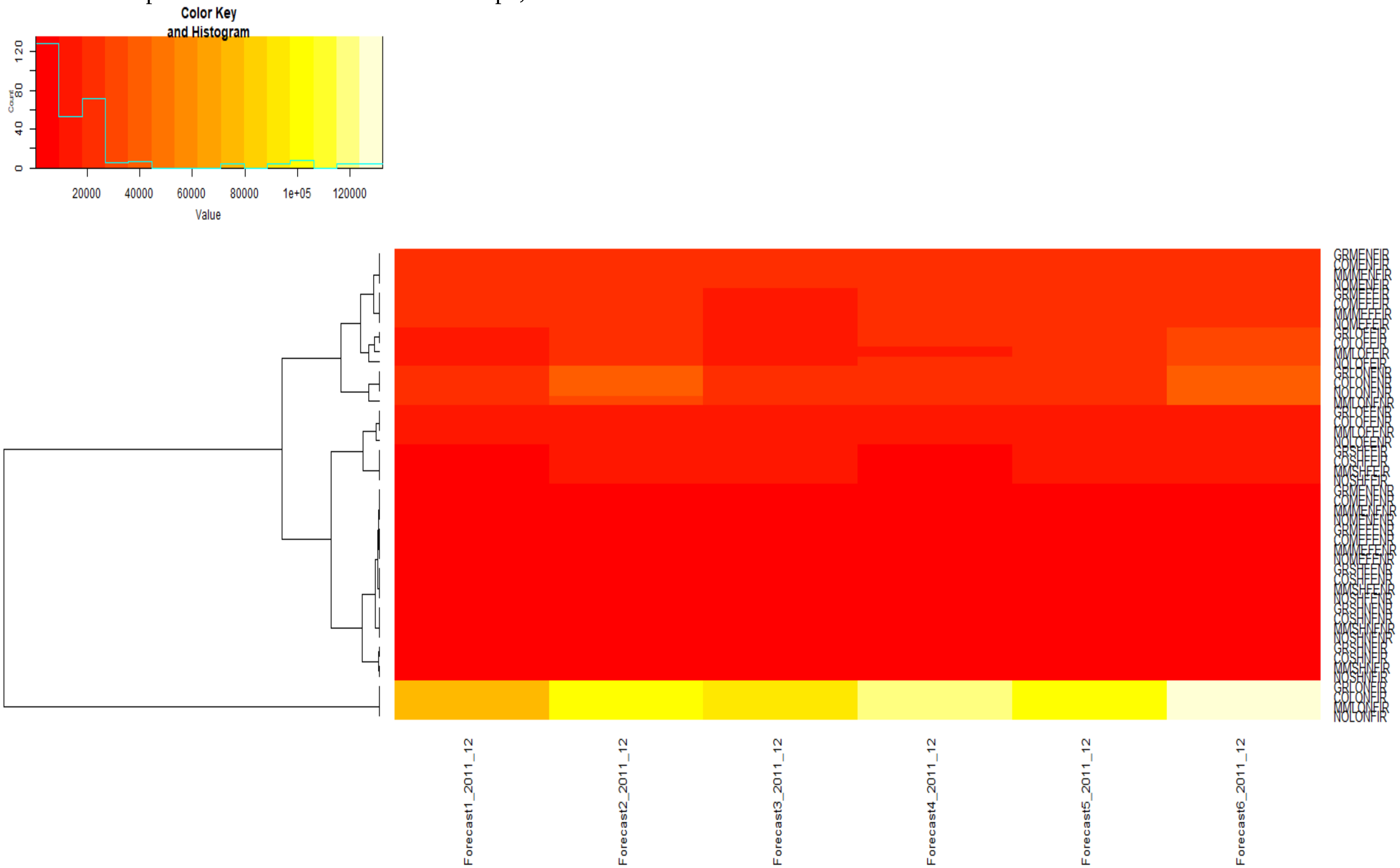
Annexure 5.4: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for enterprising pensioners farmers in the Eastern Cape, South Africa for the 2014/15 season.



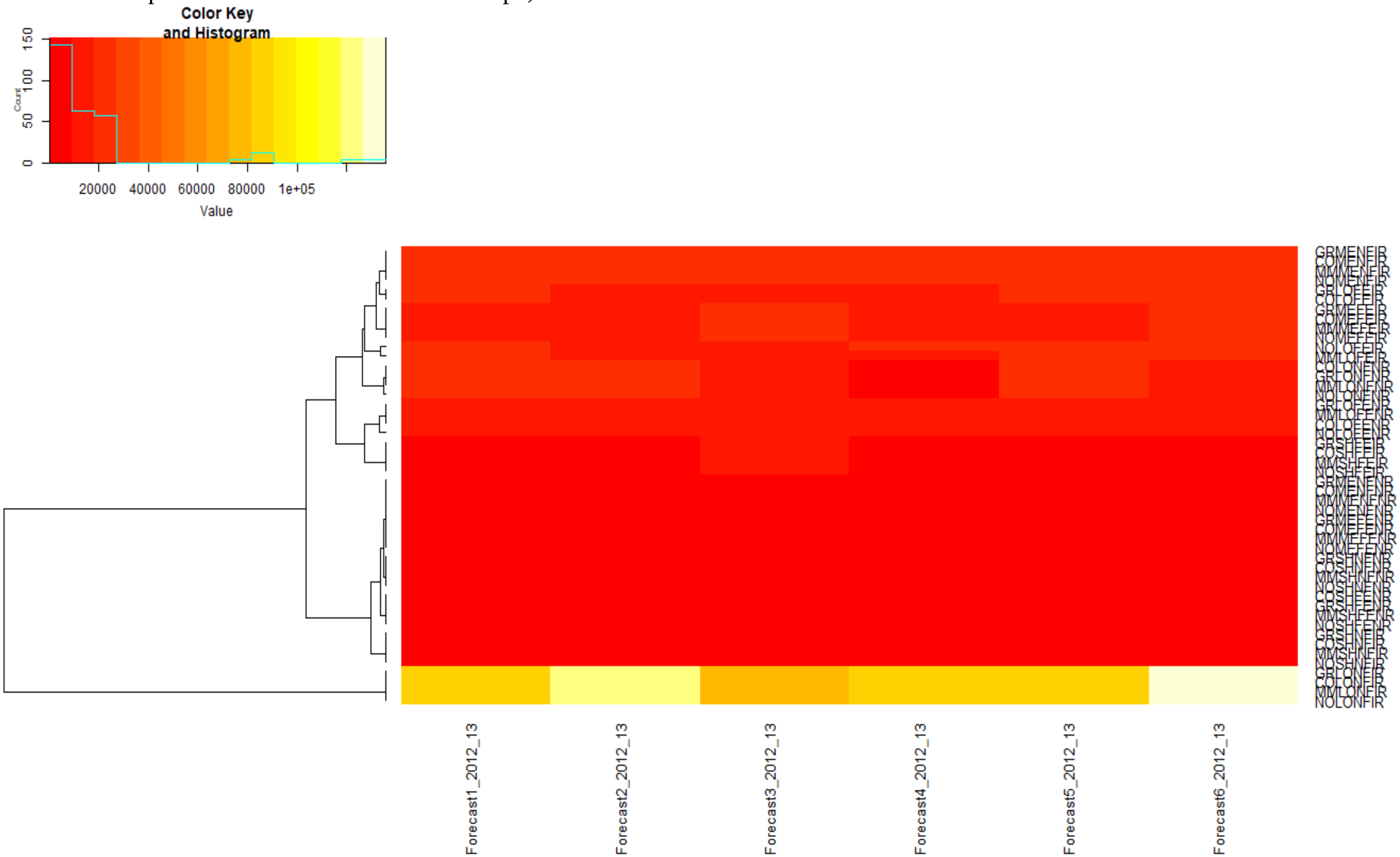
Annexure 5.5: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for enterprising pensioners farmers in the Eastern Cape, South Africa for the 2015/16 season.



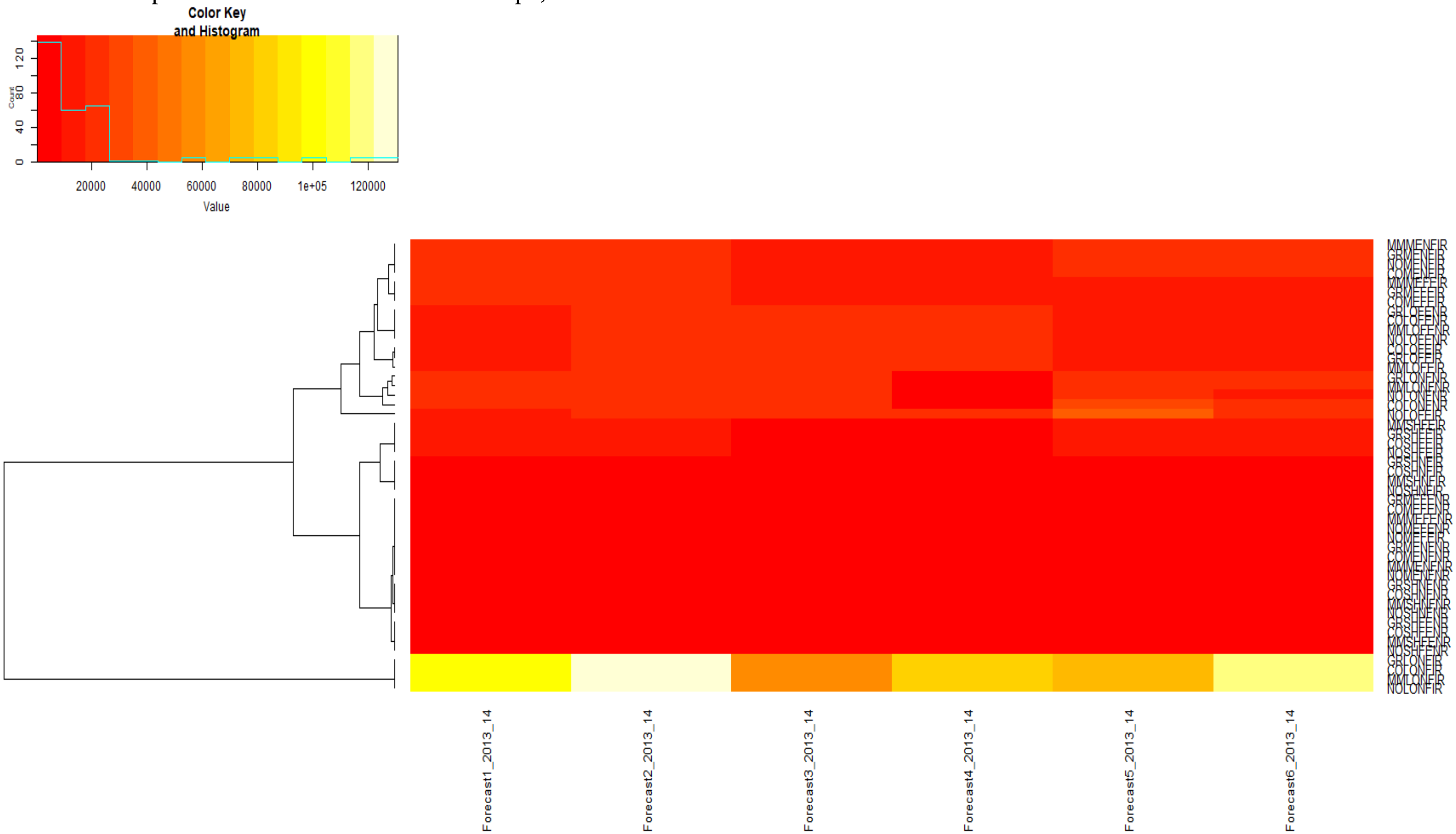
Annexure 5.6: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for horticultural dependant farmers in the Eastern Cape, South Africa for the 2011/12 season.



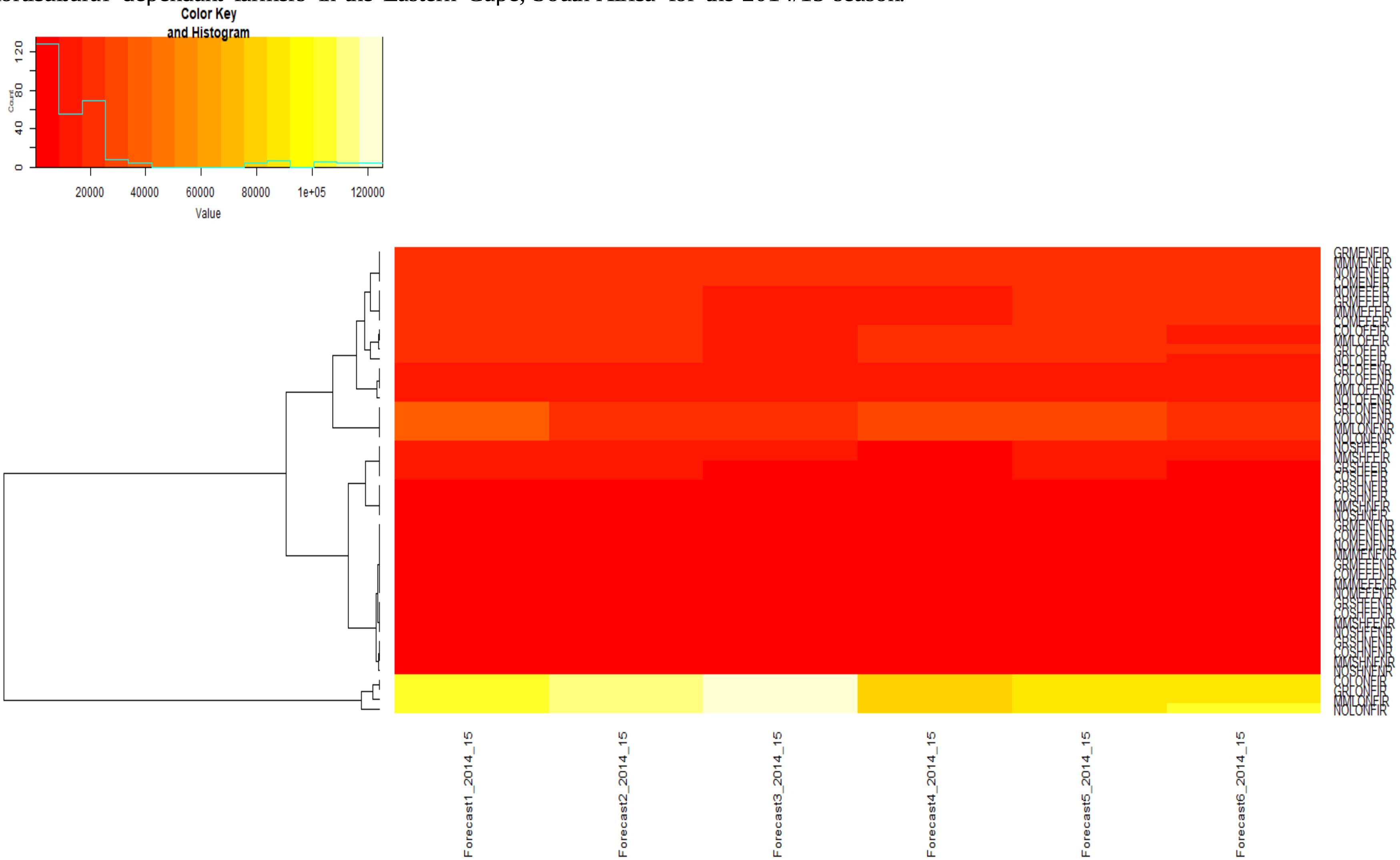
Annexure 5.7: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for horticultural dependant farmers in the Eastern Cape, South Africa for the 2012/13 season.



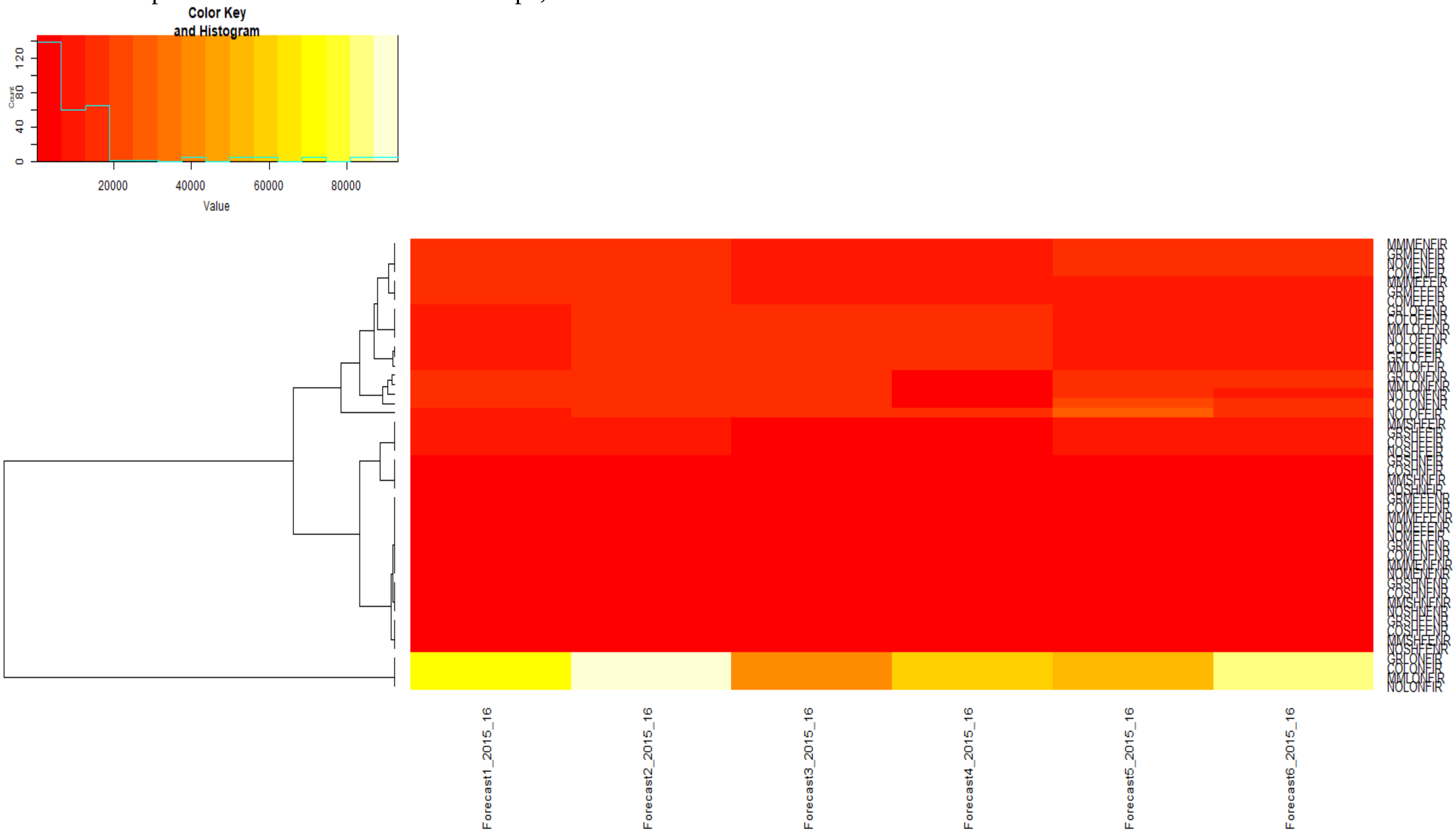
Annexure 5.8: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for horticultural dependant farmers in the Eastern Cape, South Africa for the 2013/14 season.



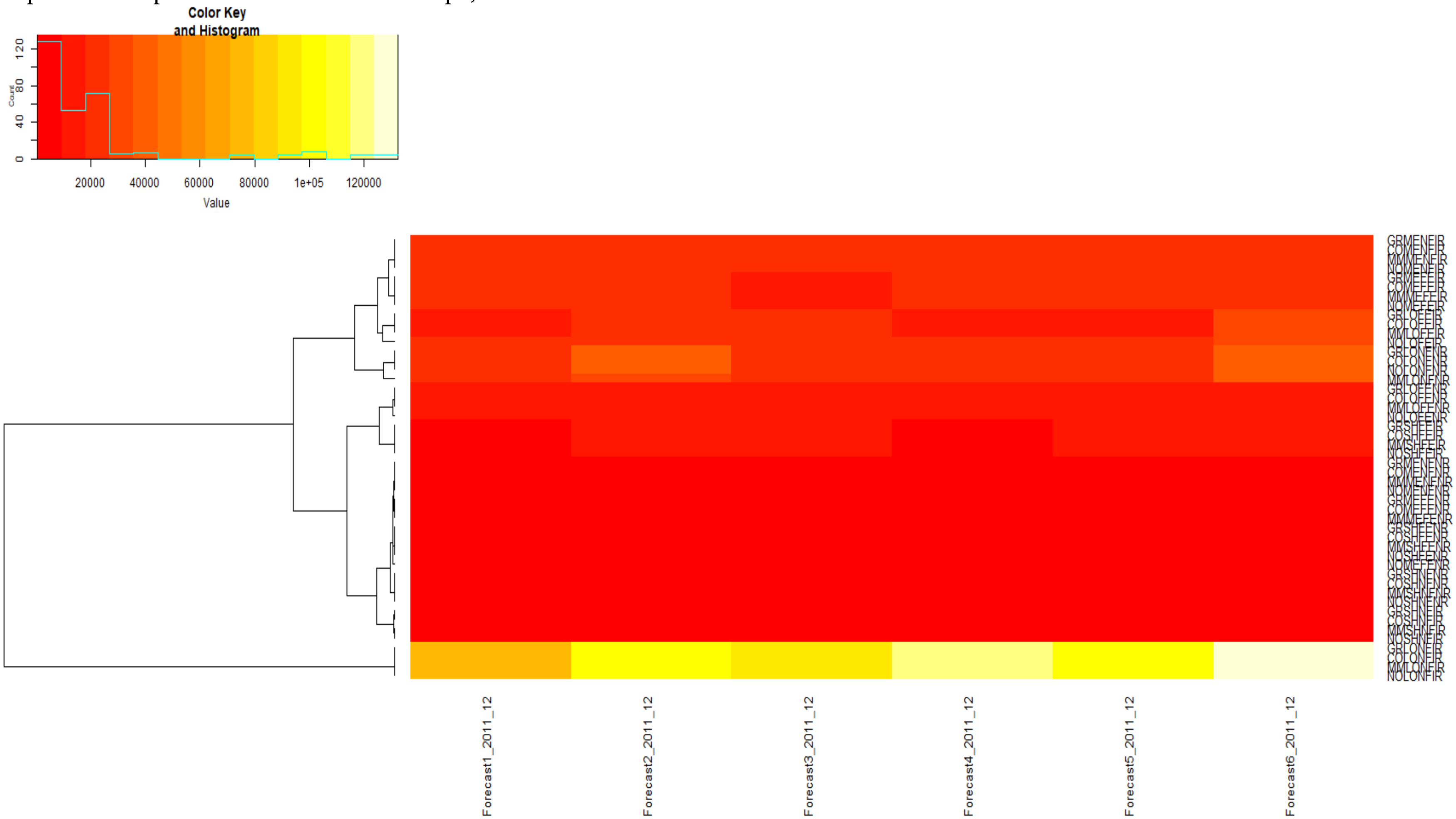
Annexure 5.9: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for horticultural dependant farmers in the Eastern Cape, South Africa for the 2014/15 season.



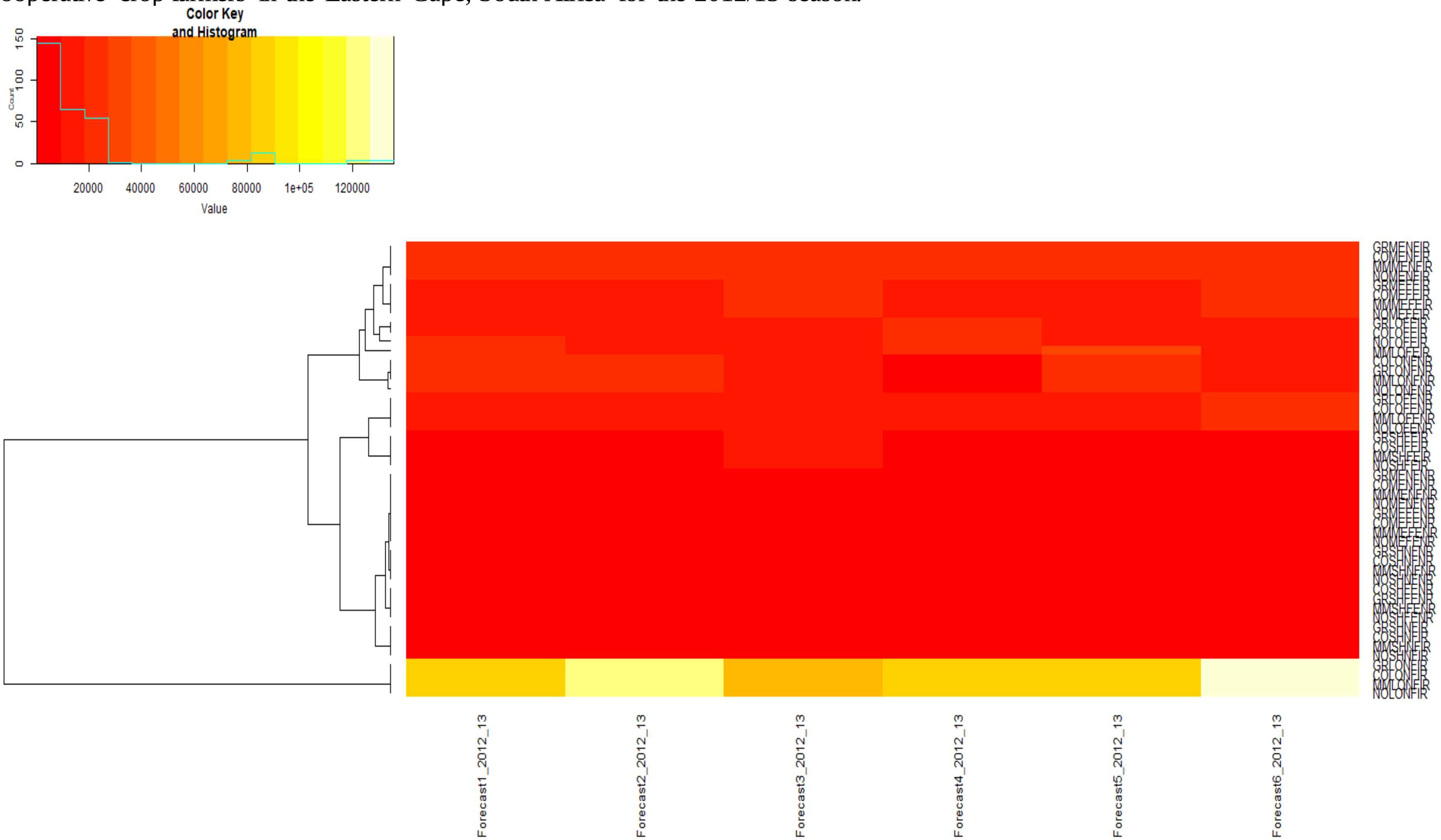
Annexure 5.10: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for horticultural dependant farmers in the Eastern Cape, South Africa for the 2015/16 season.



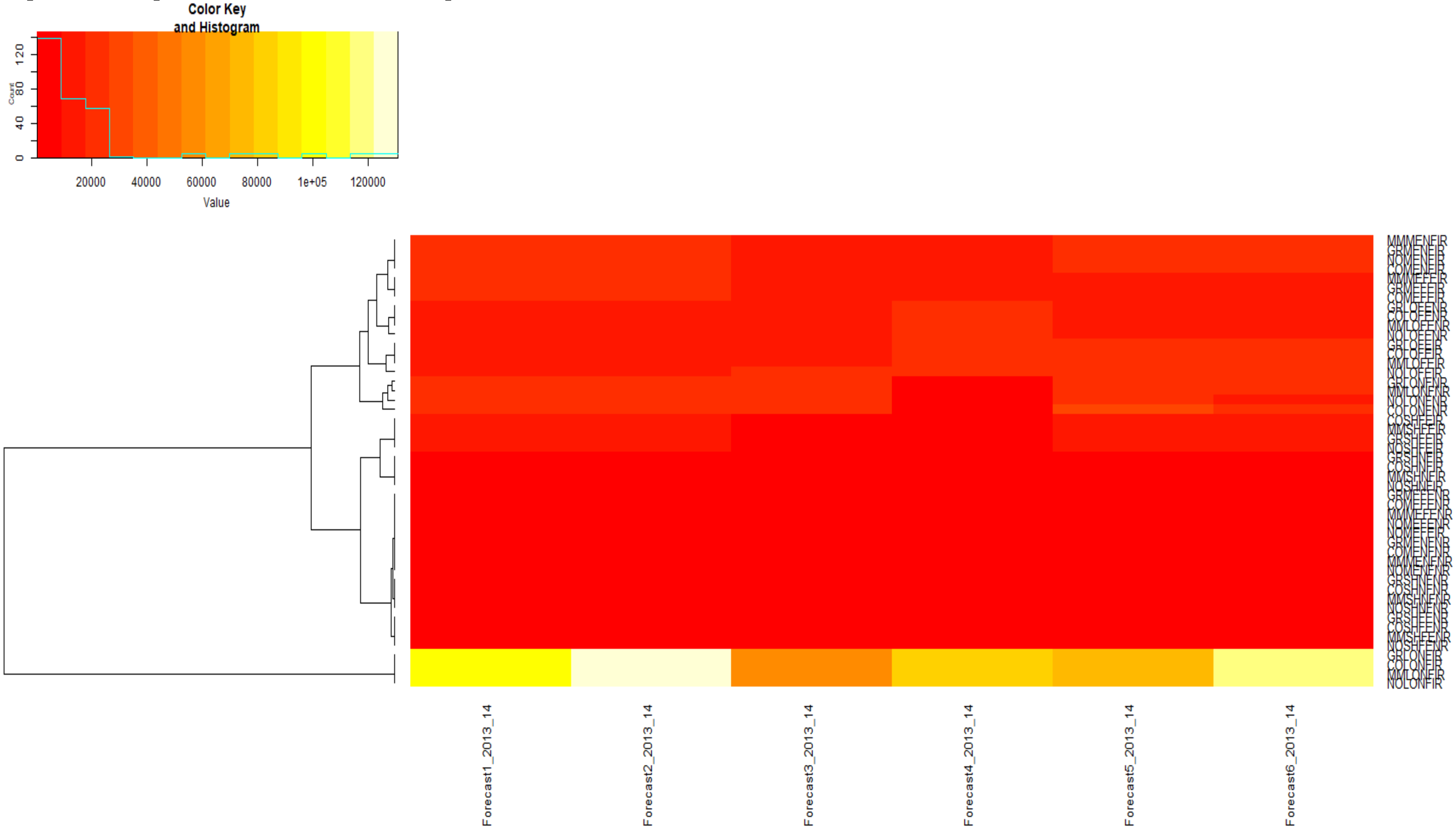
Annexure 5.11: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for cooperative crop farmers in the Eastern Cape, South Africa for the 2011/12 season.



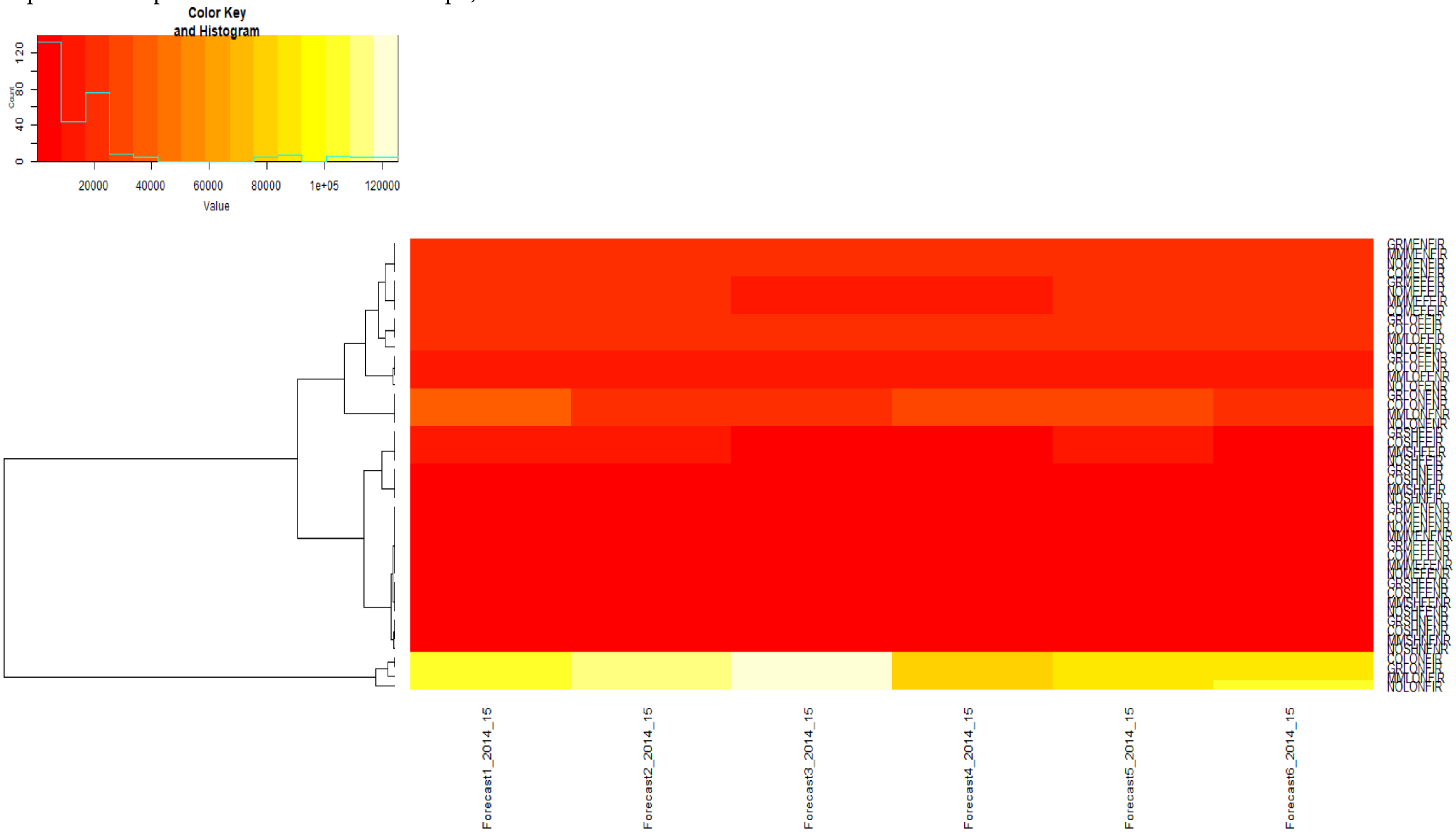
Annexure 5.12: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for cooperative crop farmers in the Eastern Cape, South Africa for the 2012/13 season.



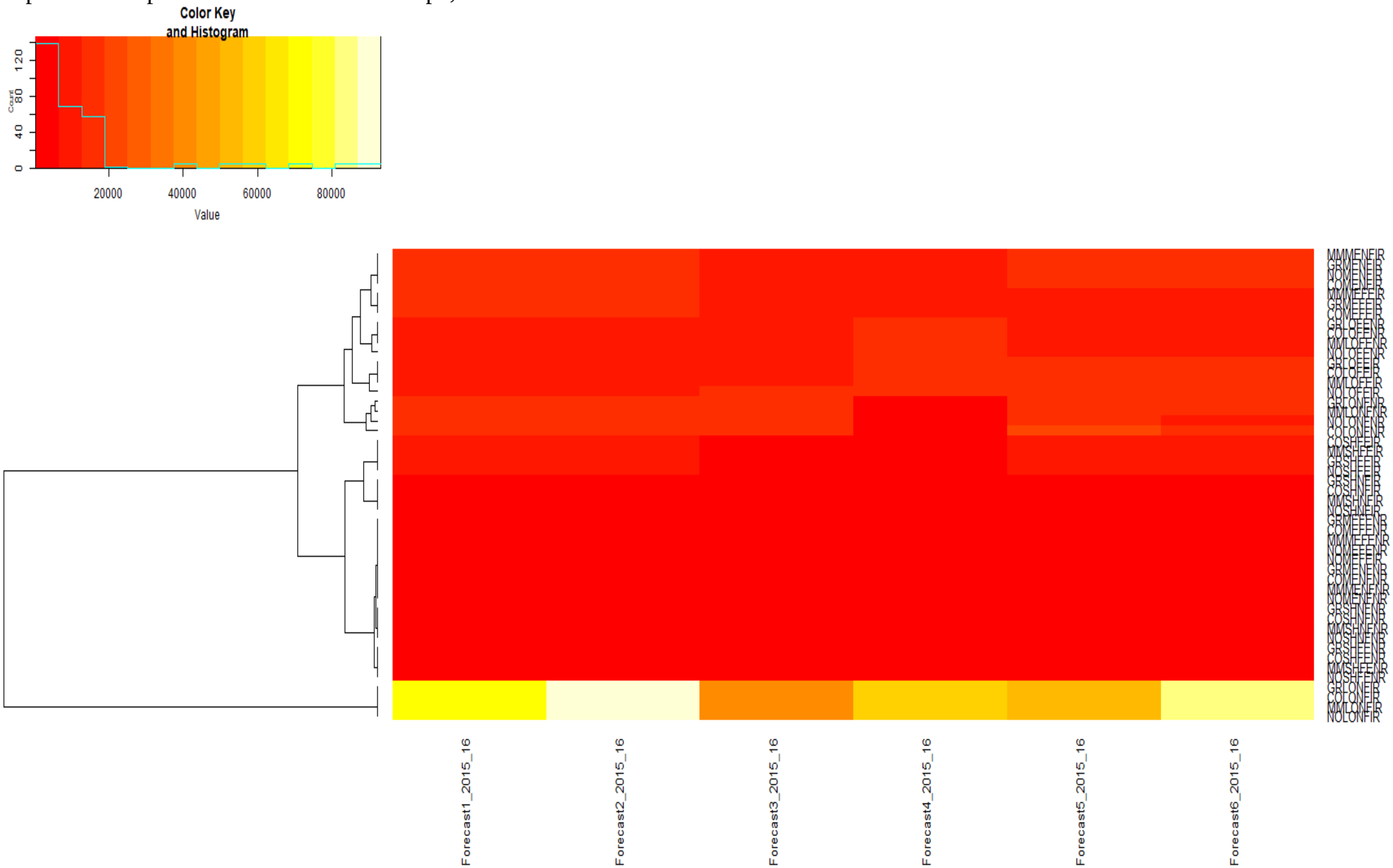
Annexure 5.13: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for cooperative crop farmers in the Eastern Cape, South Africa for the 2013/14 season.



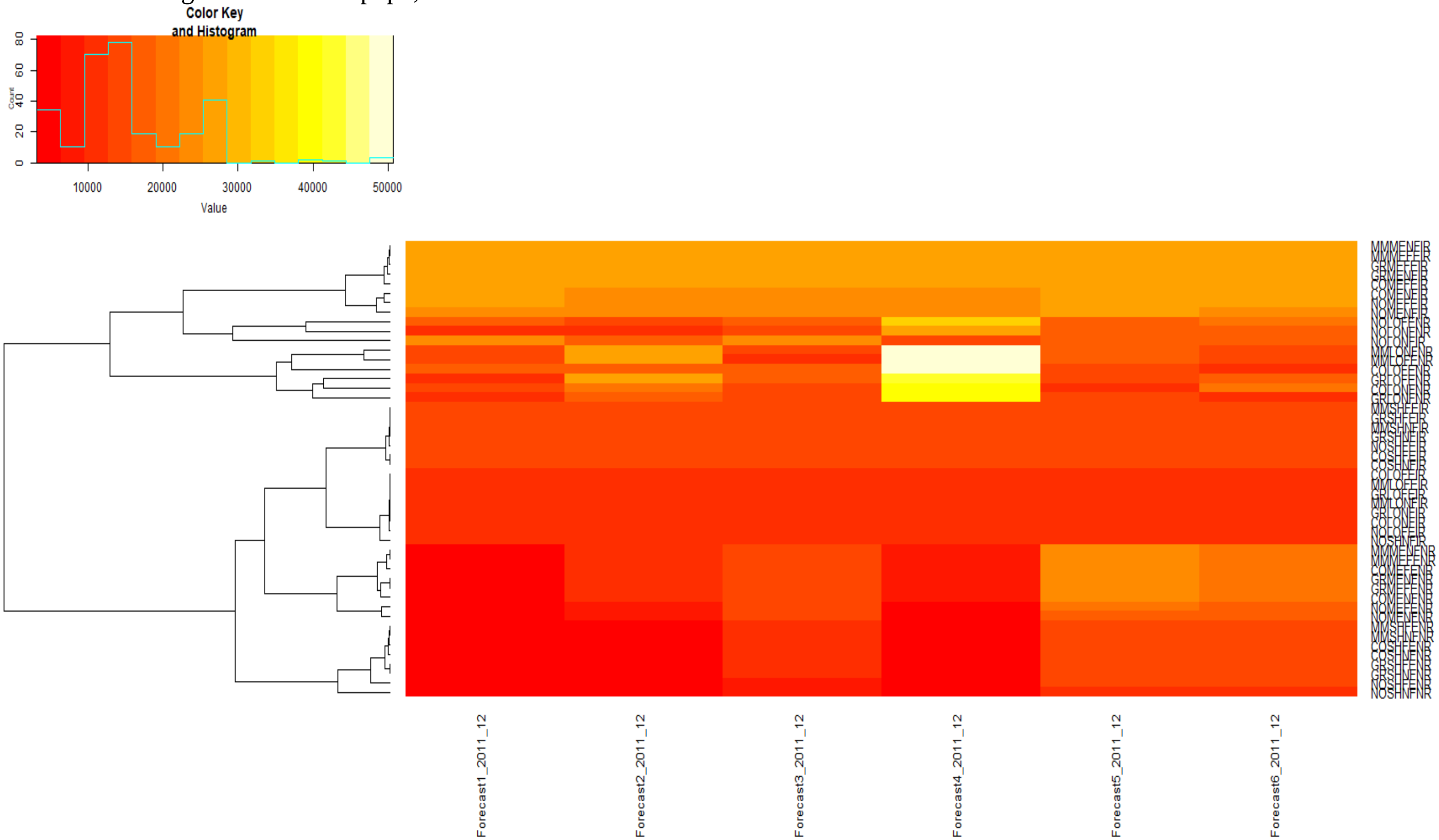
Annexure 5.14: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for cooperative crop farmers in the Eastern Cape, South Africa for the 2014/15 season.



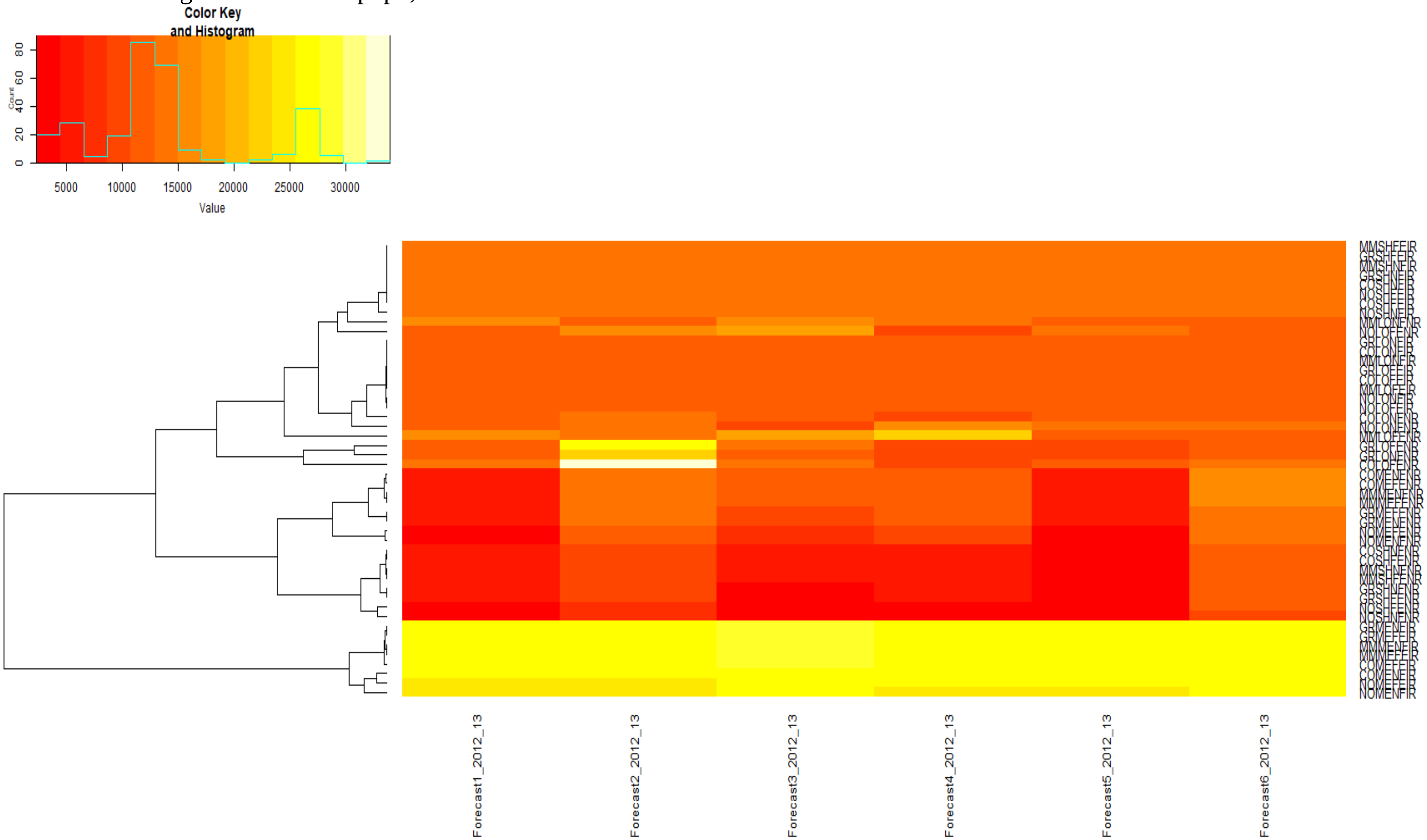
Annexure 5.15: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for cooperative crop farmers in the Eastern Cape, South Africa for the 2015/16 season.



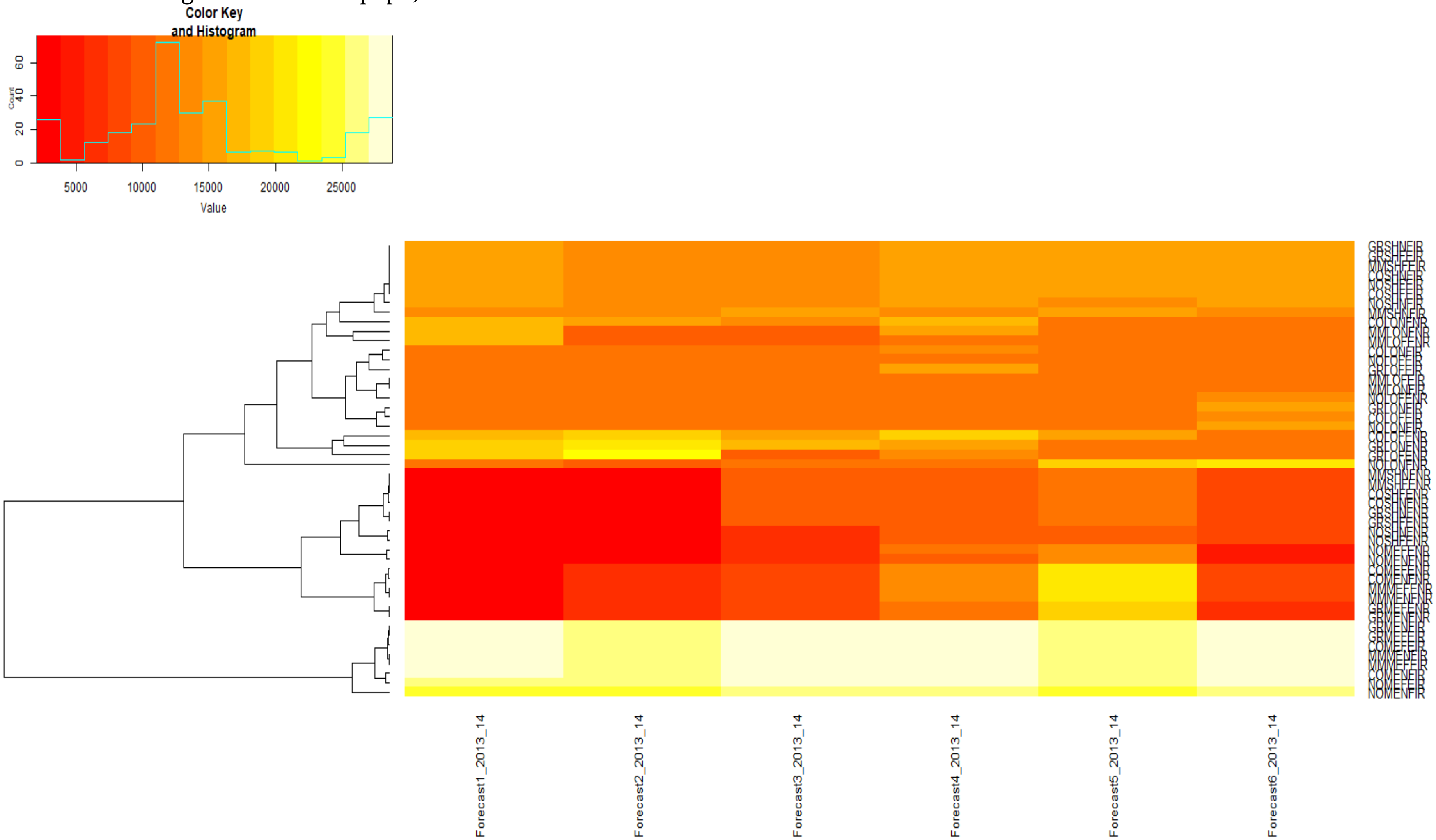
Annexure 5.16: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture farming farmers in Limpopo, South Africa for the 2011/12 season.



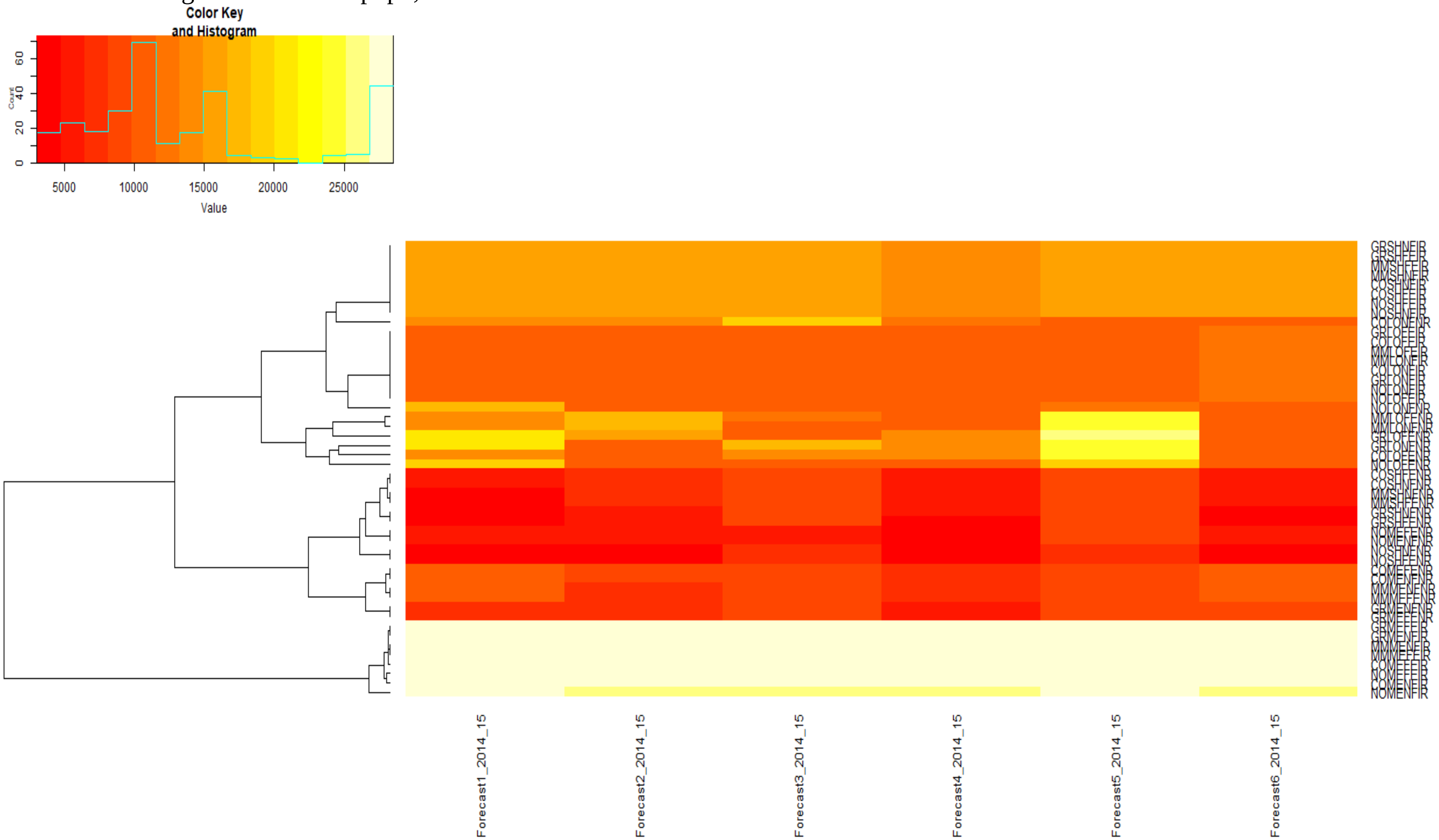
Annexure 5.17: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture farming farmers in Limpopo, South Africa for the 2012/13 season.



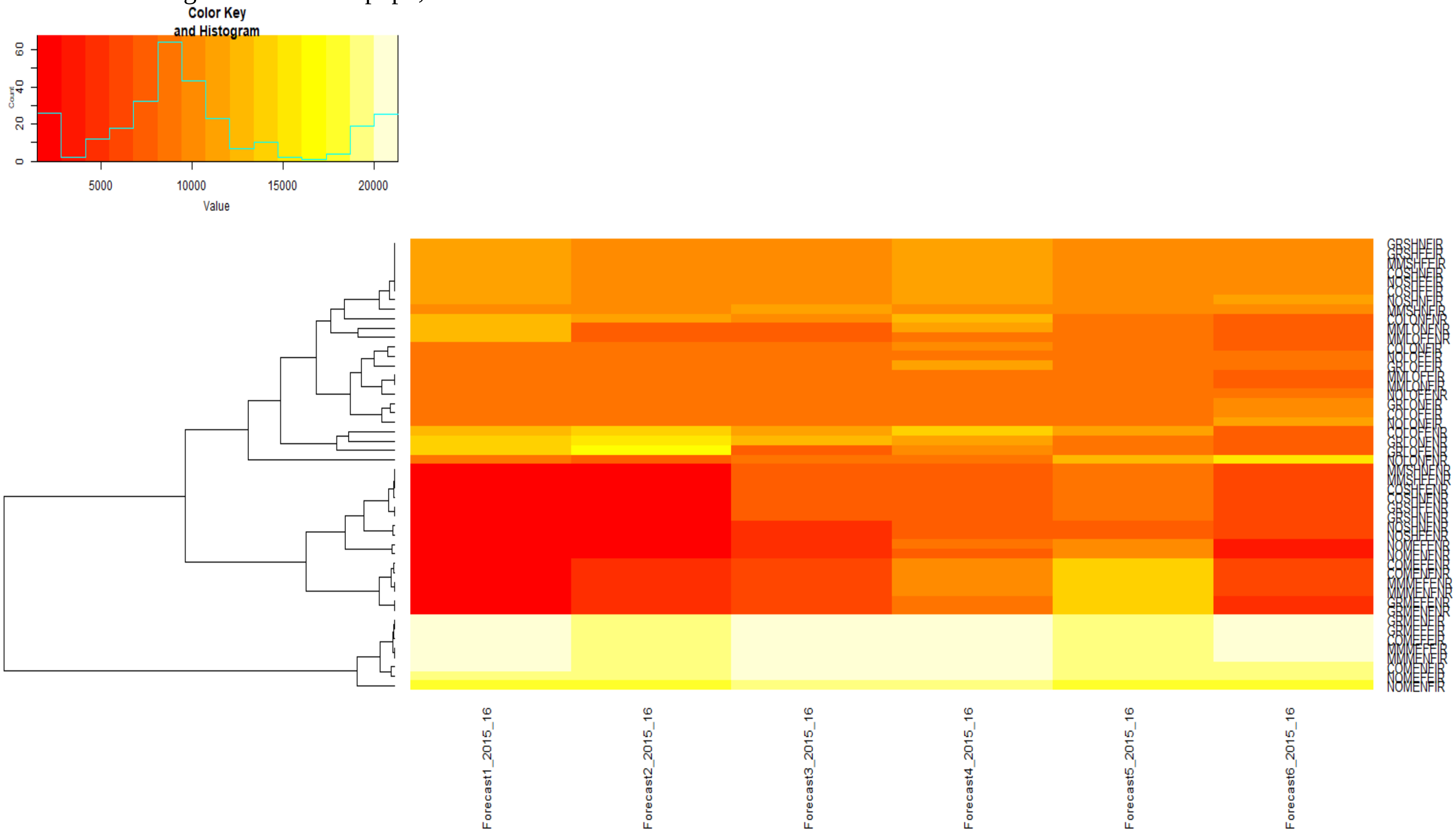
Annexure 5.18: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture farming farmers in Limpopo, South Africa for the 2013/14 season.



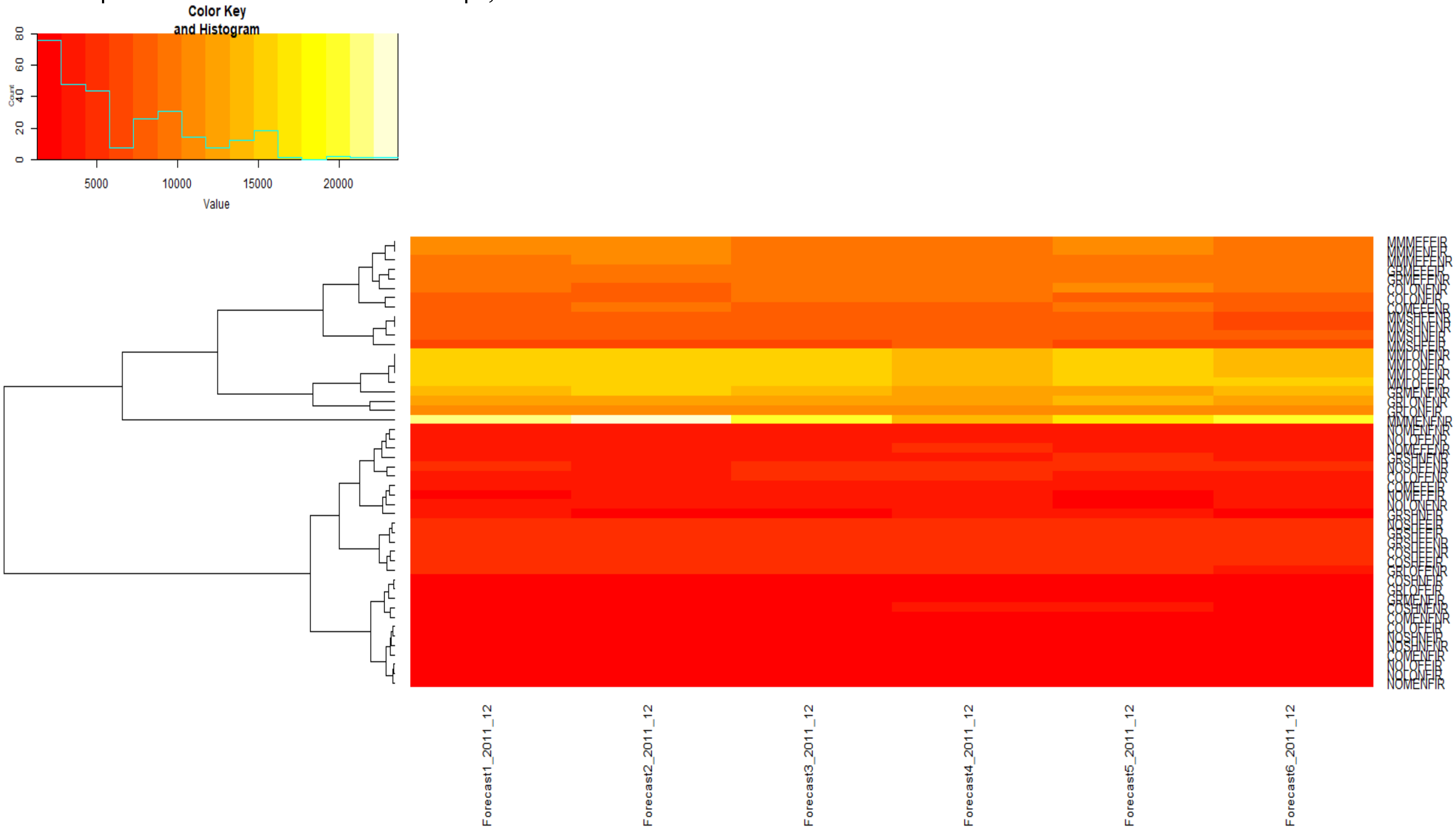
Annexure 5.19: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture farming farmers in Limpopo, South Africa for the 2014/15 season.



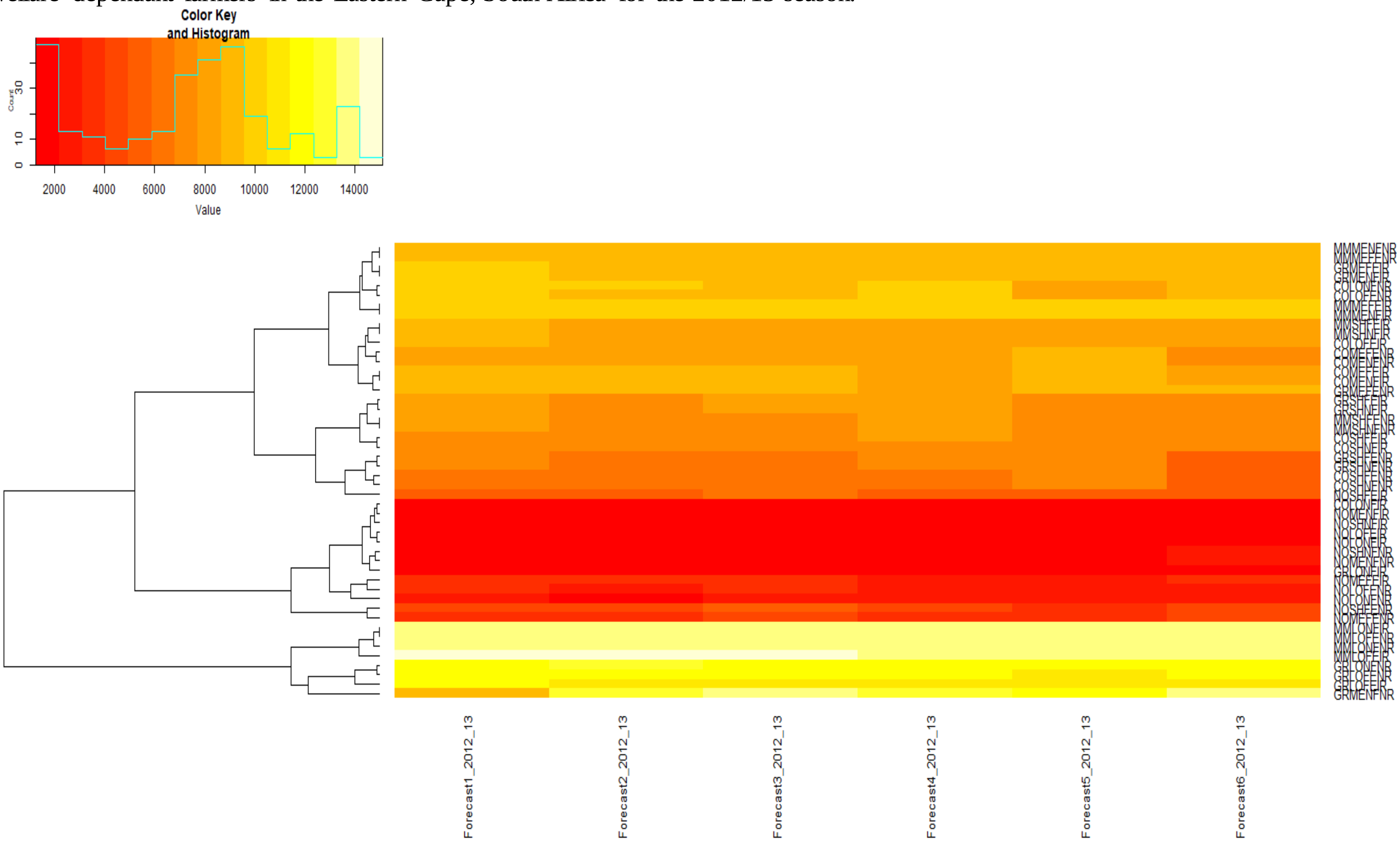
Annexure 5.20: Cabbage yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture farming farmers in Limpopo, South Africa for the 2015/16 season.



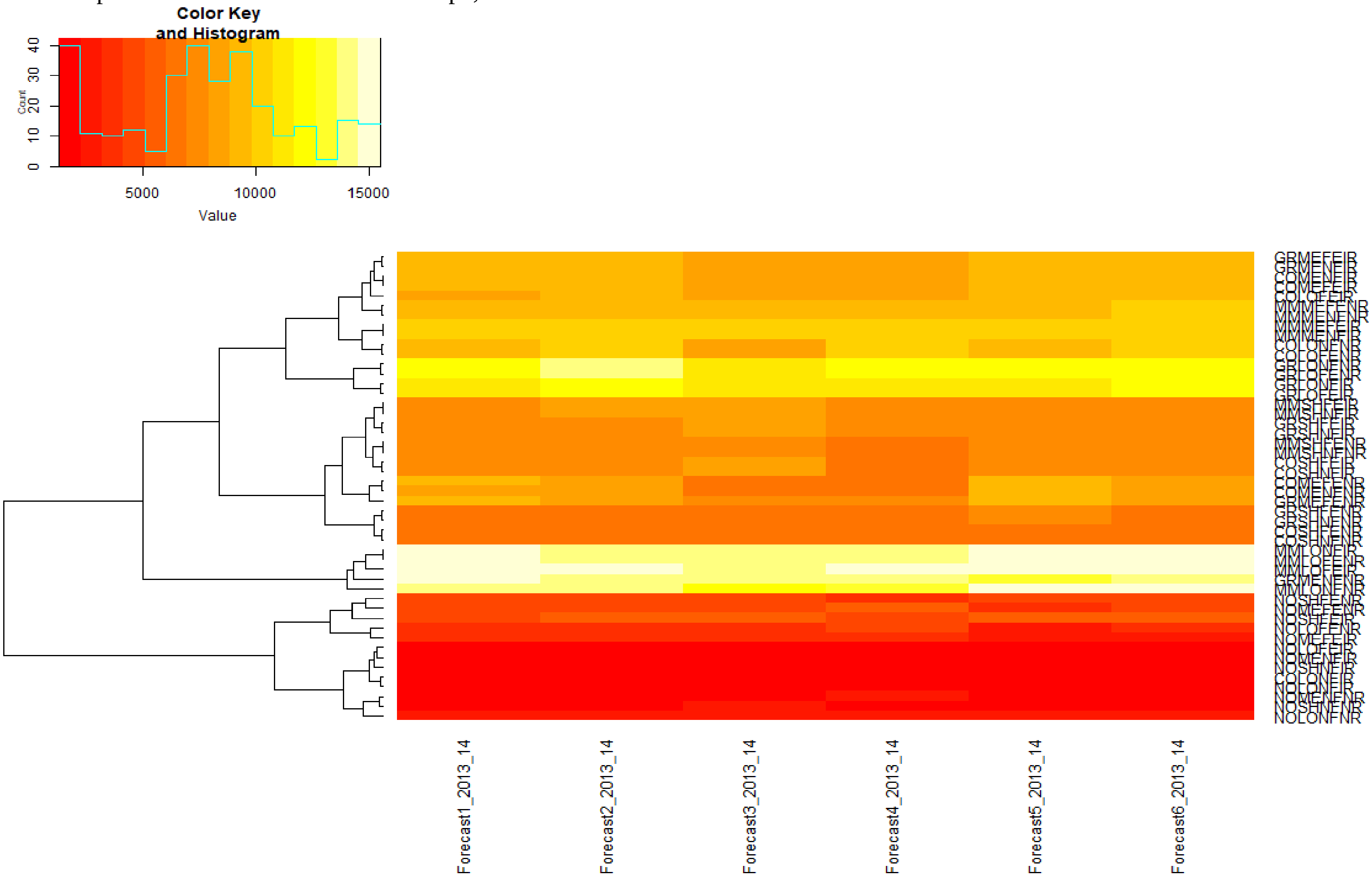
Annexure 5.21: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for social welfare dependant farmers in the Eastern Cape, South Africa for the 2011/12 season.



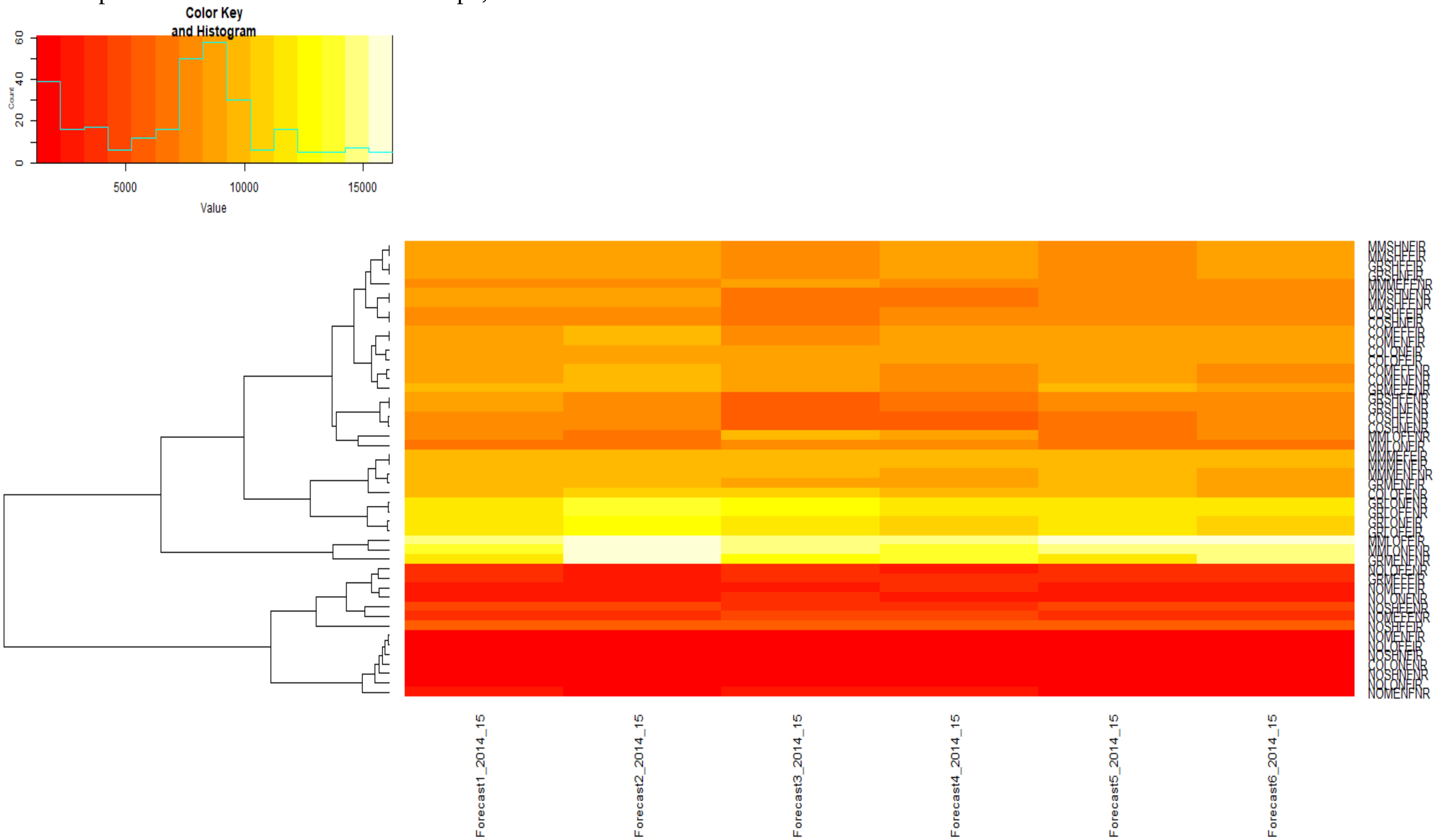
Annexure 5.22: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for social welfare dependant farmers in the Eastern Cape, South Africa for the 2012/13 season.



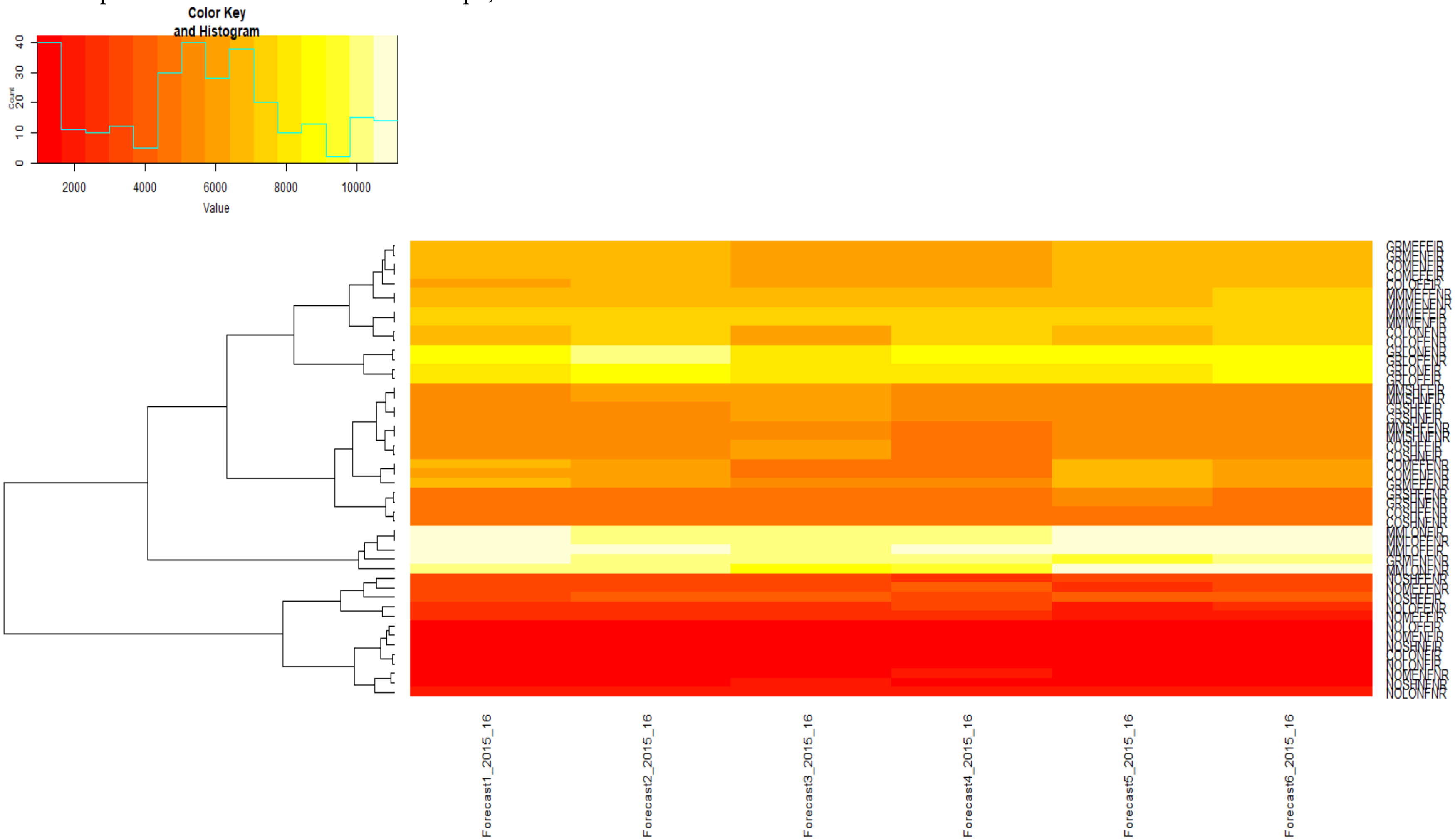
Annexure 5.23: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for social welfare dependant farmers in the Eastern Cape, South Africa for the 2013/14 season.



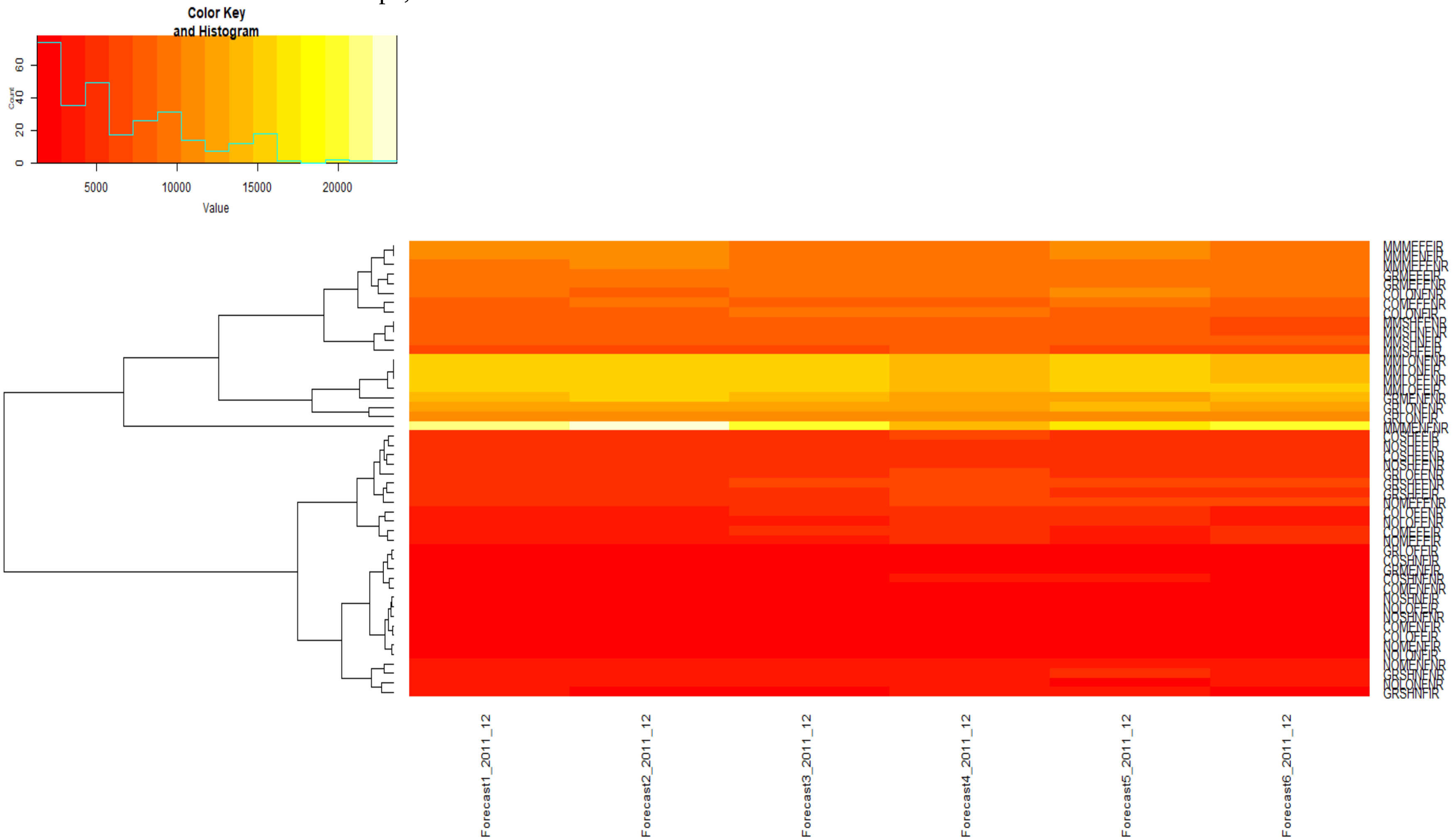
Annexure 5.24: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for social welfare dependant farmers in the Eastern Cape, South Africa for the 2014/15 season.



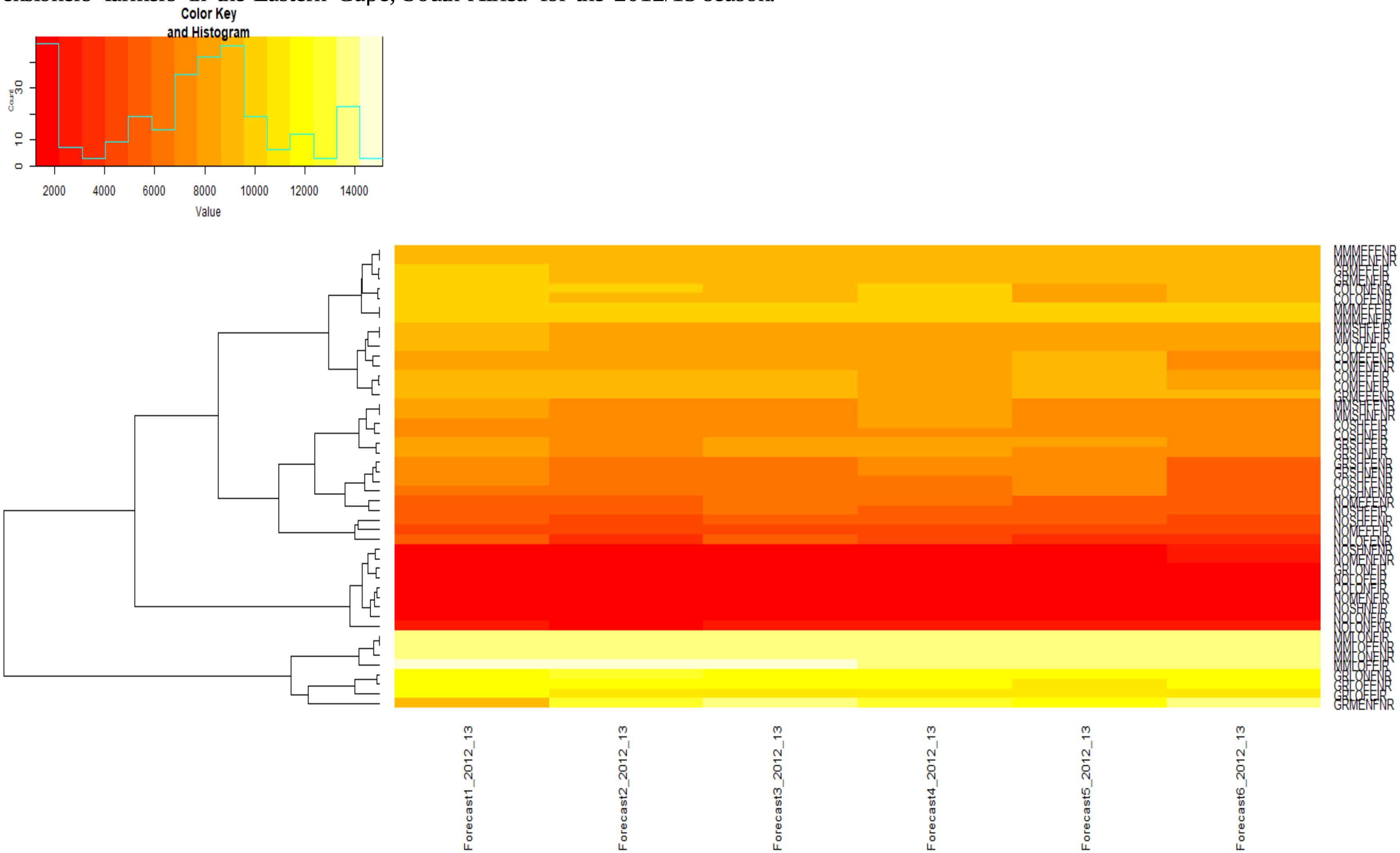
Annexure 5.25: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for social welfare dependant farmers in the Eastern Cape, South Africa for the 2015/16 season.



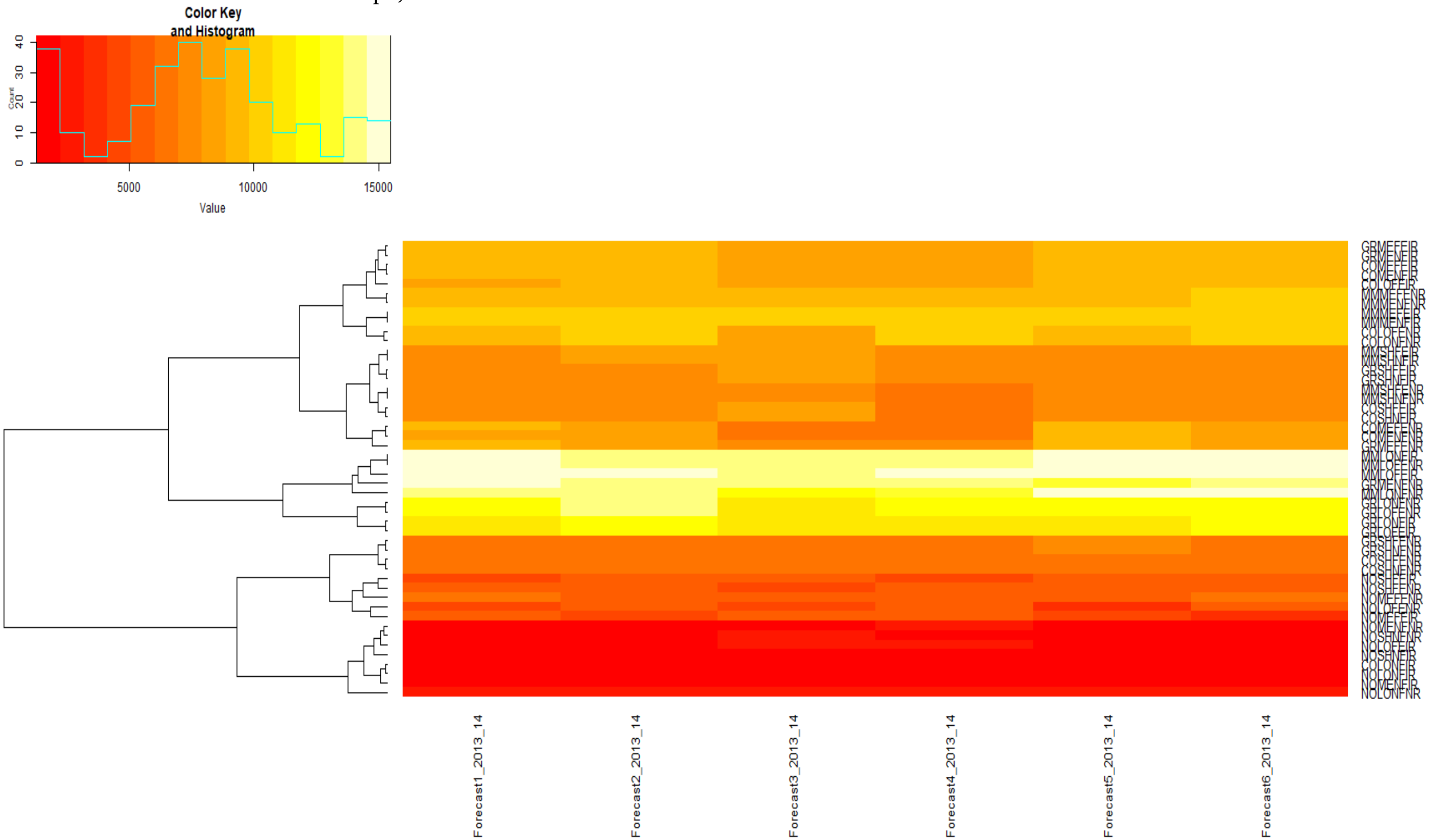
Annexure 5.26: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for enterprising pensioners farmers in the Eastern Cape, South Africa for the 2011/12 season.



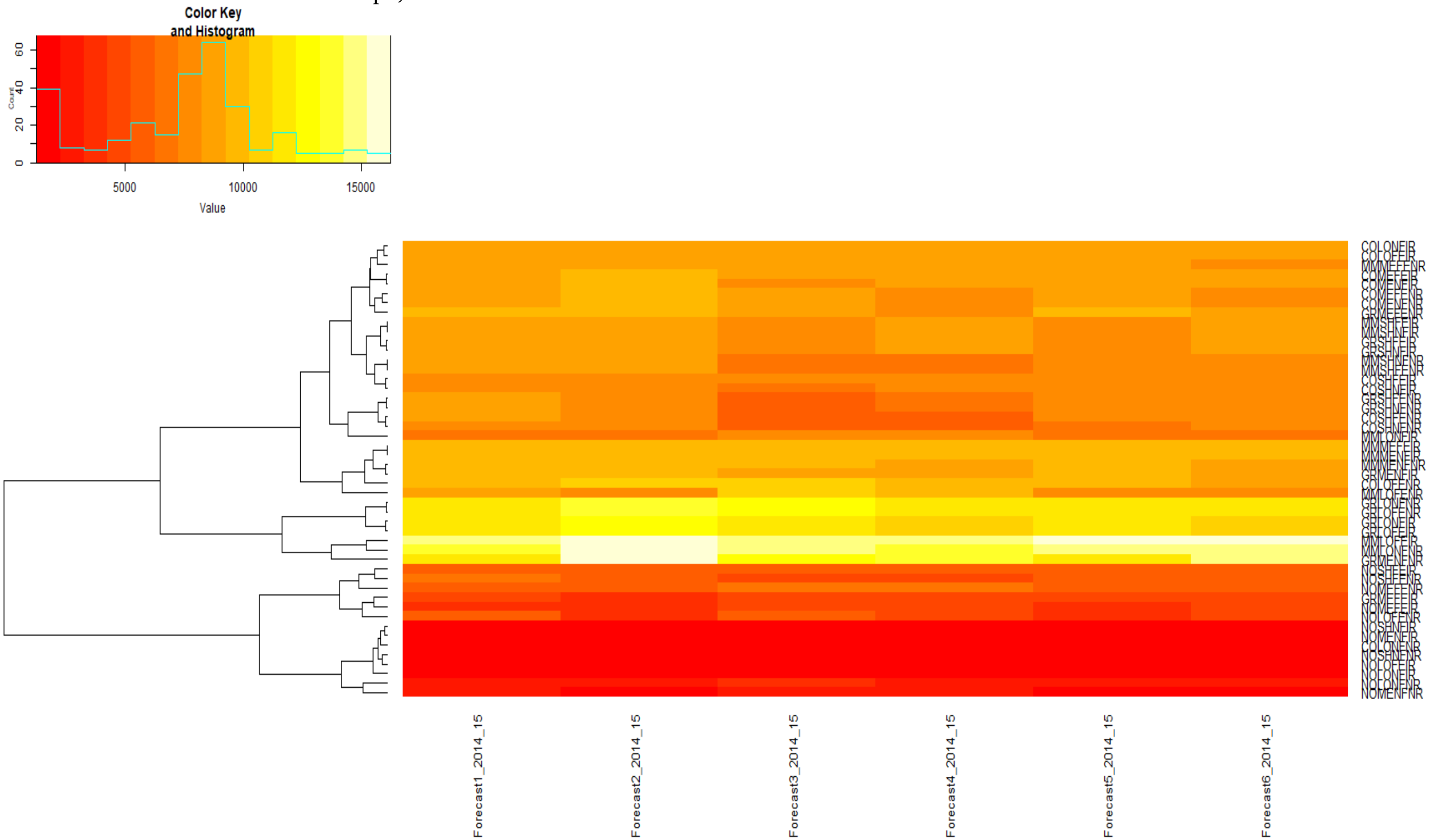
Annexure 5.27: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for enterprising pensioners farmers in the Eastern Cape, South Africa for the 2012/13 season.



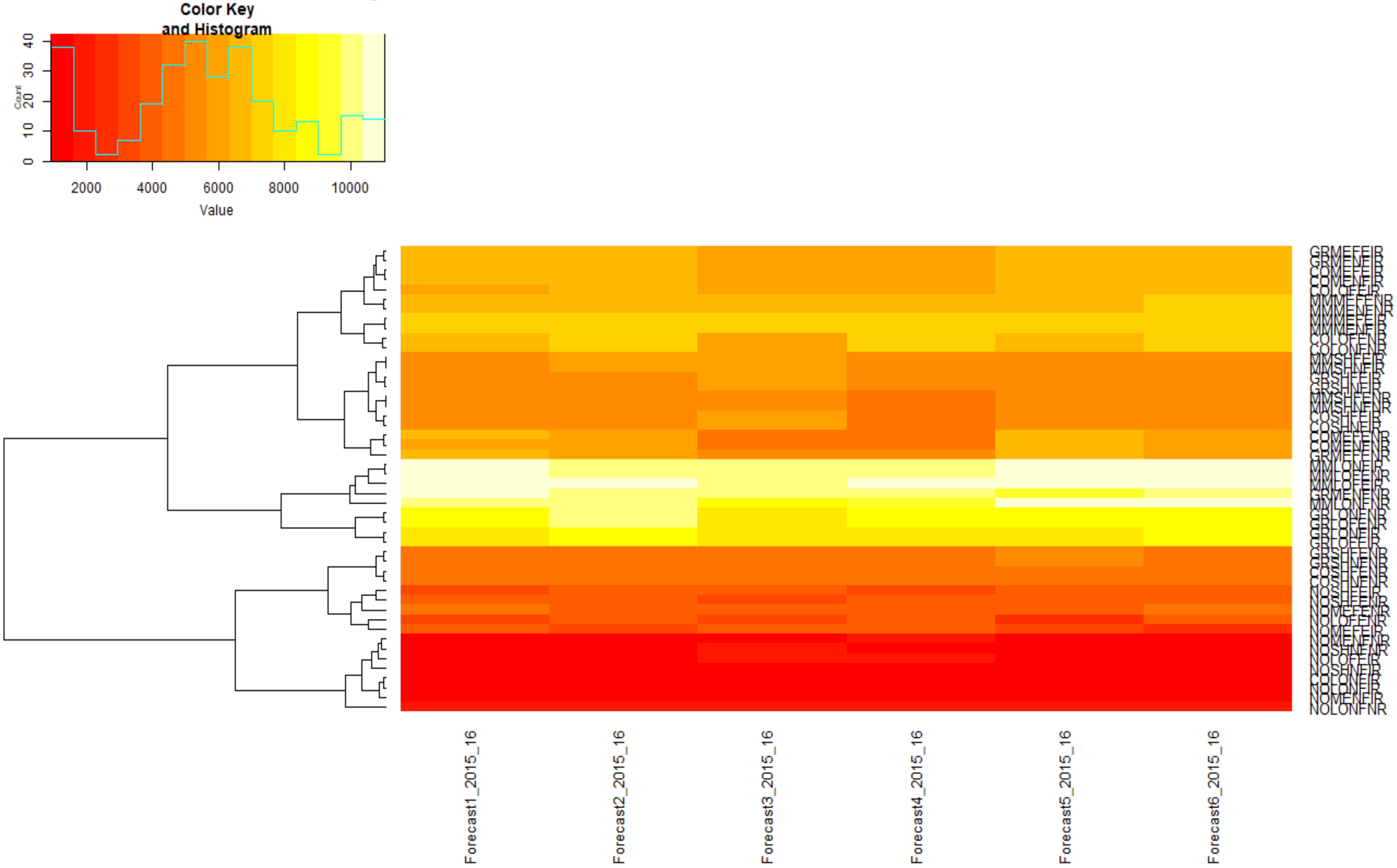
Annexure 5.28: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for enterprising pensioners farmers in the Eastern Cape, South Africa for the 2013/14 season.



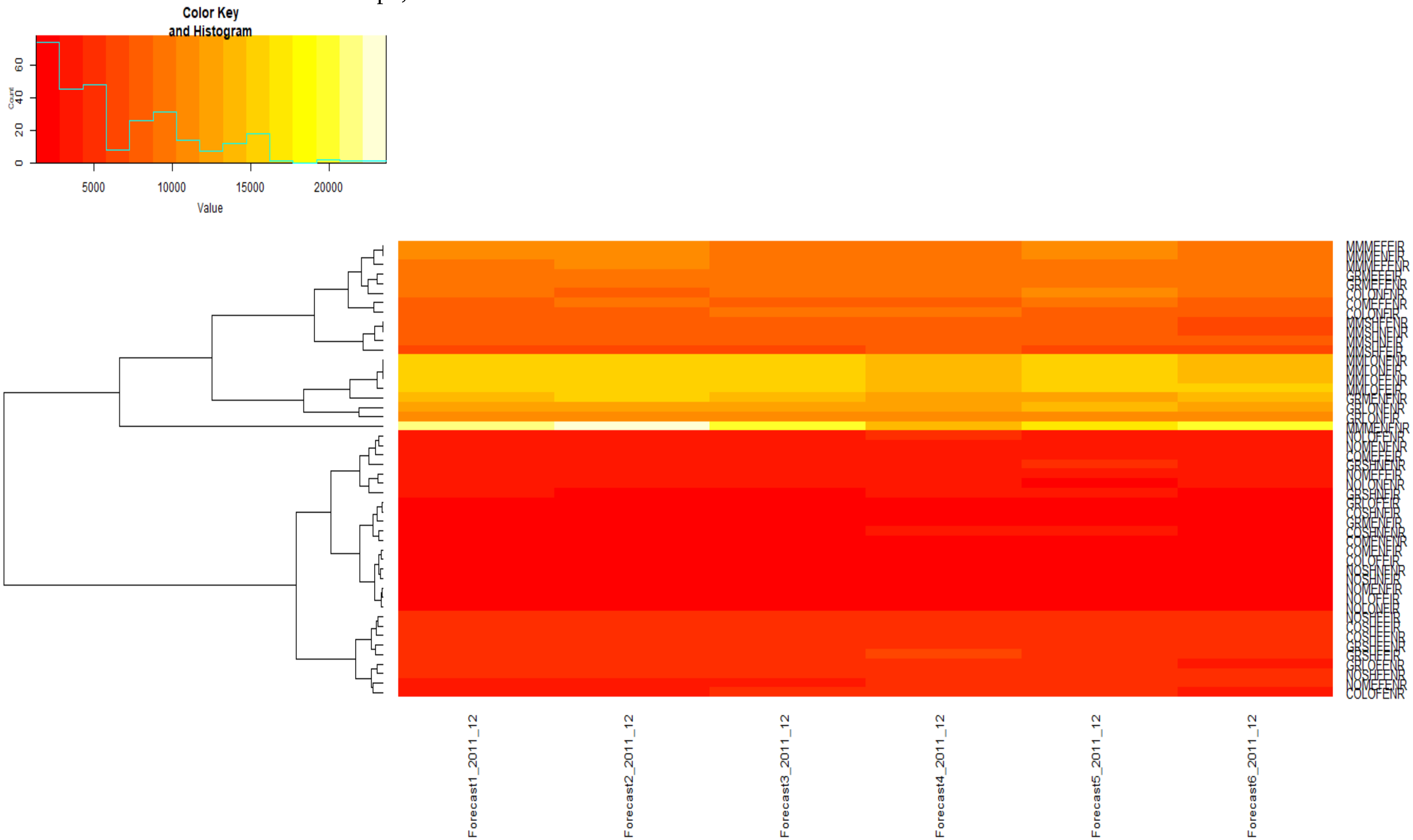
Annexure 5.29: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for enterprising pensioners farmers in the Eastern Cape, South Africa for the 2014/15 season.



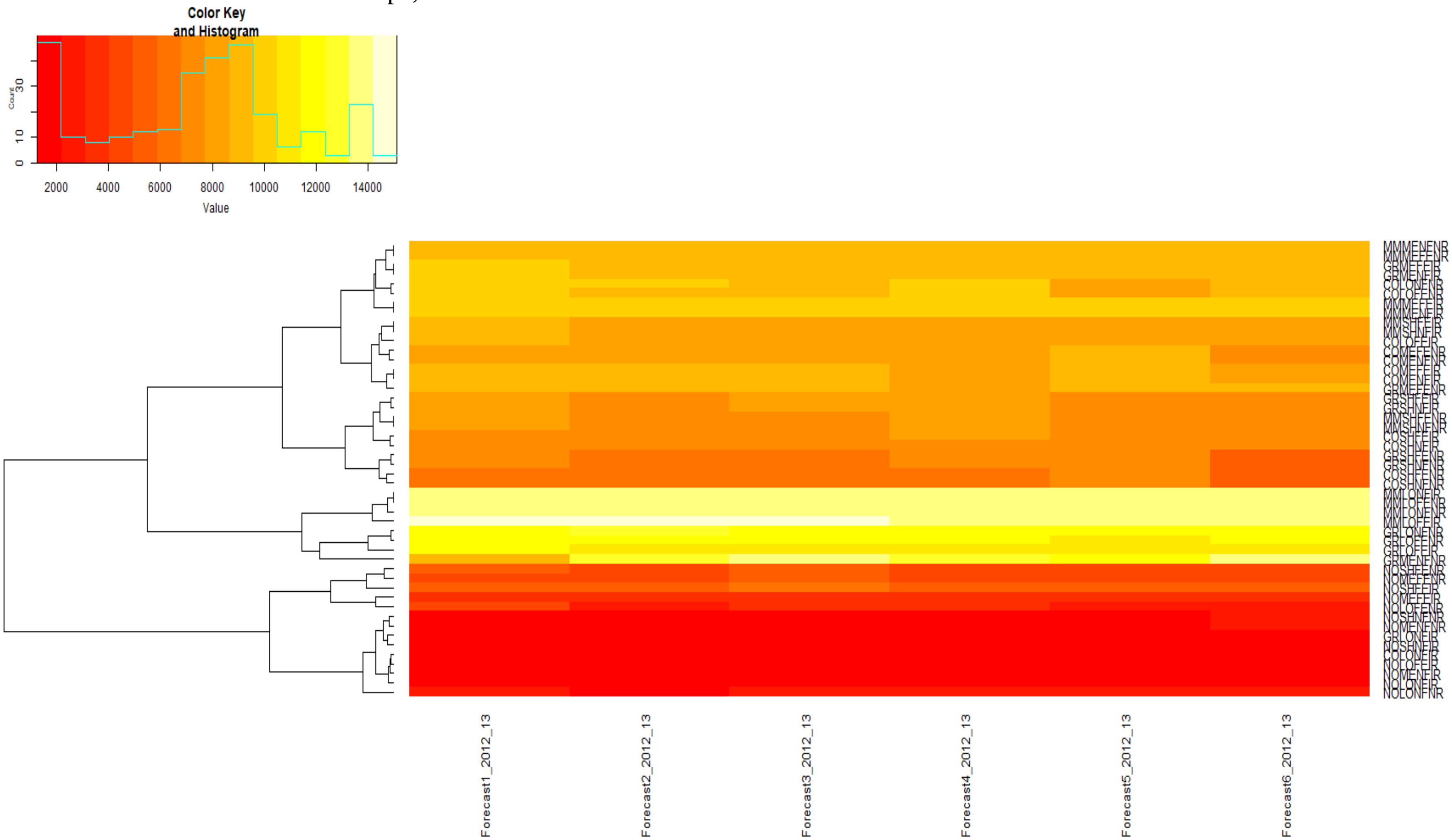
Annexure 5.30: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for enterprising pensioners farmers in the Eastern Cape, South Africa for the 2015/16 season.



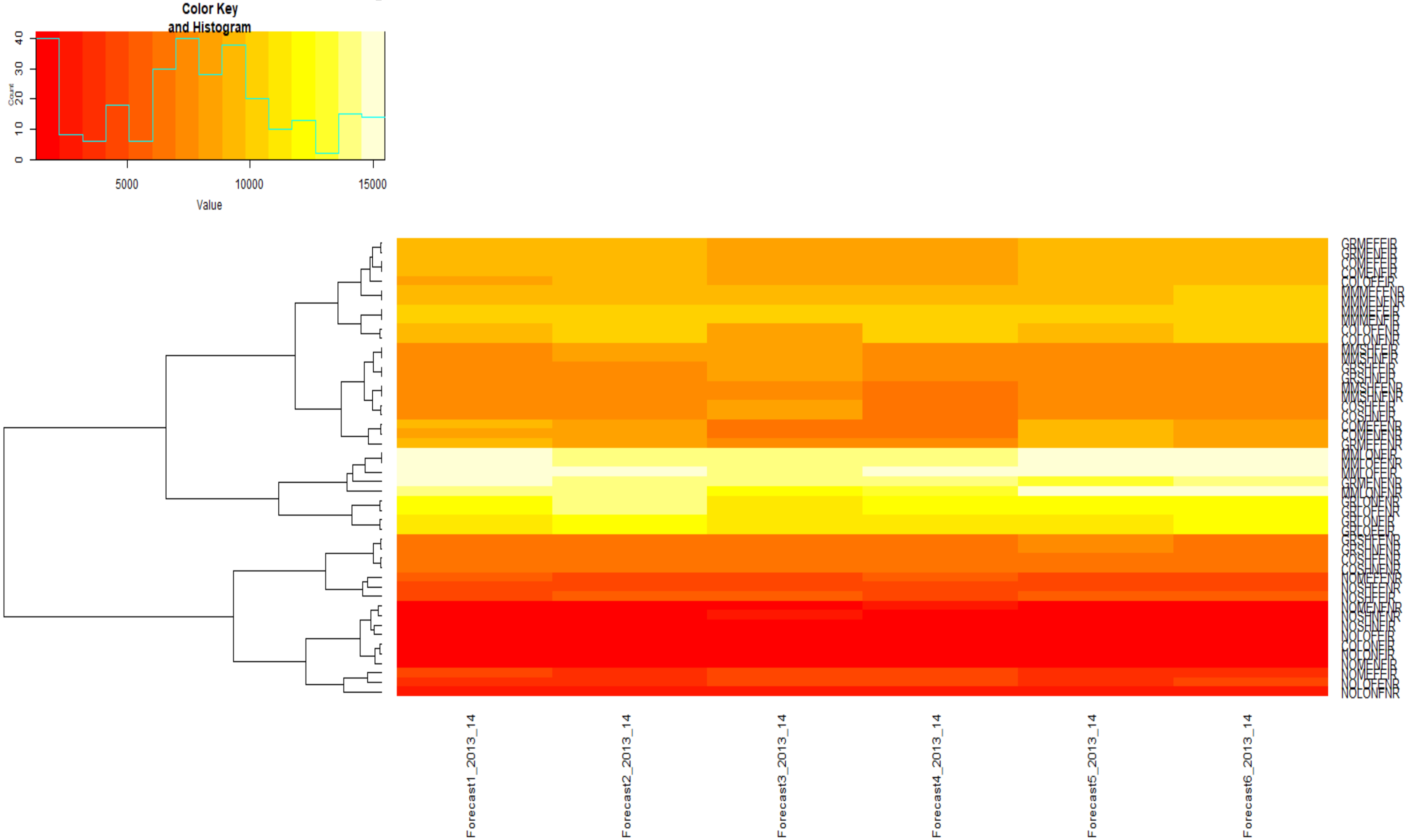
Annexure 5.31: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for struggling subsistence farmers in the Eastern Cape, South Africa for the 2011/12 season.



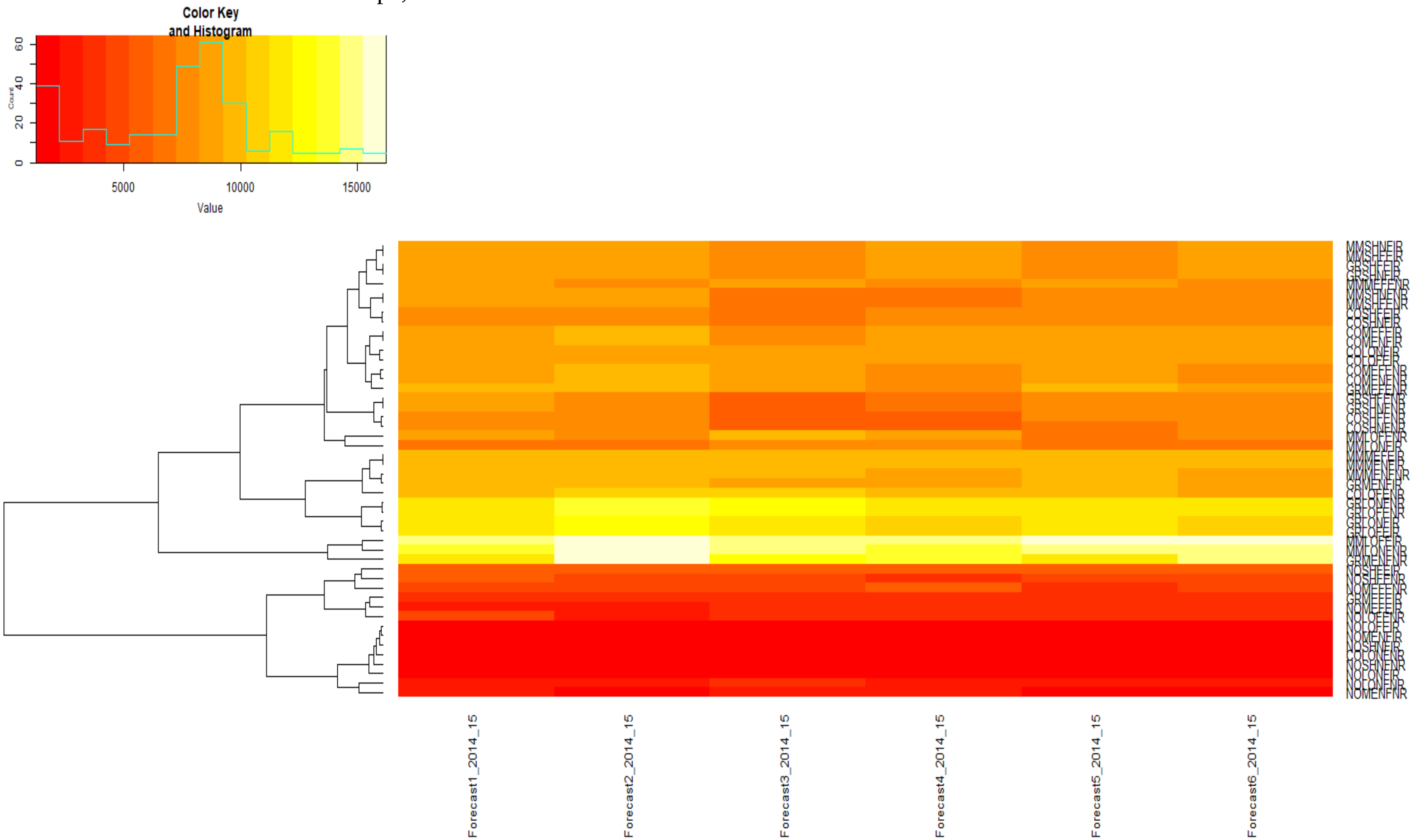
Annexure 5.32: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for struggling subsistence farmers in the Eastern Cape, South Africa for the 2012/13 season.



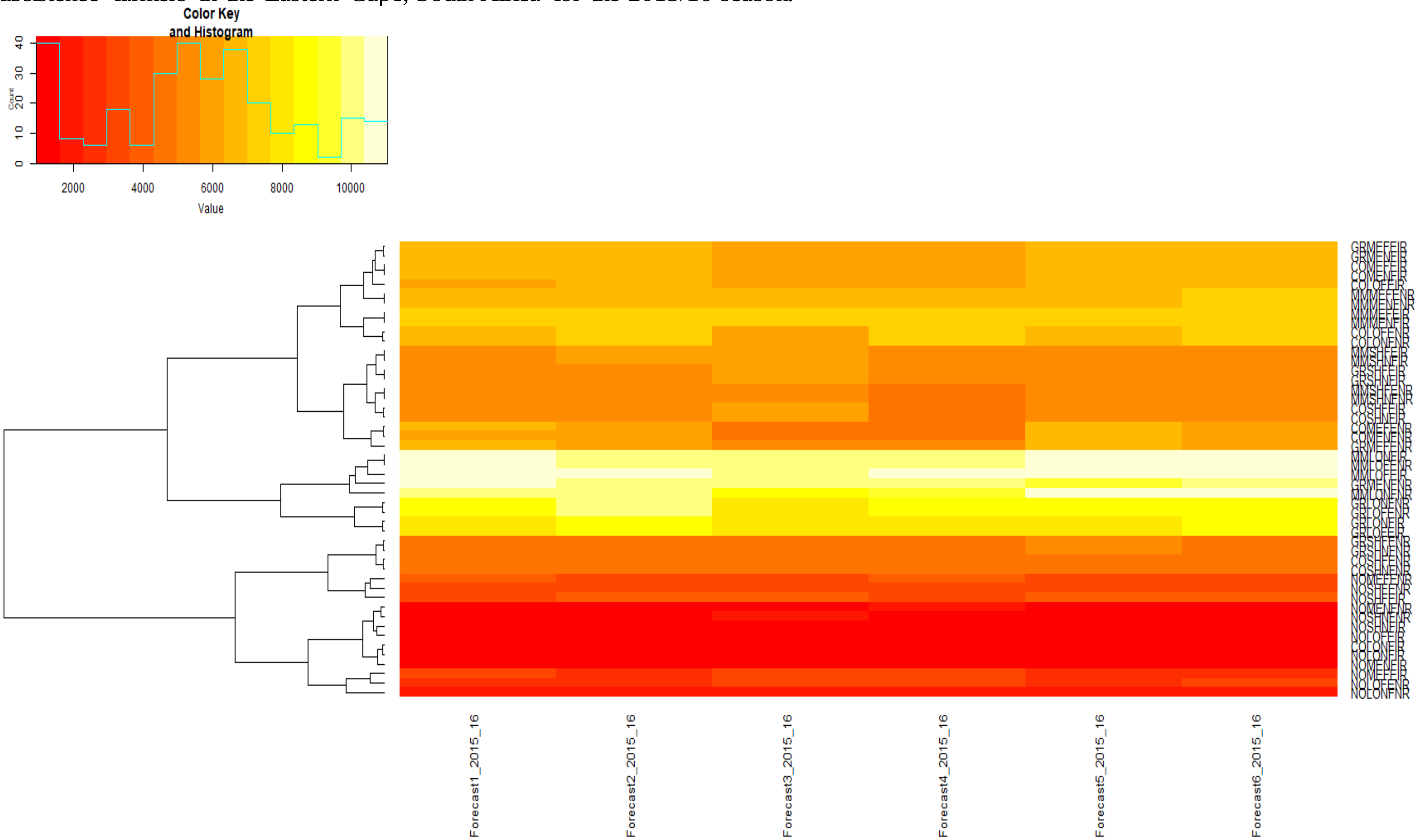
Annexure 5.33: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for struggling subsistence farmers in the Eastern Cape, South Africa for the 2013/14 season.



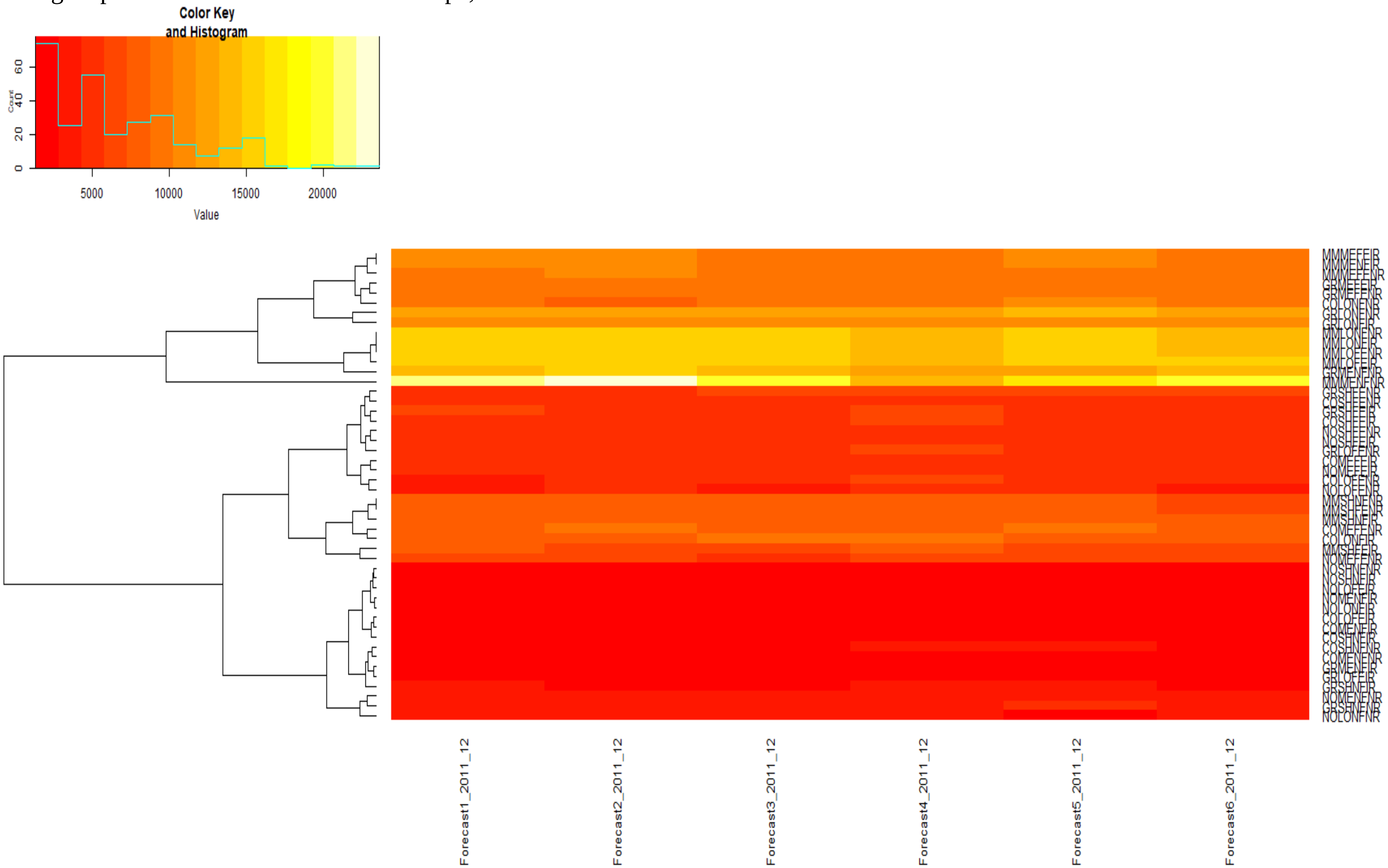
Annexure 5.34: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for struggling subsistence farmers in the Eastern Cape, South Africa for the 2014/15 season.



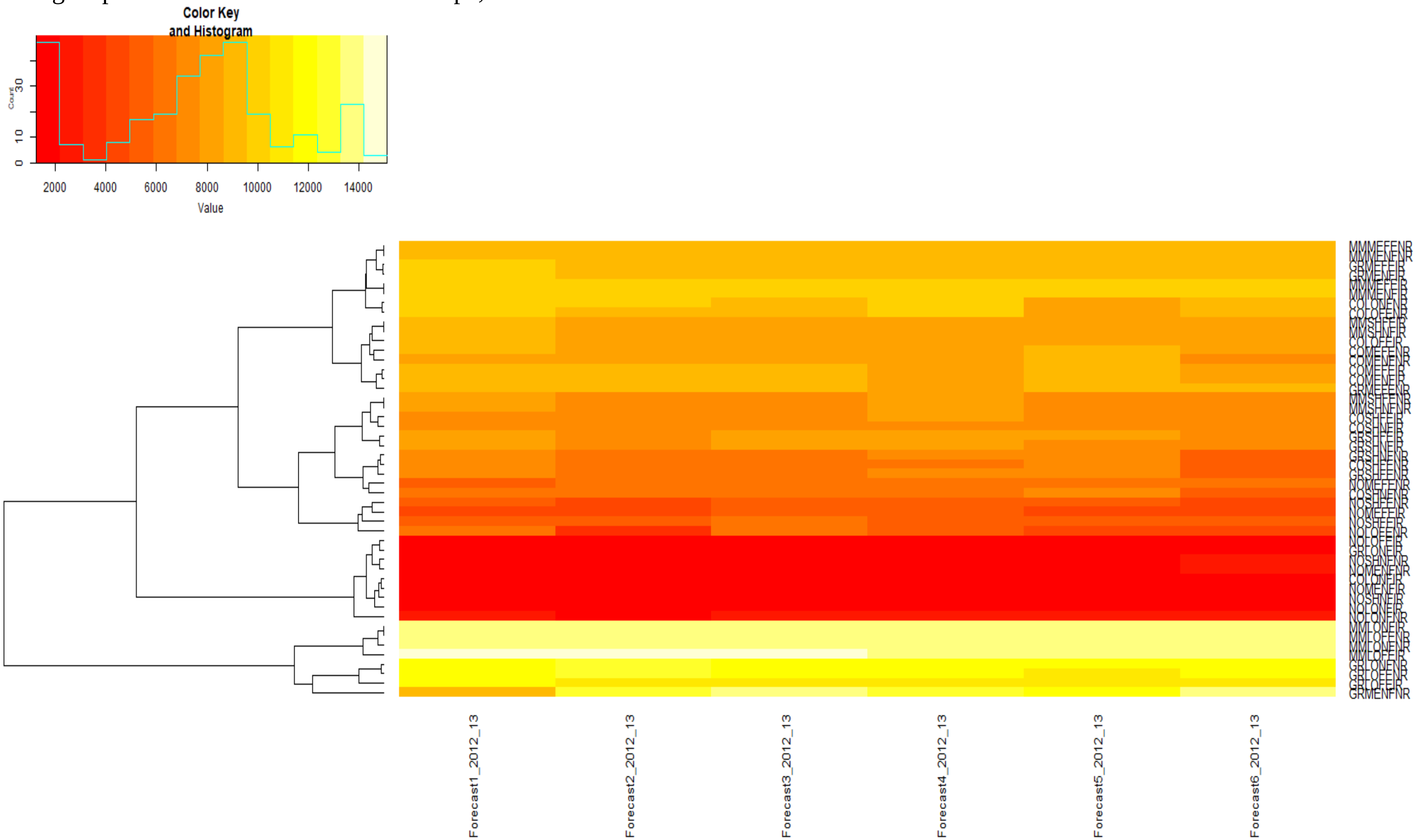
Annexure 5.35: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for struggling subsistence farmers in the Eastern Cape, South Africa for the 2015/16 season.



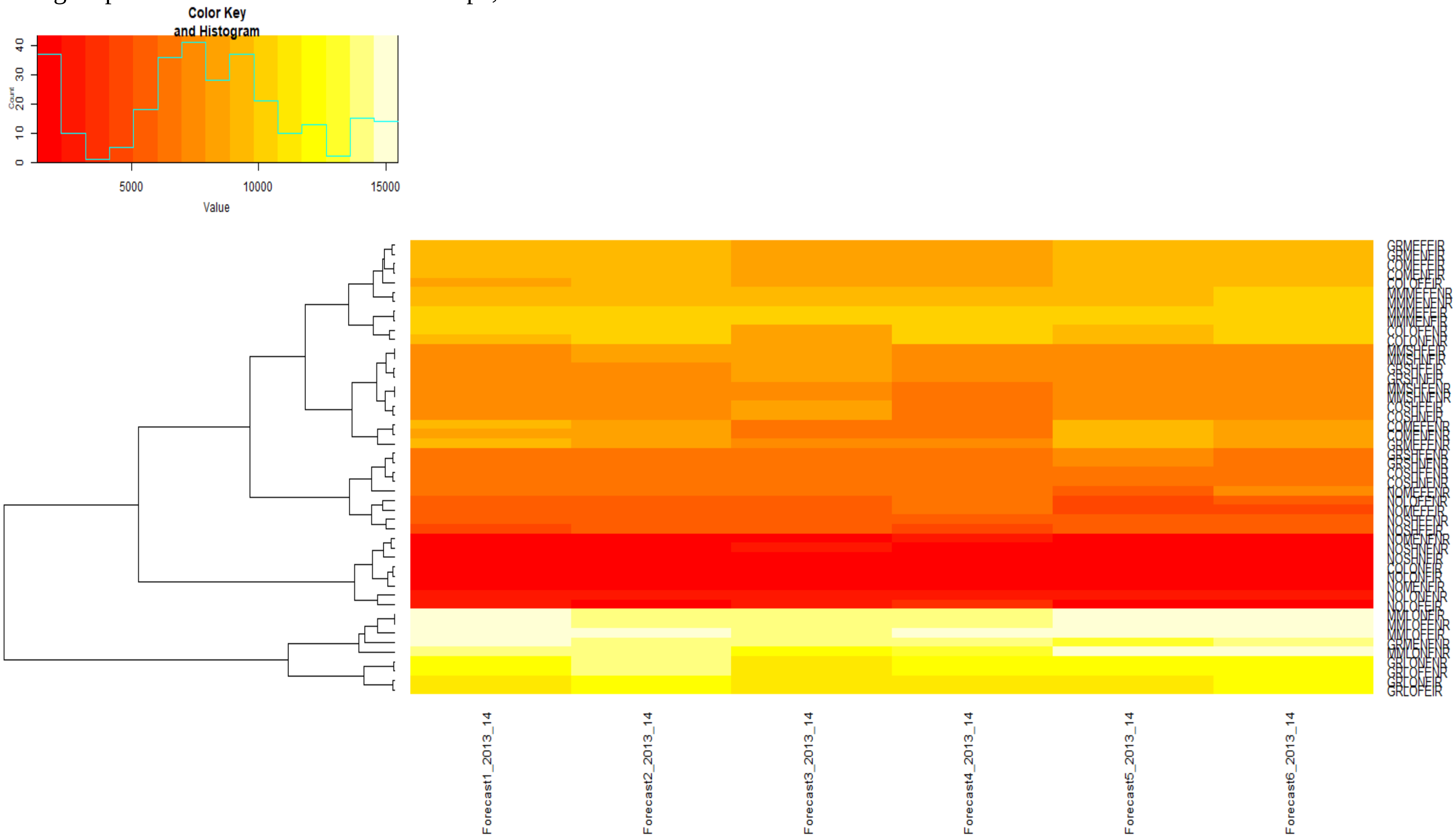
Annexure 5.36: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture farming dependent farmers in the Eastern Cape, South Africa for the 2011/12 season.



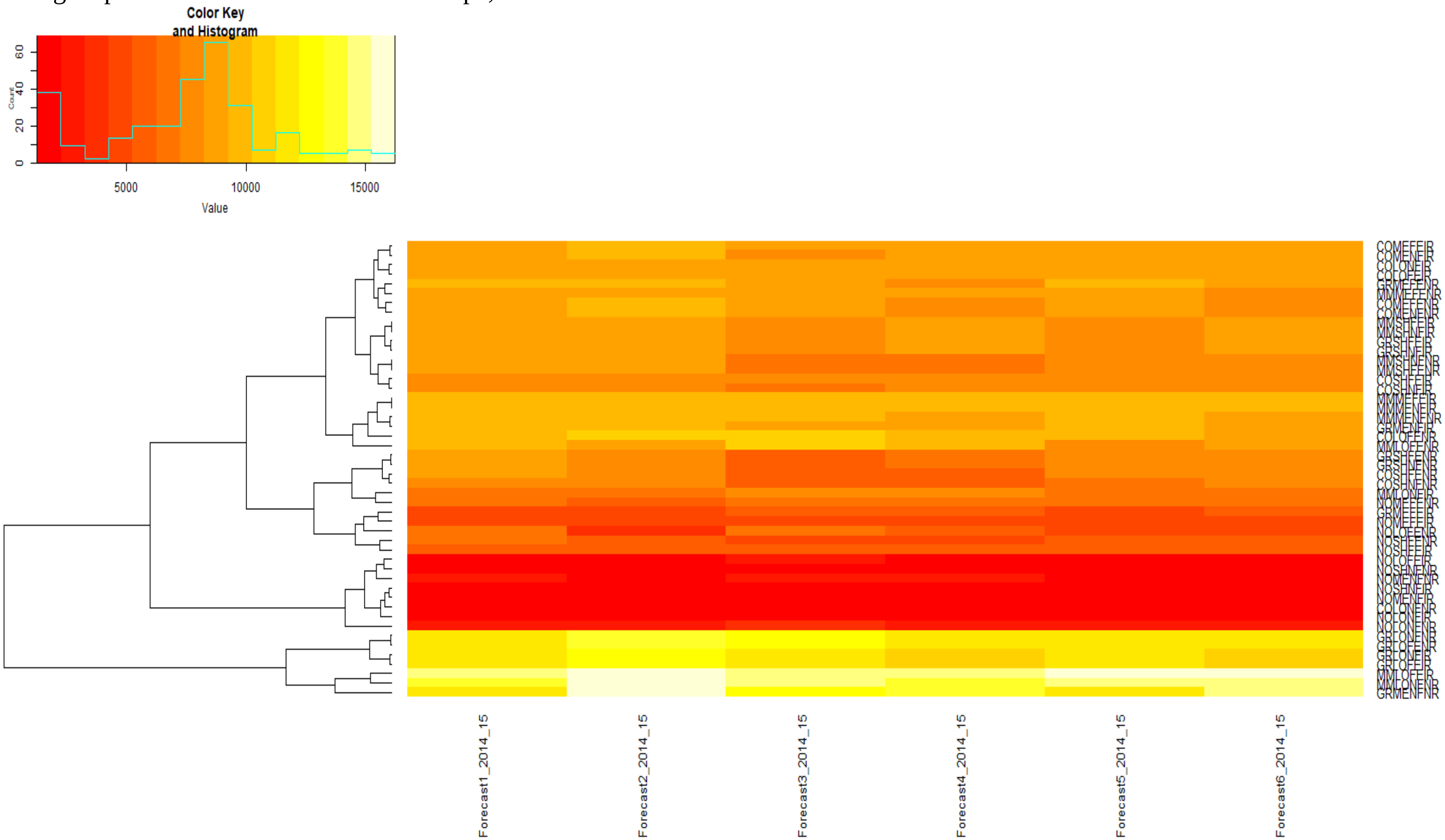
Annexure 5.37: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture farming dependent farmers in the Eastern Cape, South Africa for the 2012/13 season.



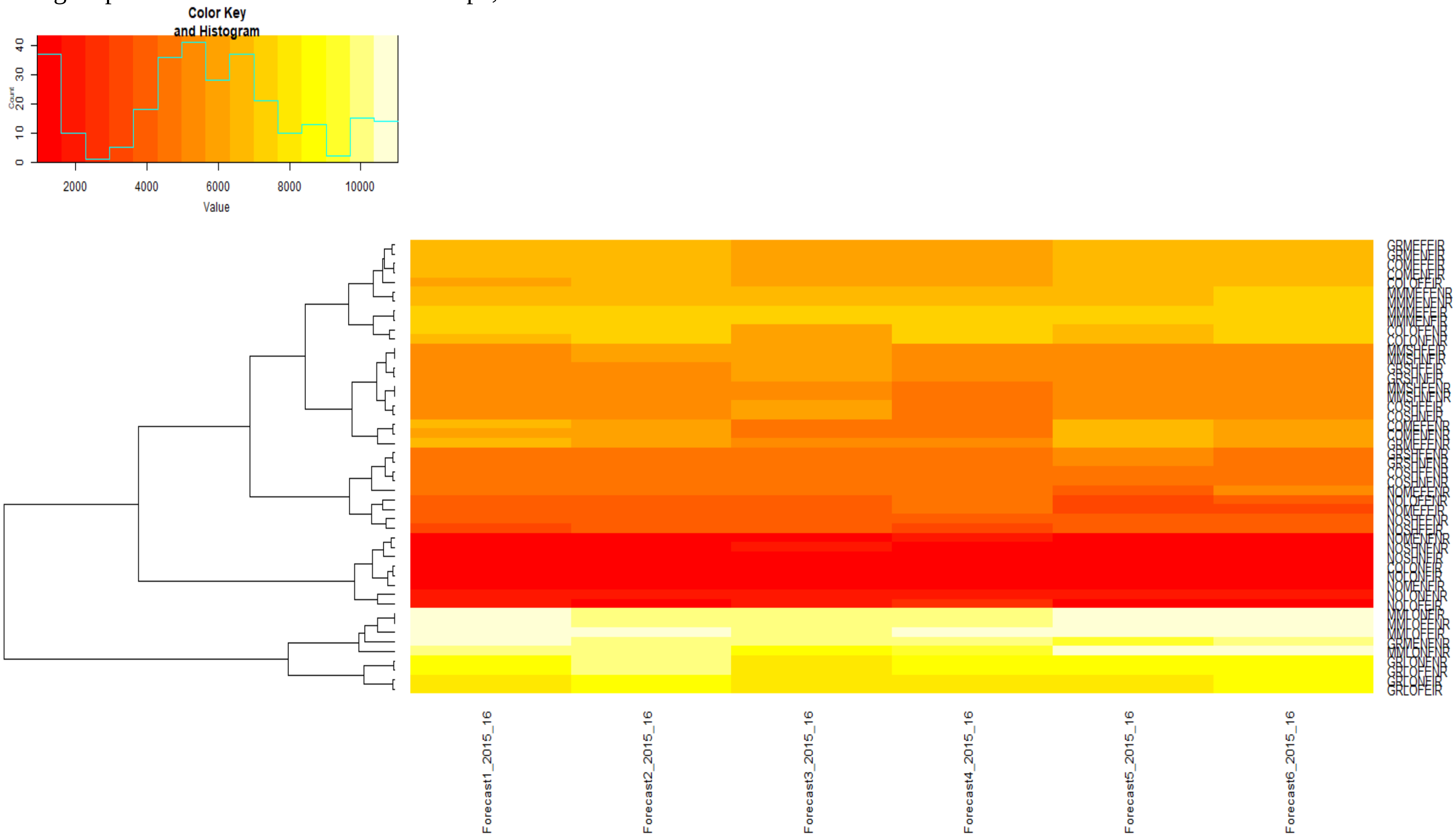
Annexure 5.38: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture farming dependent farmers in the Eastern Cape, South Africa for the 2013/14 season.



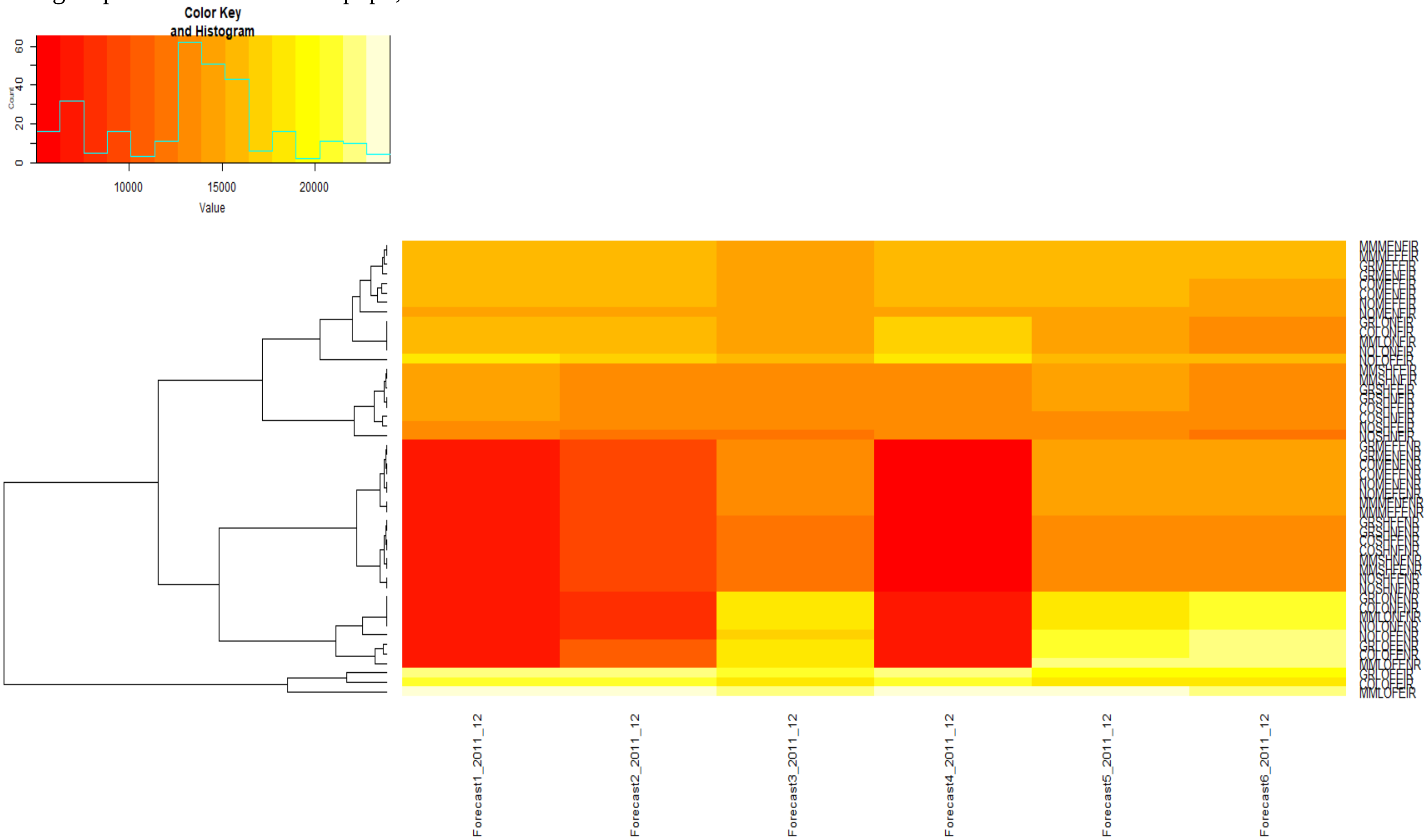
Annexure 5.39: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture farming dependent farmers in the Eastern Cape, South Africa for the 2014/15 season.



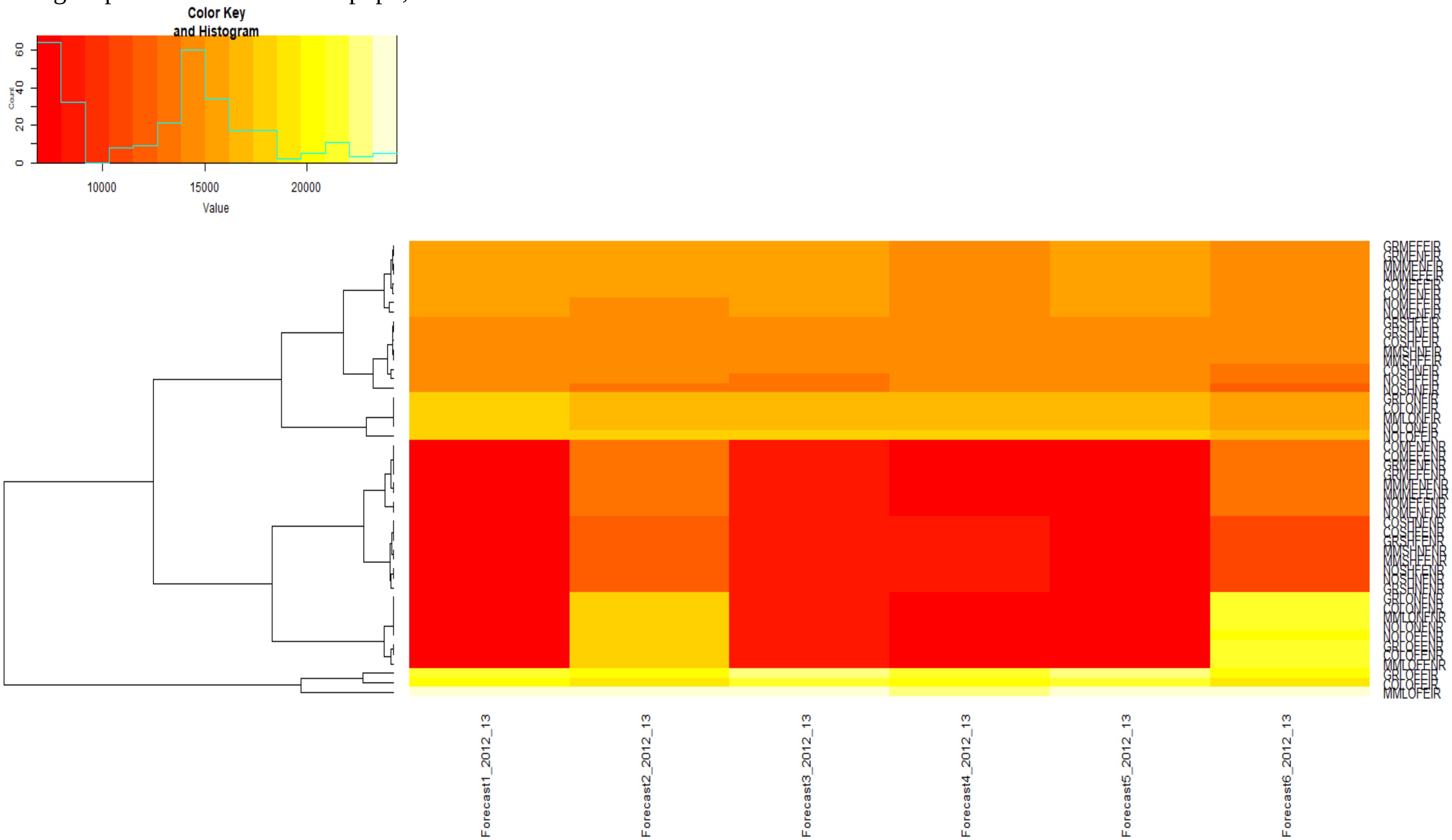
Annexure 5.40: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture farming dependent farmers in the Eastern Cape, South Africa for the 2015/16 season.



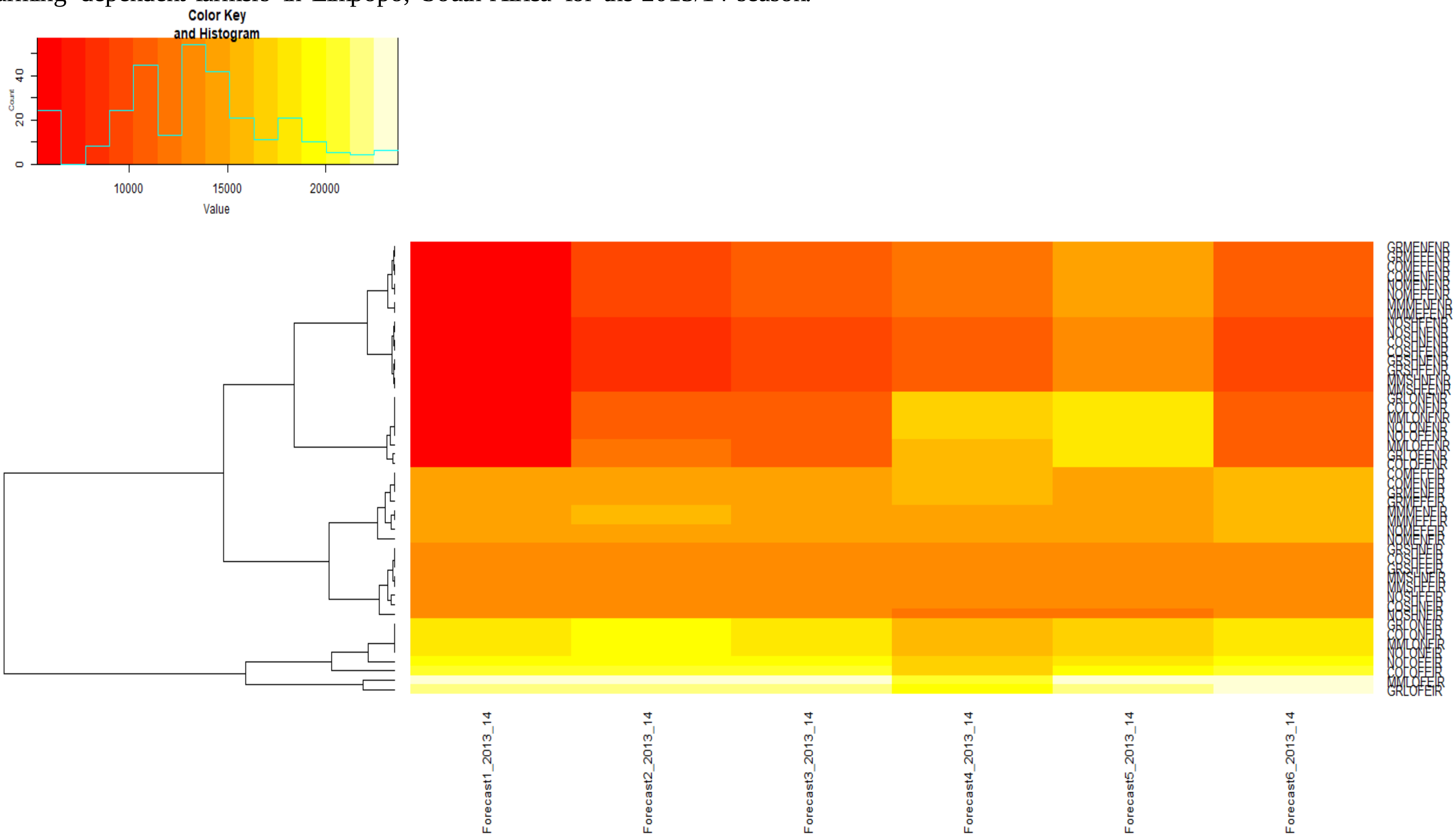
Annexure 5.41: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming dependent farmers in Limpopo, South Africa for the 2011/12 season.



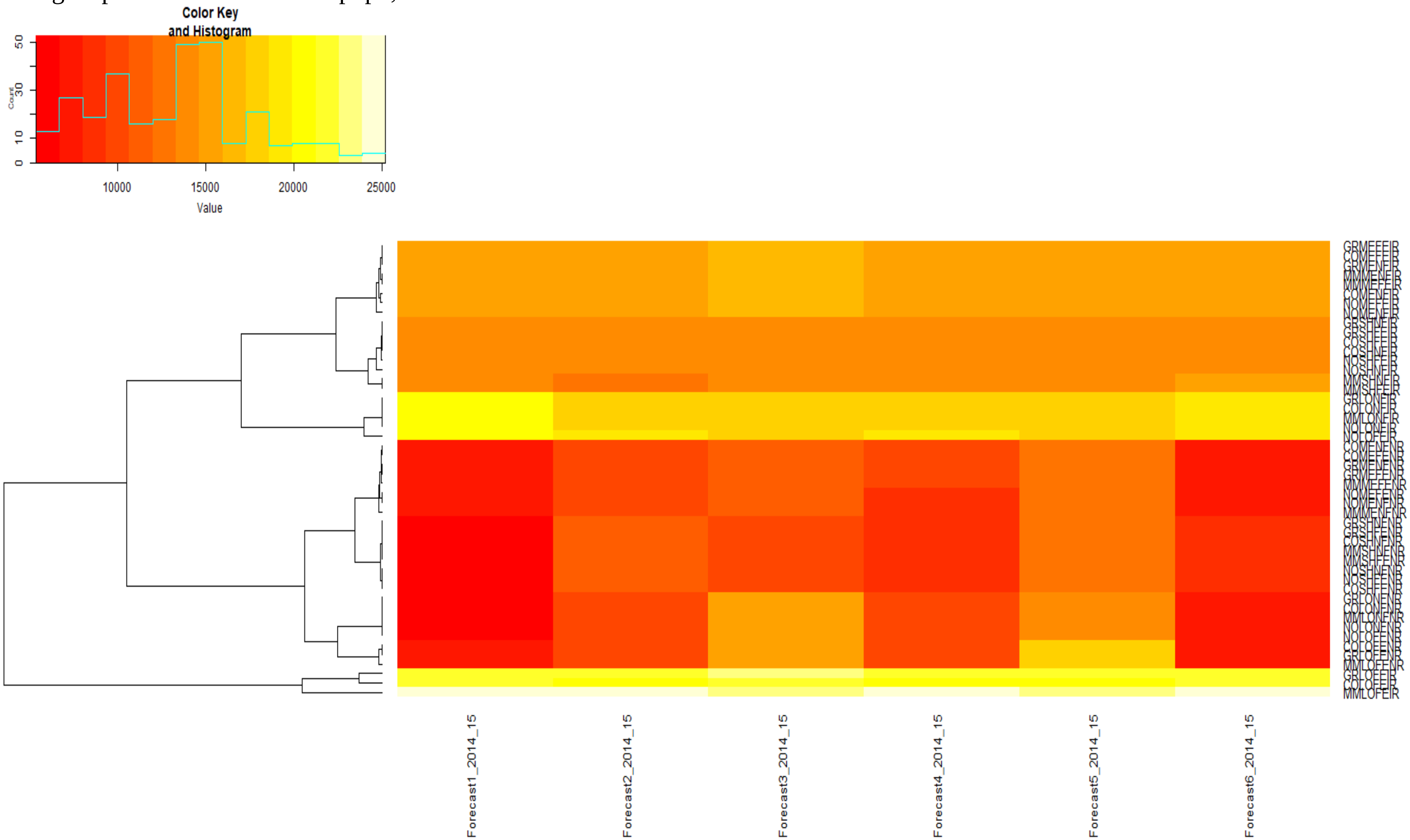
Annexure 5.42: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming dependent farmers in Limpopo, South Africa for the 2012/13 season.



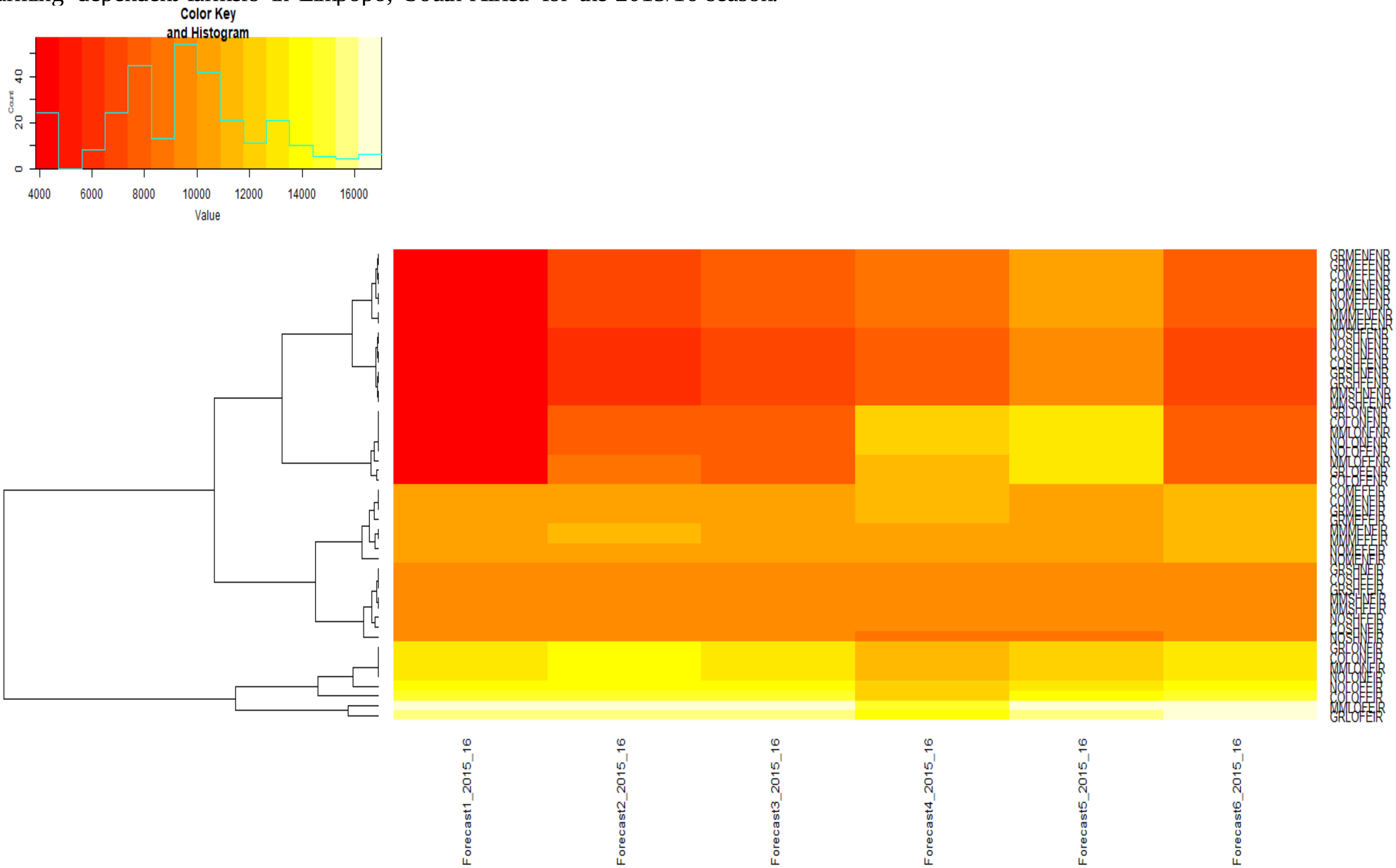
Annexure 5.43: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming dependent farmers in Limpopo, South Africa for the 2013/14 season.



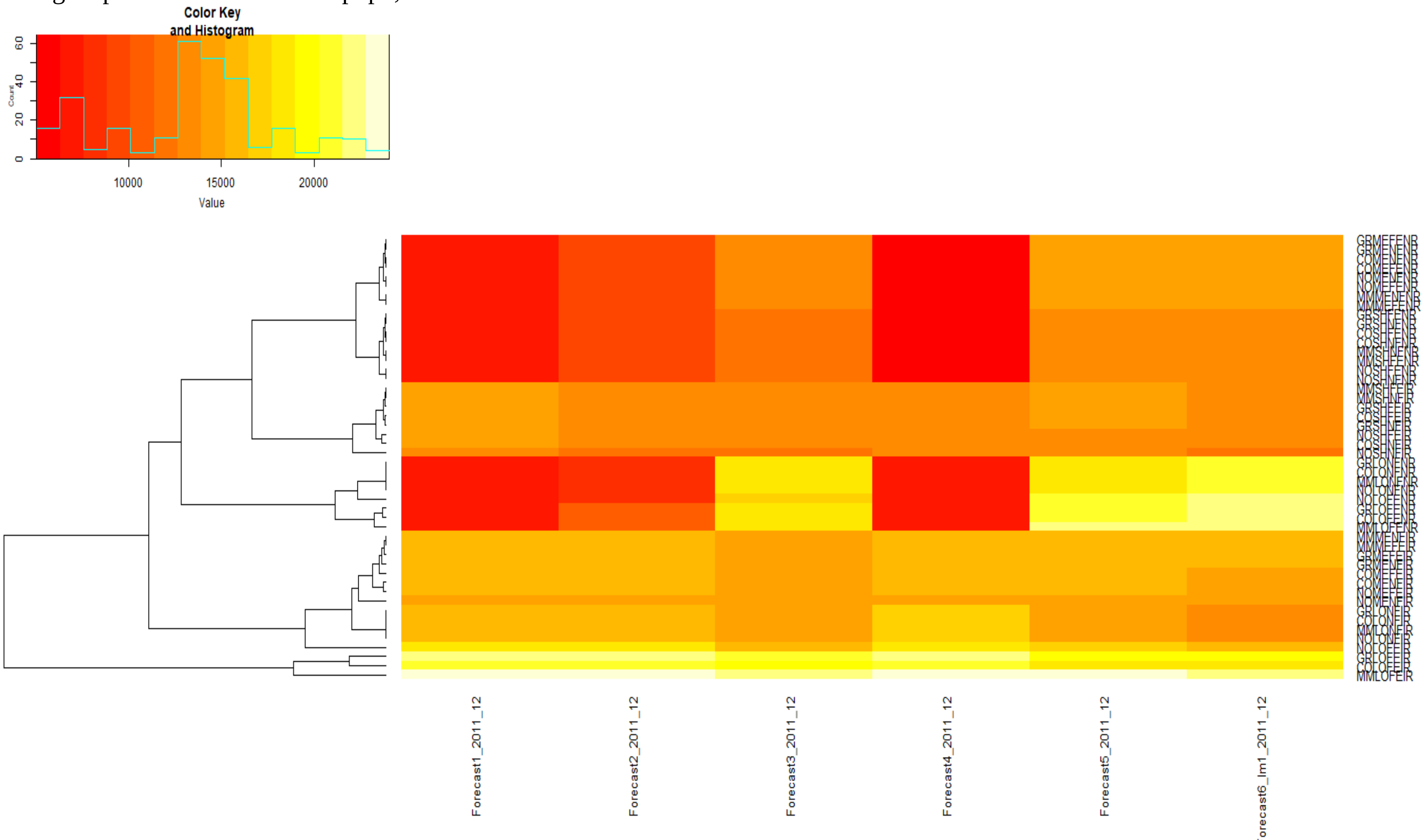
Annexure 5.44: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming dependent farmers in Limpopo, South Africa for the 2014/15 season.



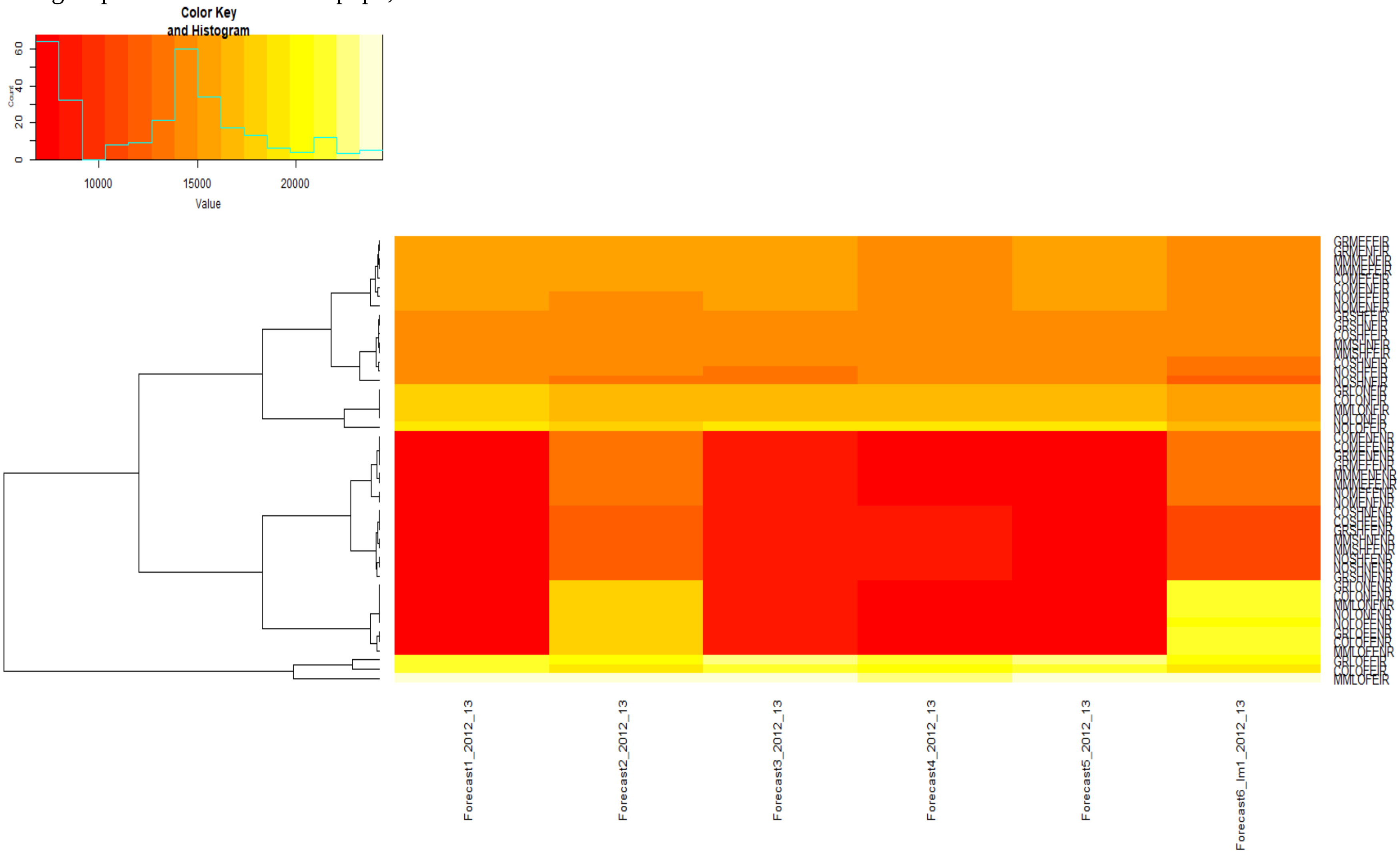
Annexure 5.45: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming dependent farmers in Limpopo, South Africa for the 2015/16 season.



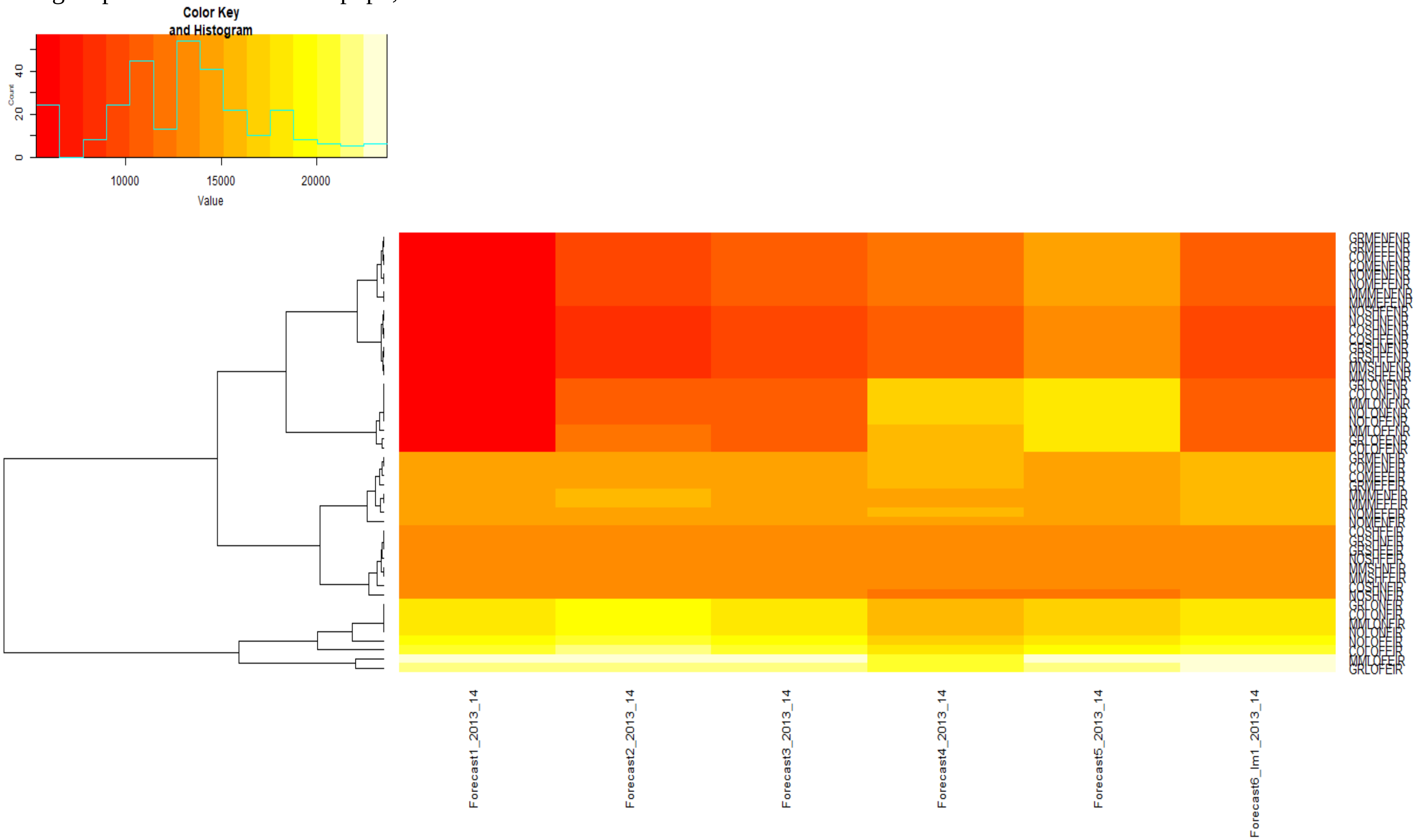
Annexure 5.46: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture farming dependent farmers in Limpopo, South Africa for the 2011/12 season.



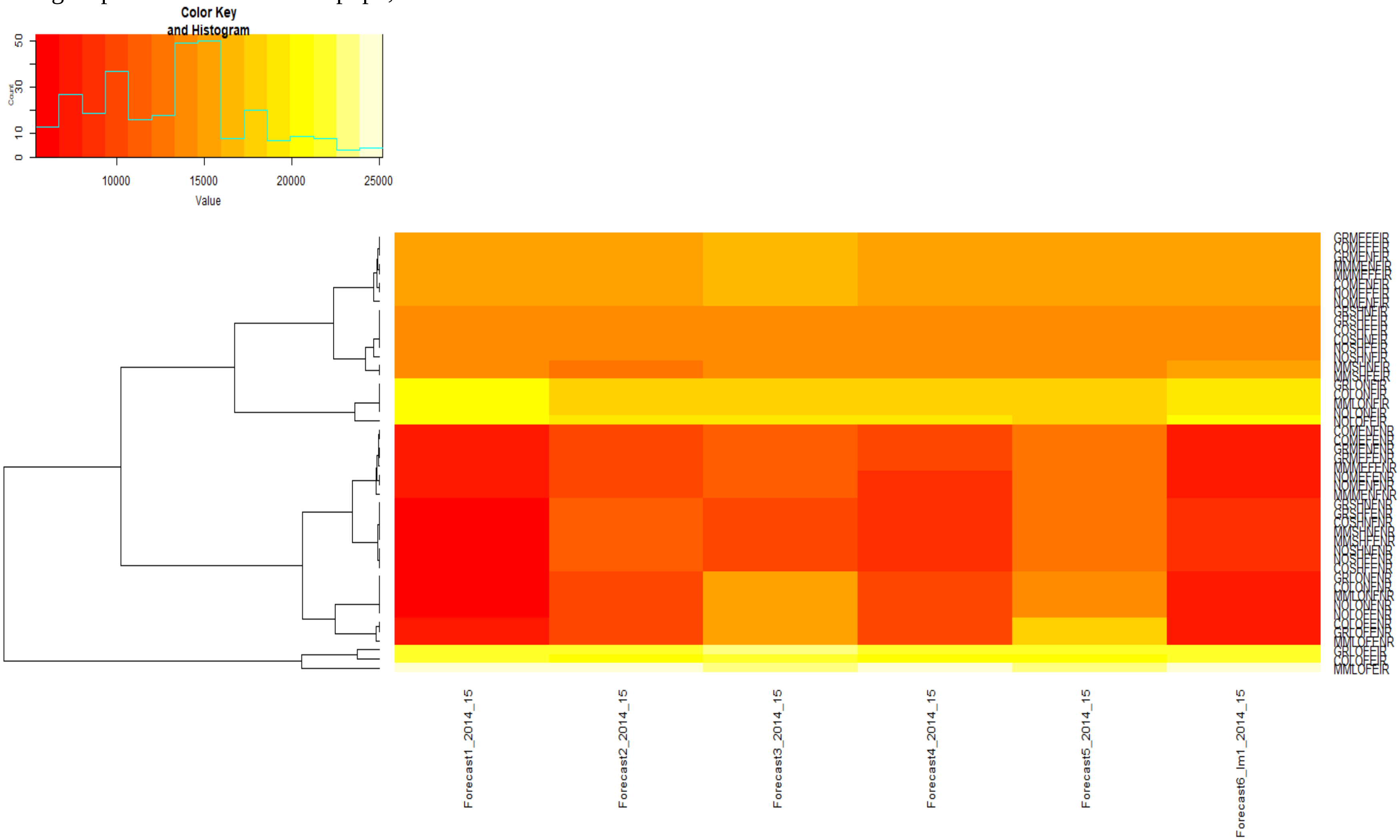
Annexure 5.47: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture farming dependent farmers in Limpopo, South Africa for the 2012/13 season.



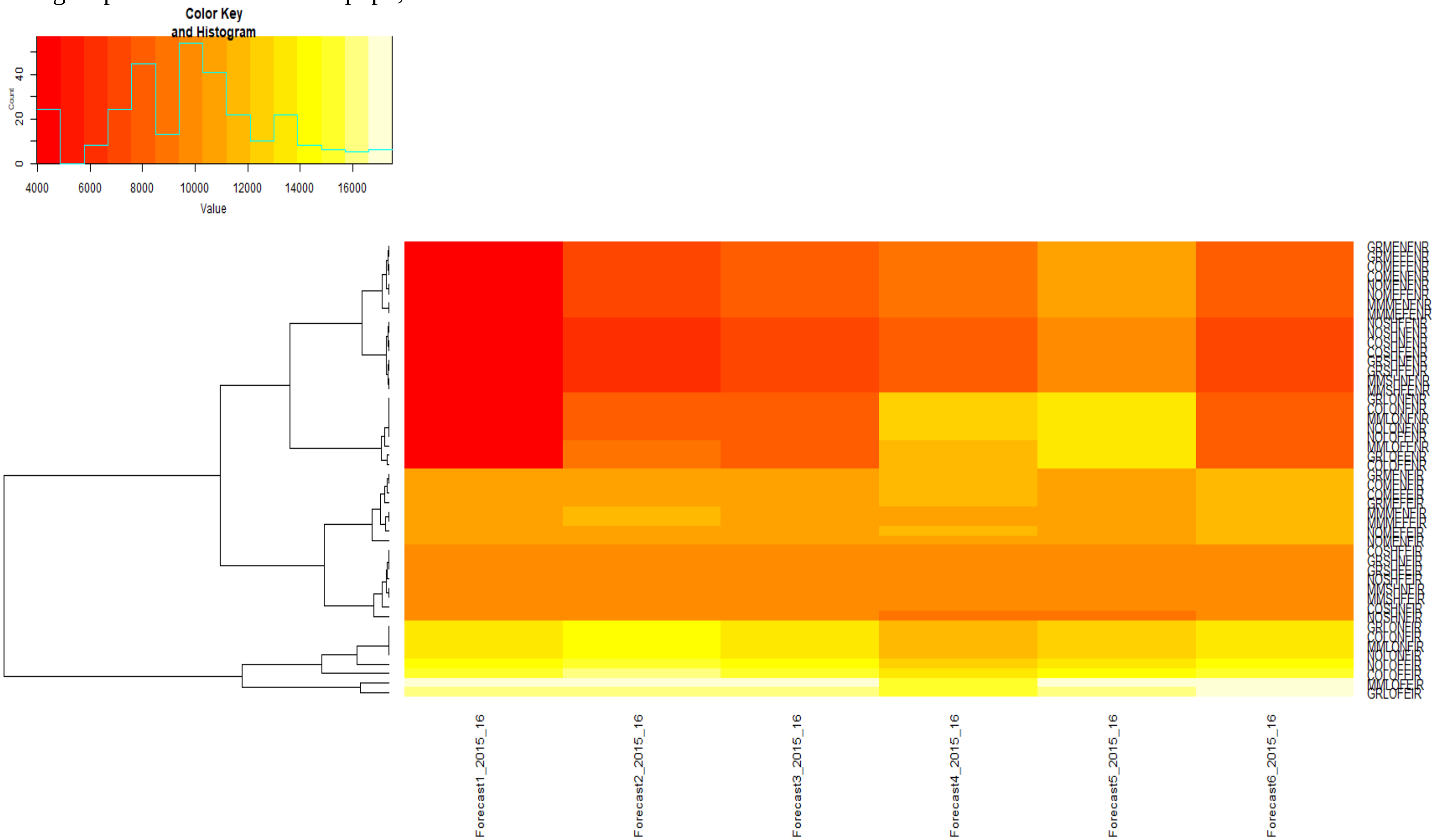
Annexure 5.48: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture farming dependent farmers in Limpopo, South Africa for the 2013/14 season.



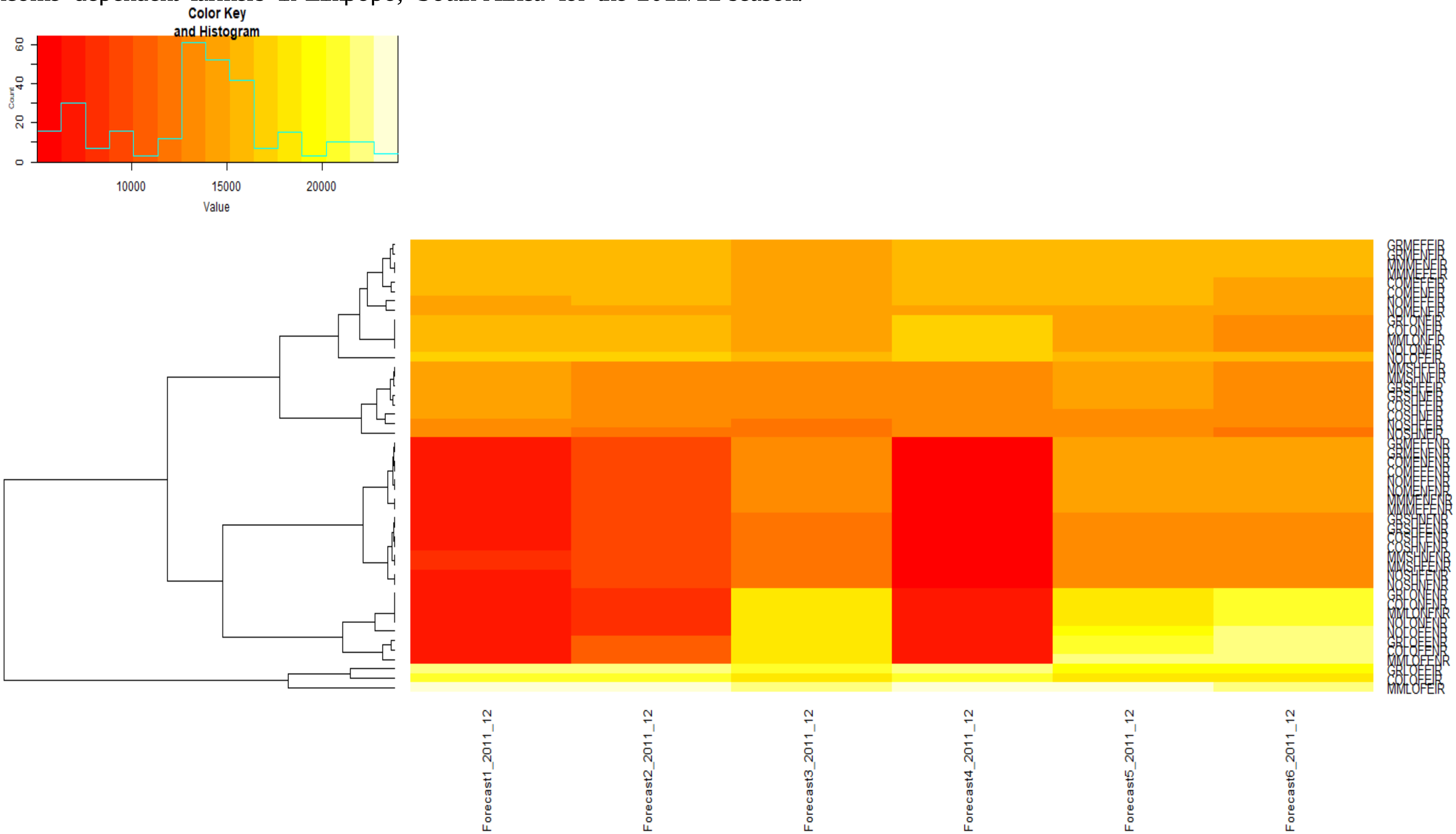
Annexure 5.49: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture farming dependent farmers in Limpopo, South Africa for the 2014/15 season.



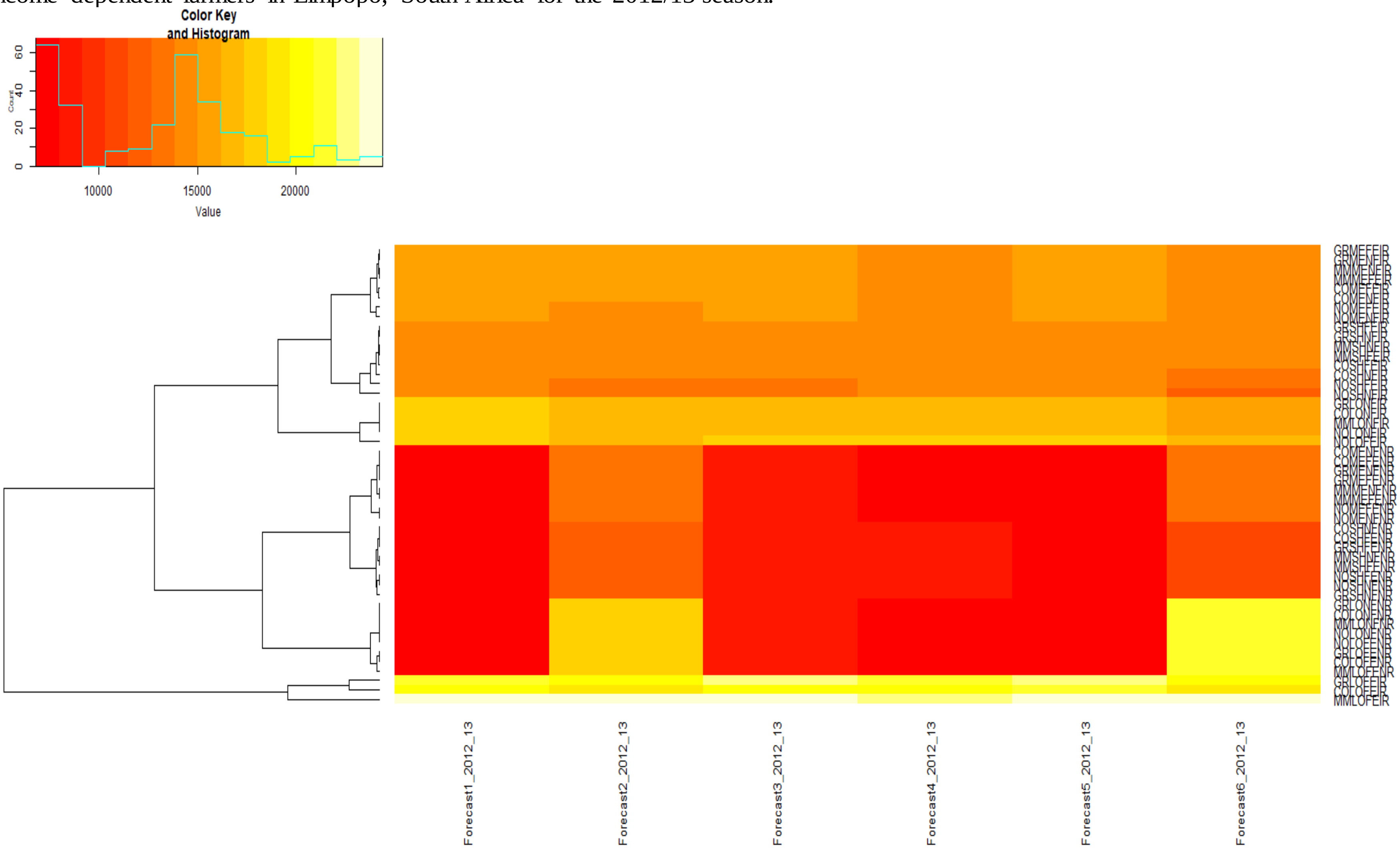
Annexure 5.50: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture farming dependent farmers in Limpopo, South Africa for the 2015/16 season.



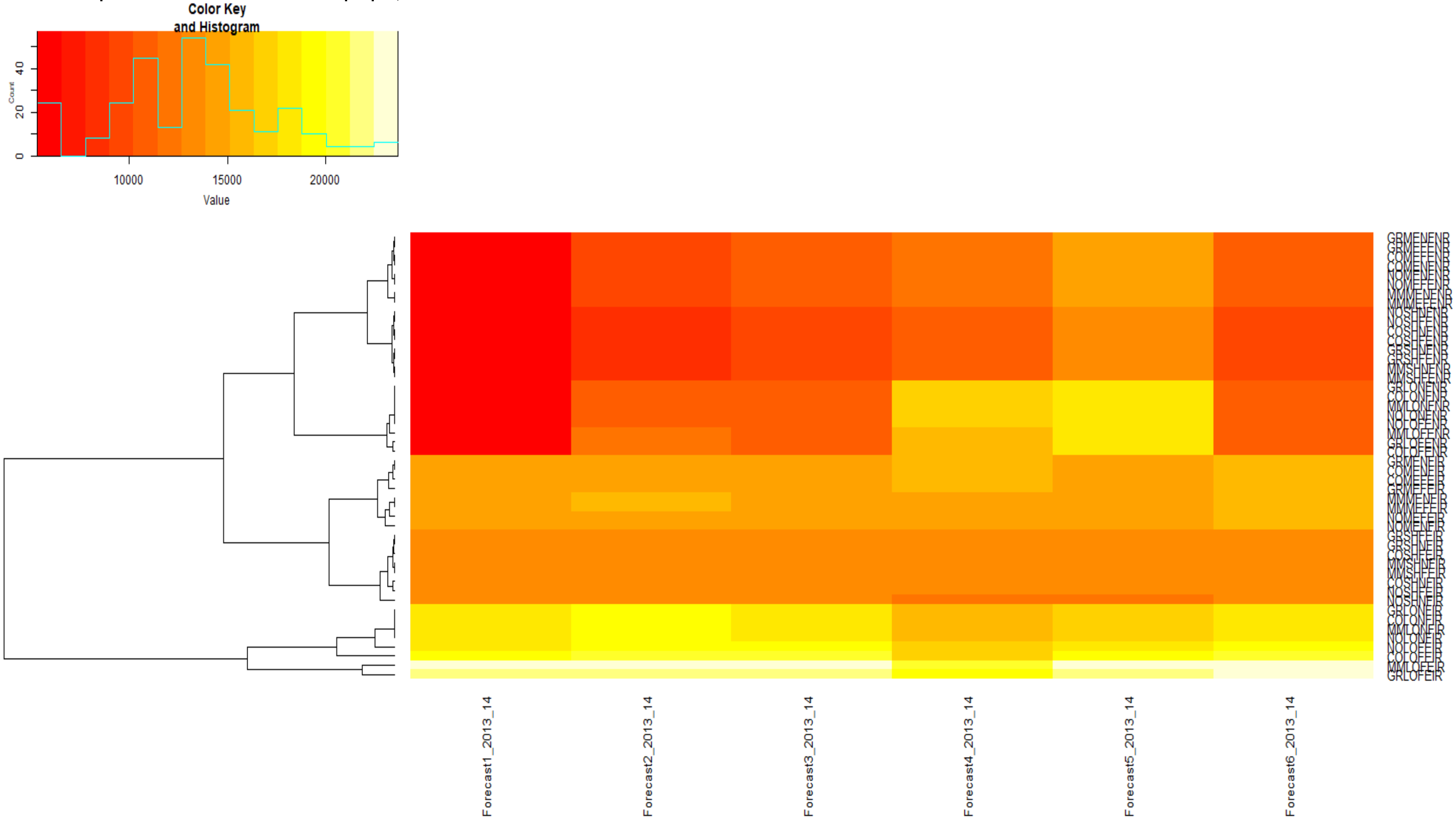
Annexure 5.51: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for off-farm income dependent farmers in Limpopo, South Africa for the 2011/12 season.



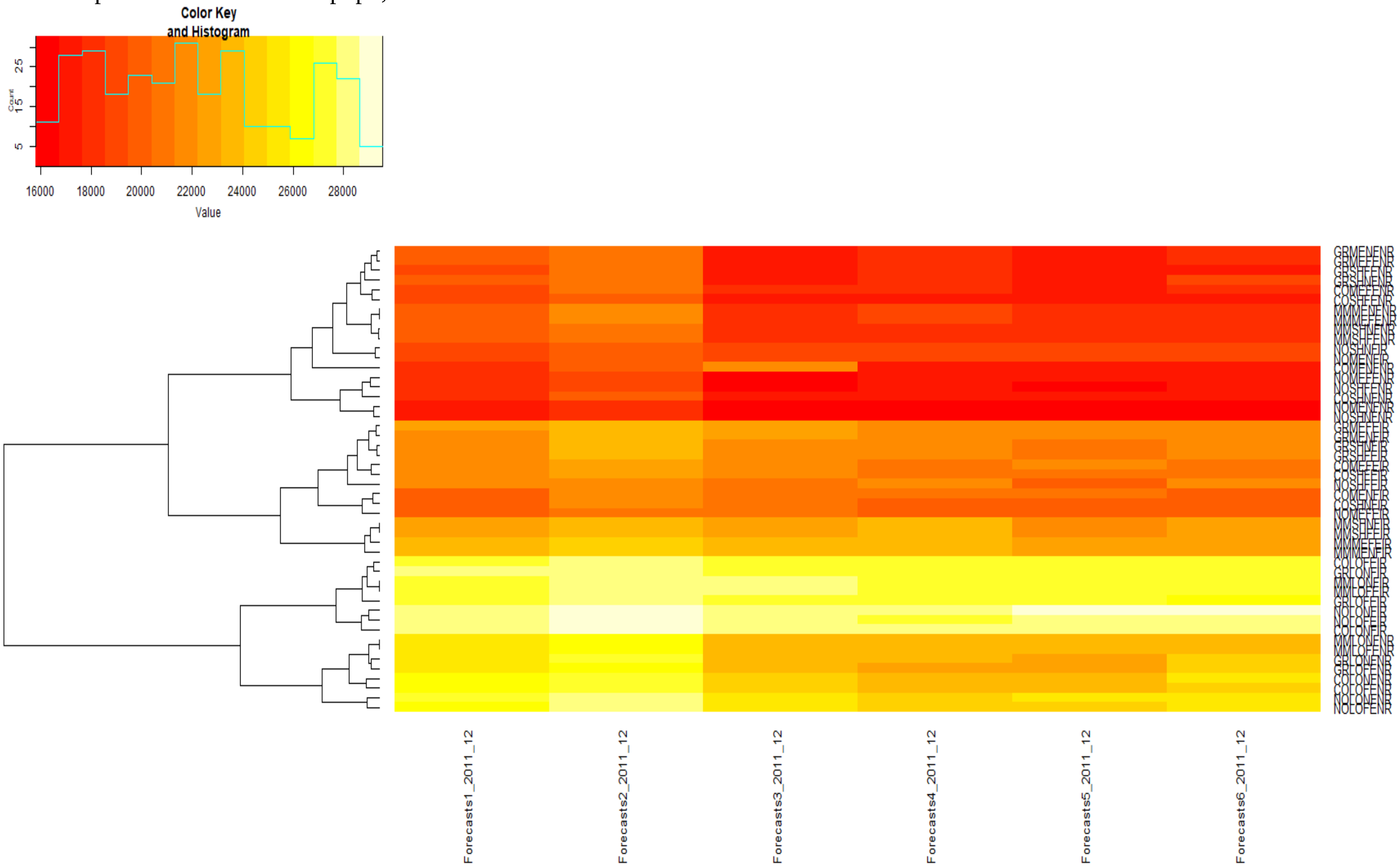
Annexure 5.52: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for off-farm income dependent farmers in Limpopo, South Africa for the 2012/13 season.



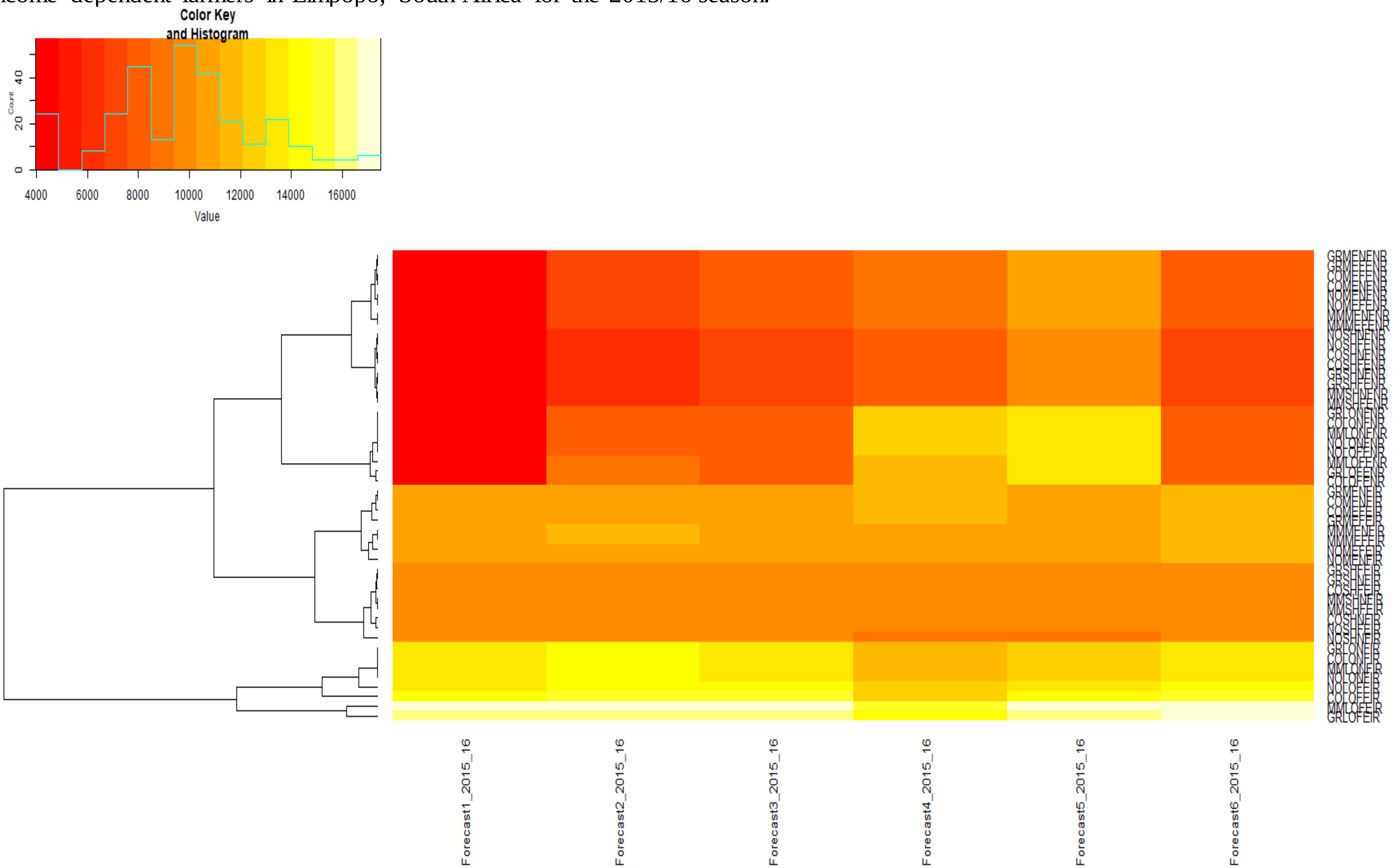
Annexure 5.53: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for off-farm income dependent farmers in Limpopo, South Africa for the 2013/14 season.



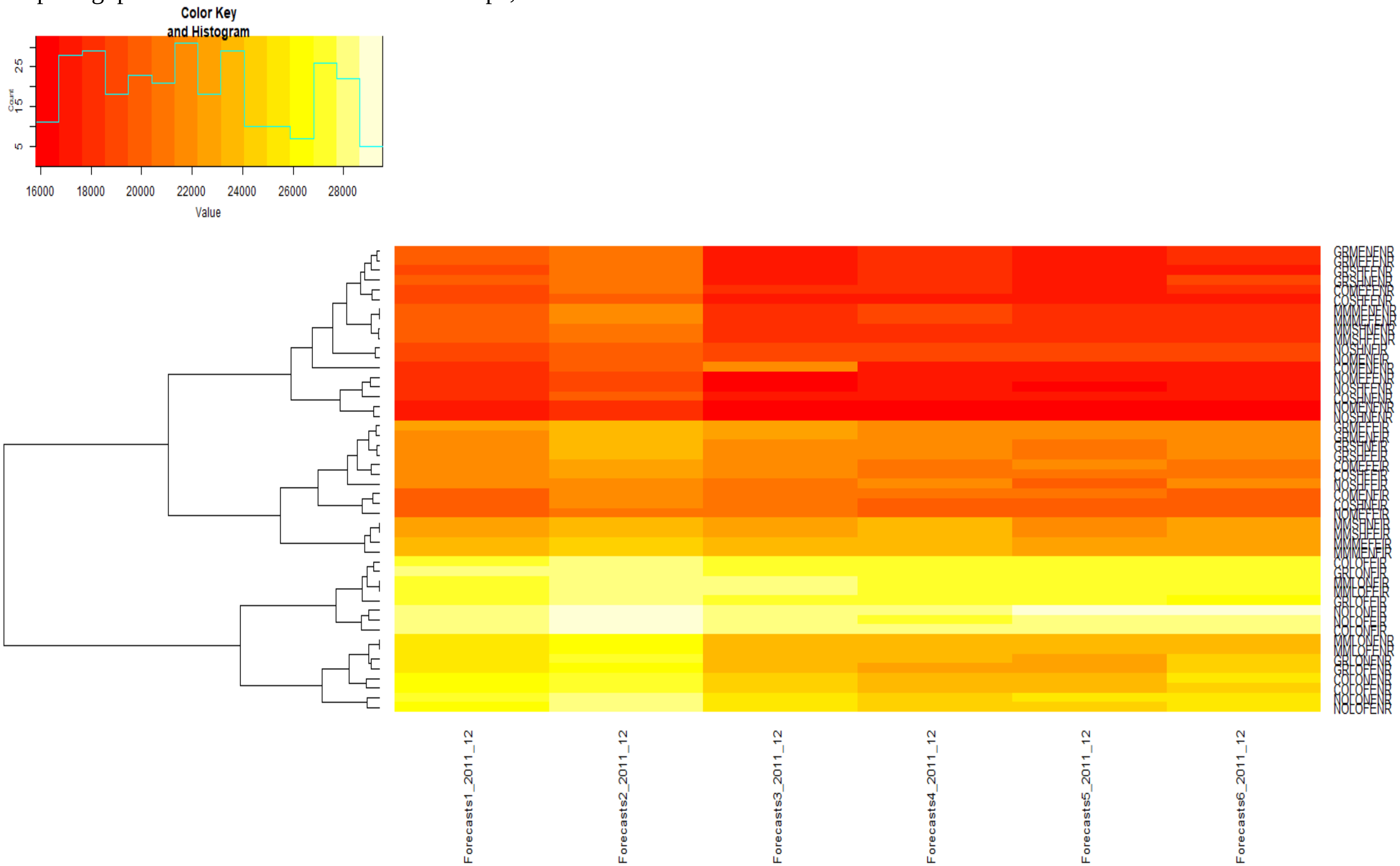
Annexure 5.54: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for off-farm income dependent farmers in Limpopo, South Africa for the 2014/15 season.



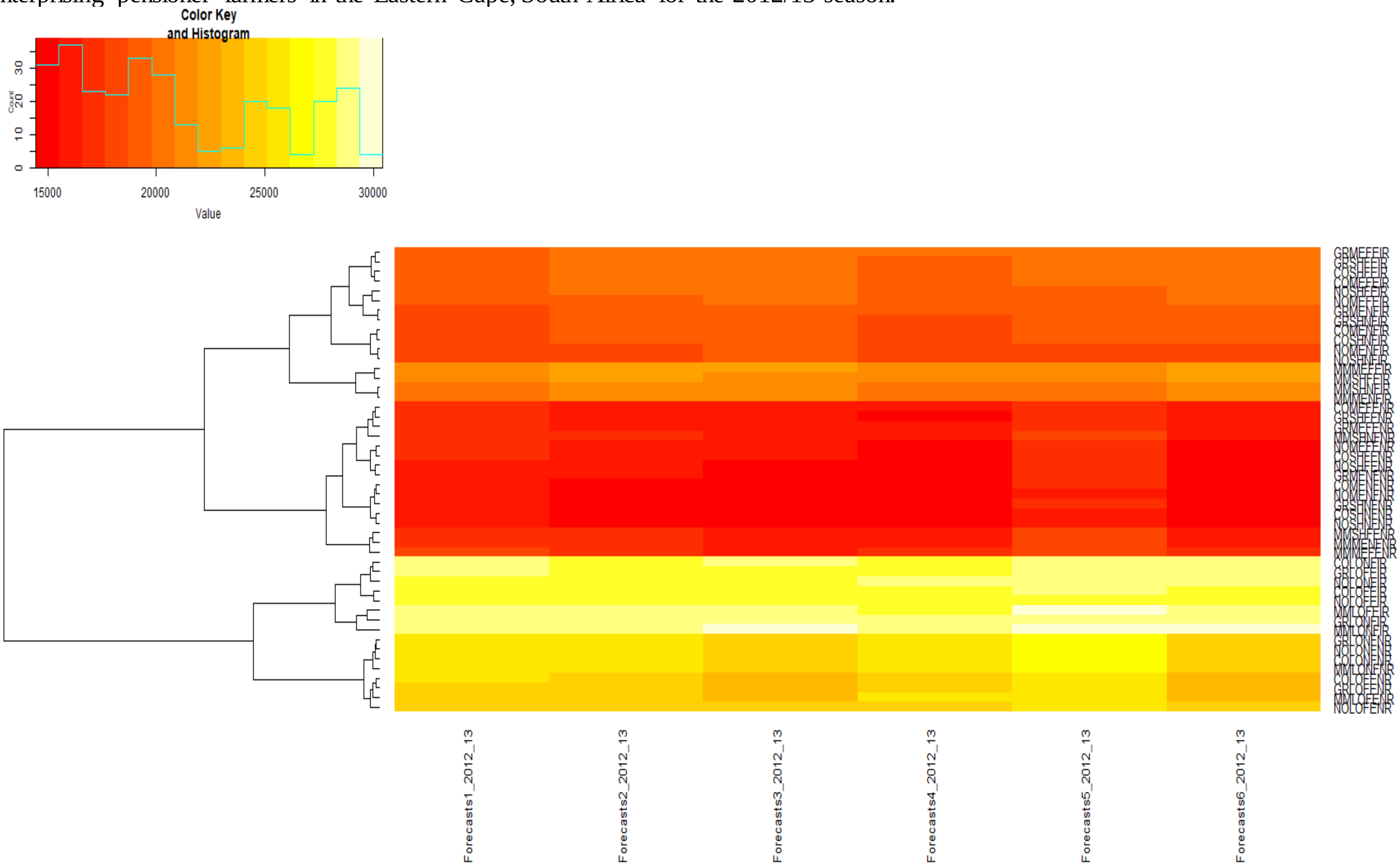
Annexure 5.55: Maize yields amongst the different climate variability management strategies and historical seasonal forecasts for off-farm income dependent farmers in Limpopo, South Africa for the 2015/16 season.



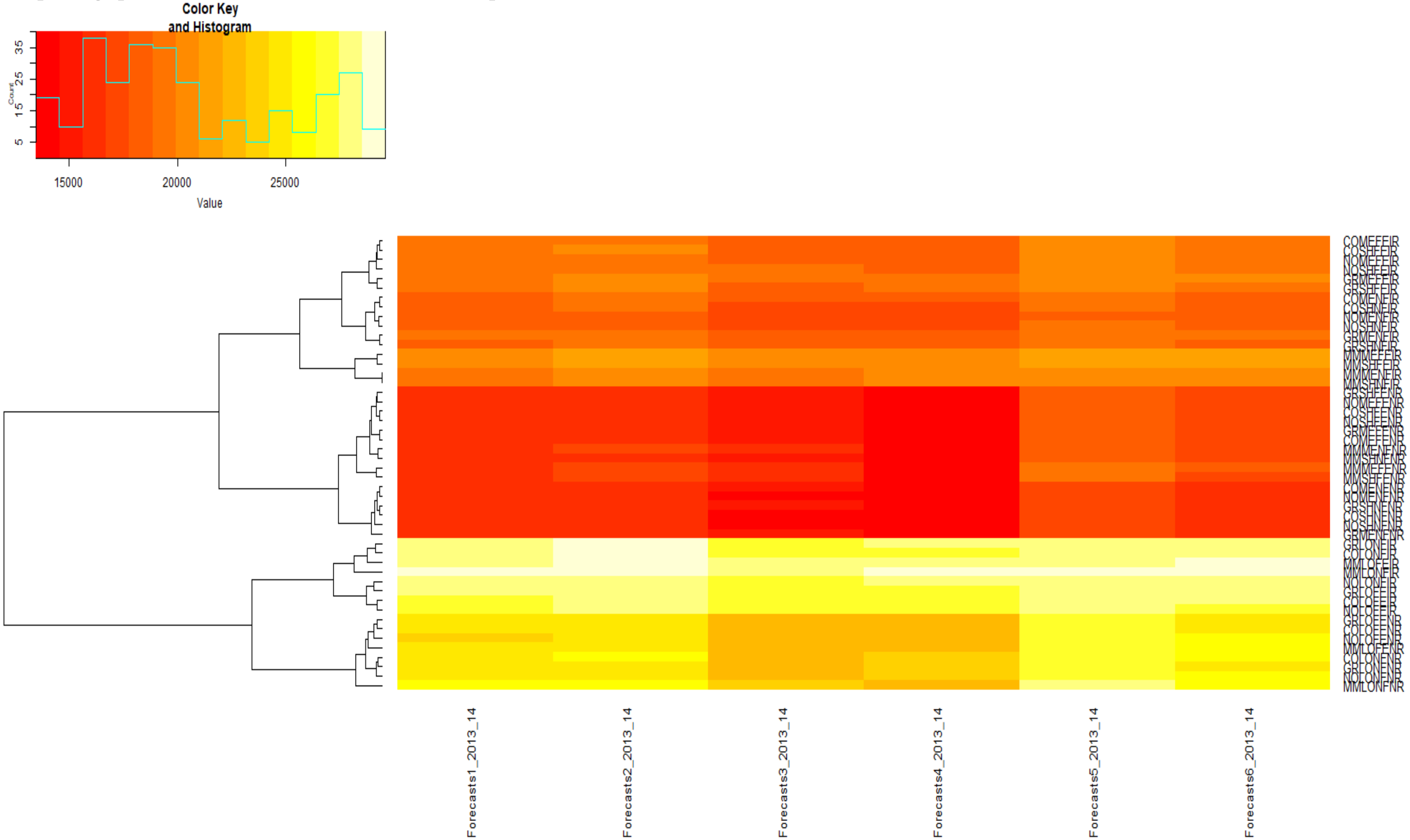
Annexure 5.56: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for off-farm enterprising pensioner farmers in the Eastern Cape, South Africa for the 2011/12 season.



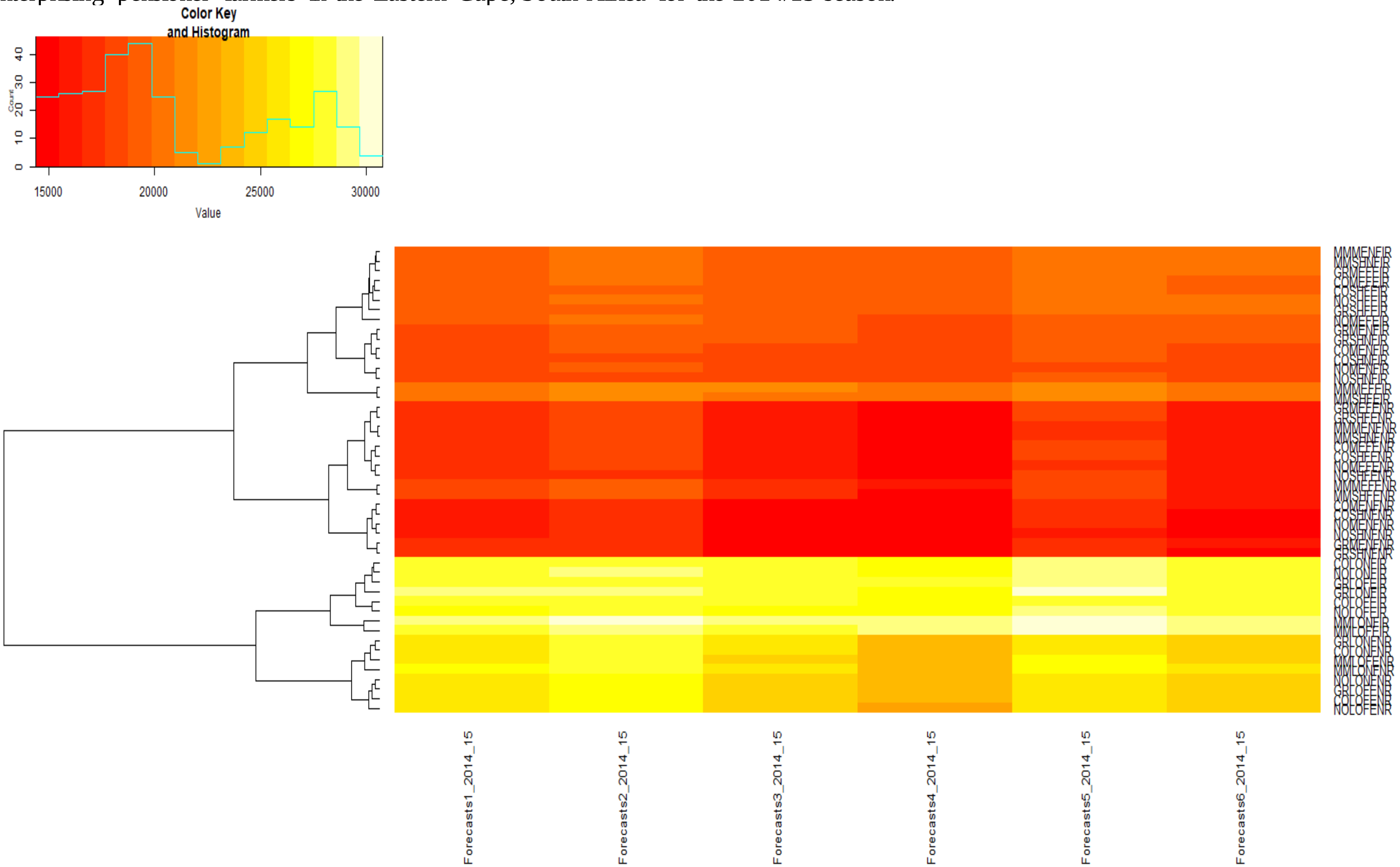
Annexure 5.57: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for off-farm enterprising pensioner farmers in the Eastern Cape, South Africa for the 2012/13 season.



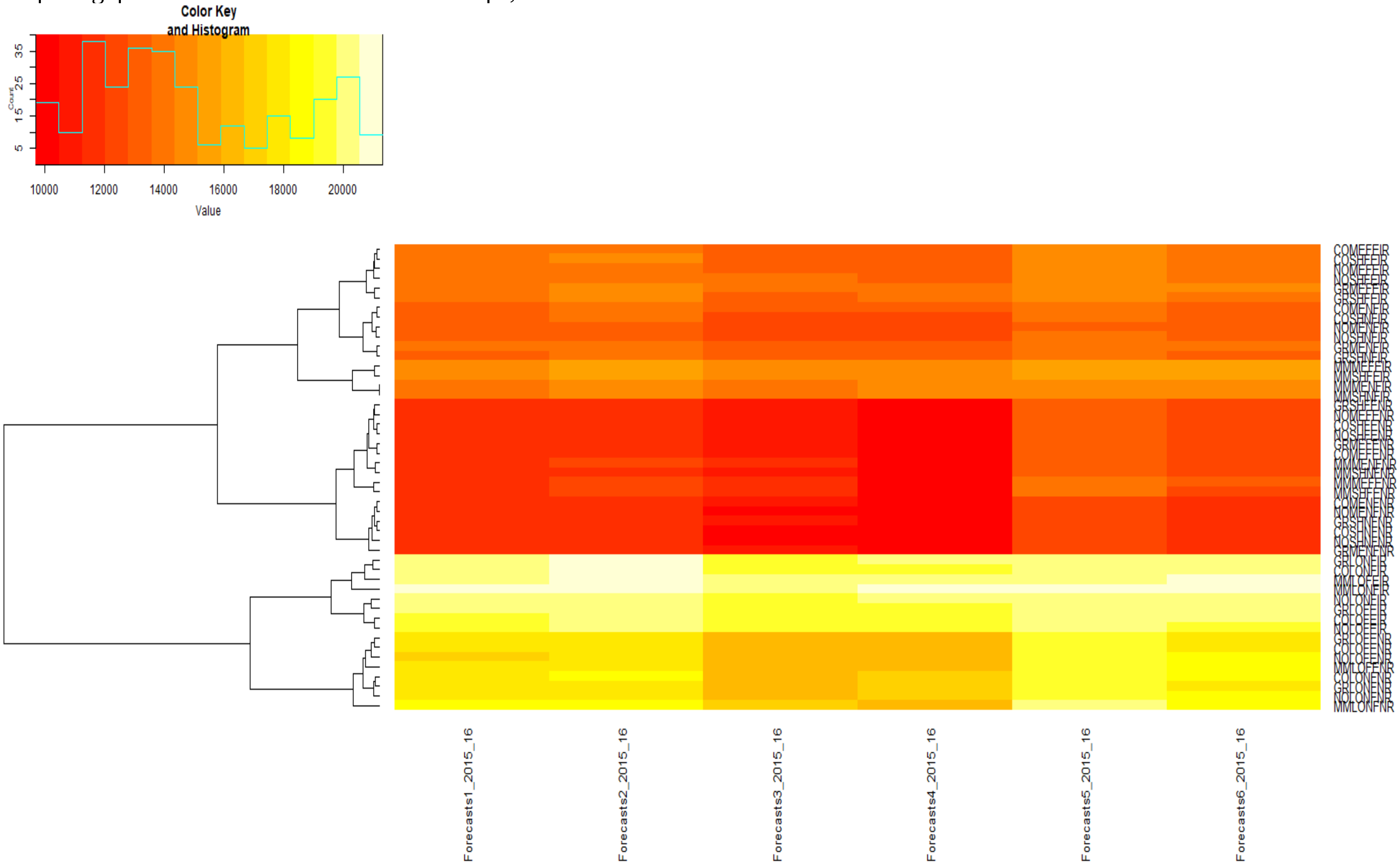
Annexure 5.58: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for off-farm enterprising pensioner farmers in the Eastern Cape, South Africa for the 2013/14 season.



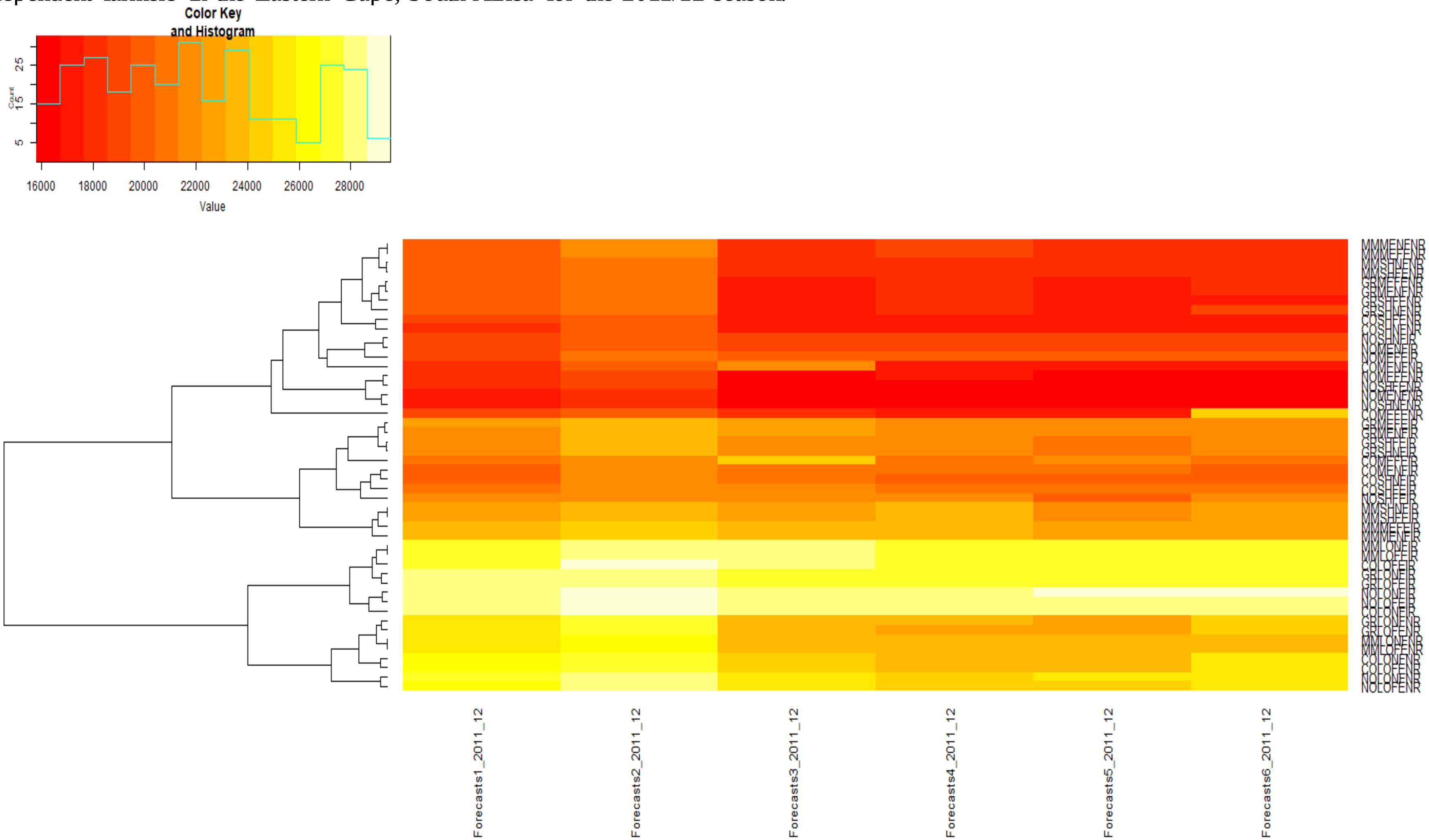
Annexure 5.59: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for off-farm enterprising pensioner farmers in the Eastern Cape, South Africa for the 2014/15 season.



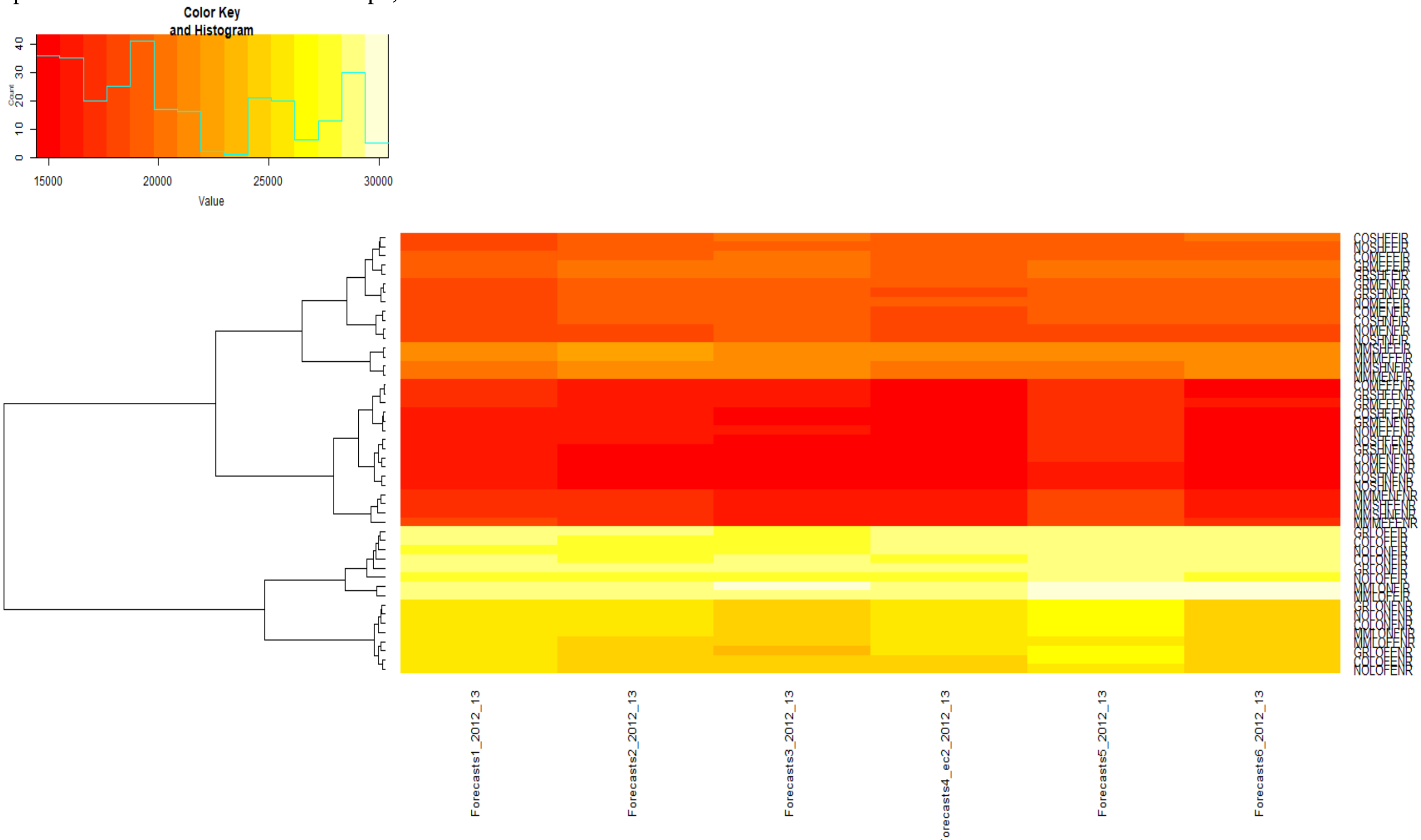
Annexure 5.60: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for off-farm enterprising pensioner farmers in the Eastern Cape, South Africa for the 2015/16 season.



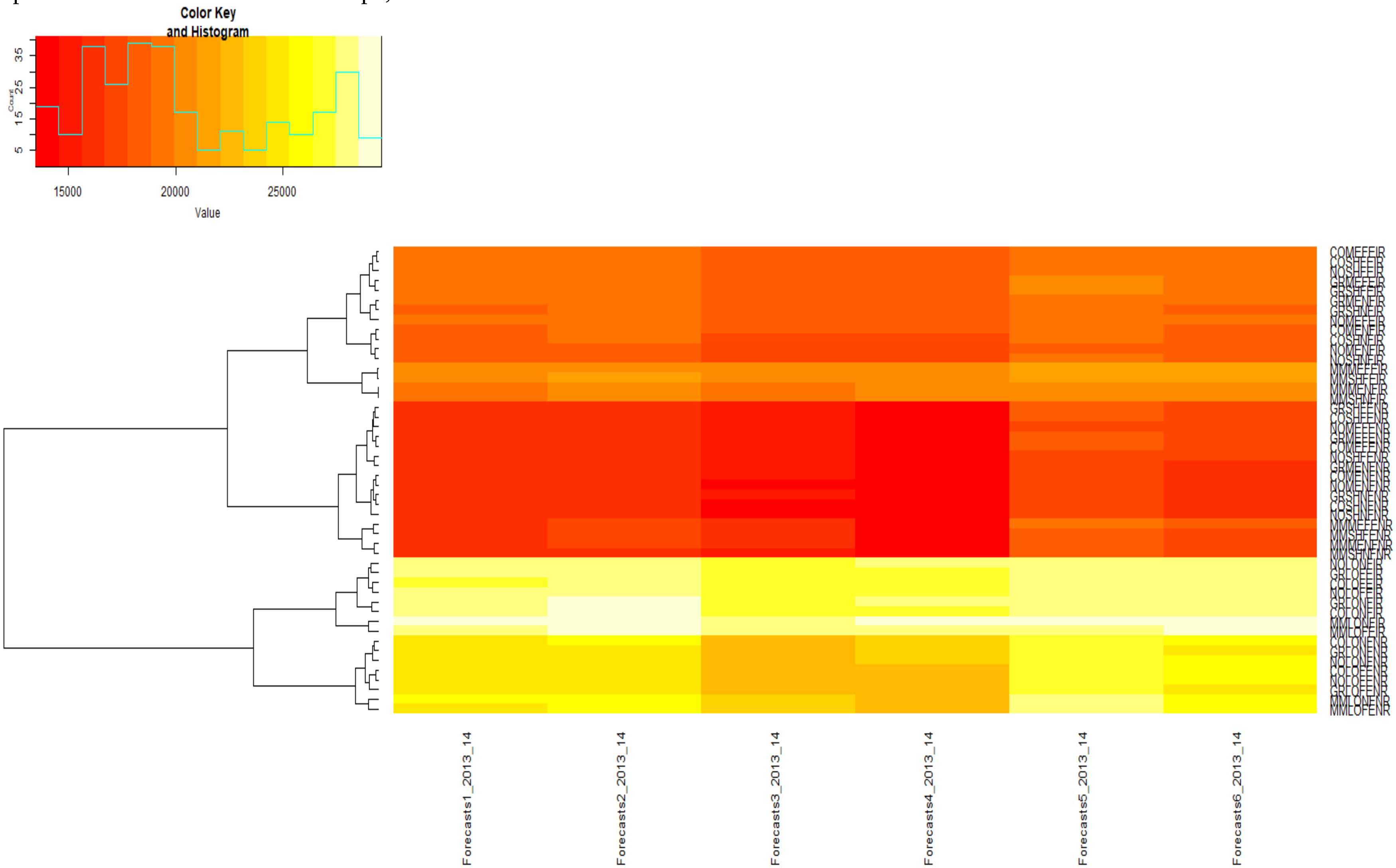
Annexure 5.61: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture dependent farmers in the Eastern Cape, South Africa for the 2011/12 season.



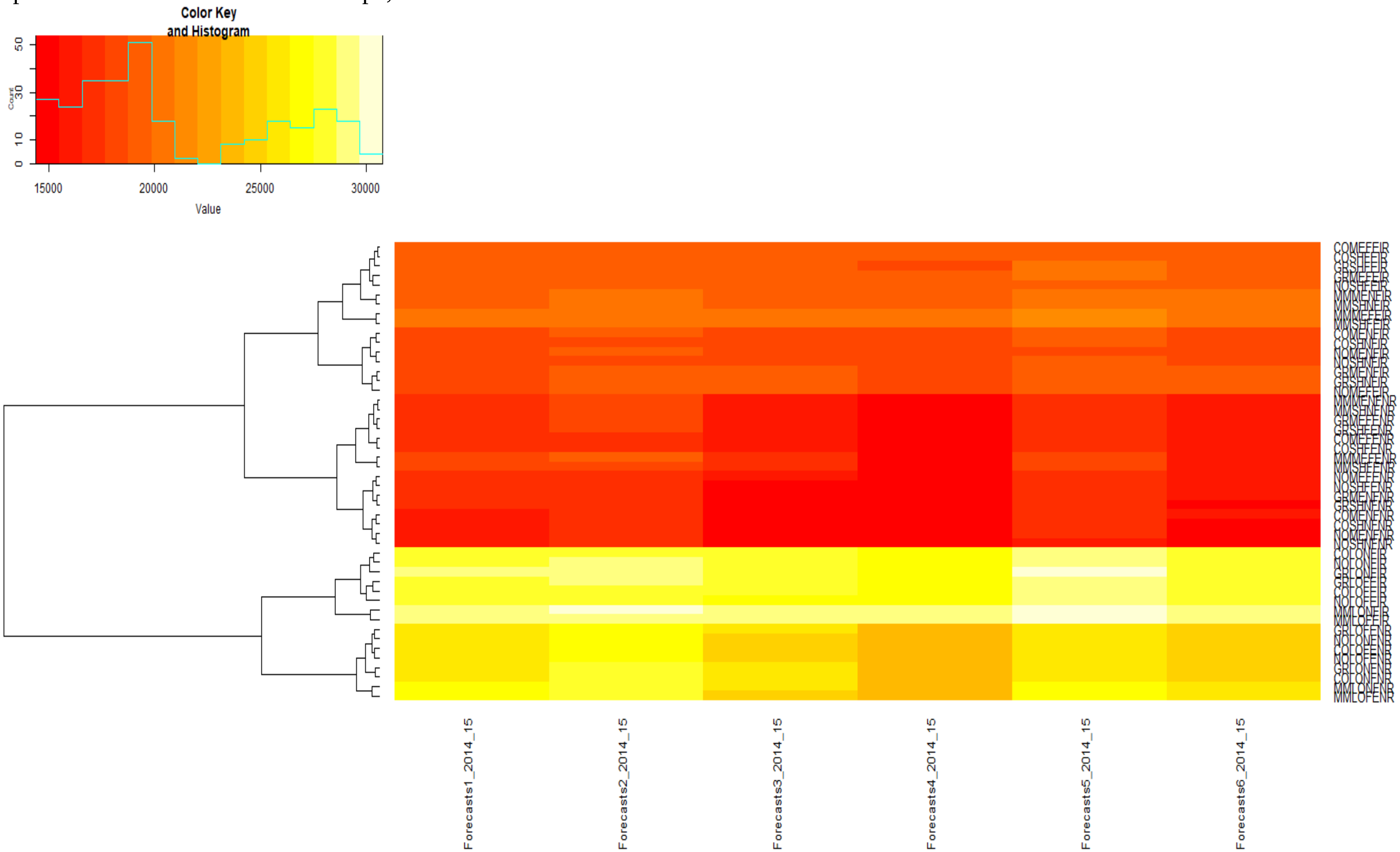
Annexure 5.62: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture dependent farmers in the Eastern Cape, South Africa for the 2012/13 season.



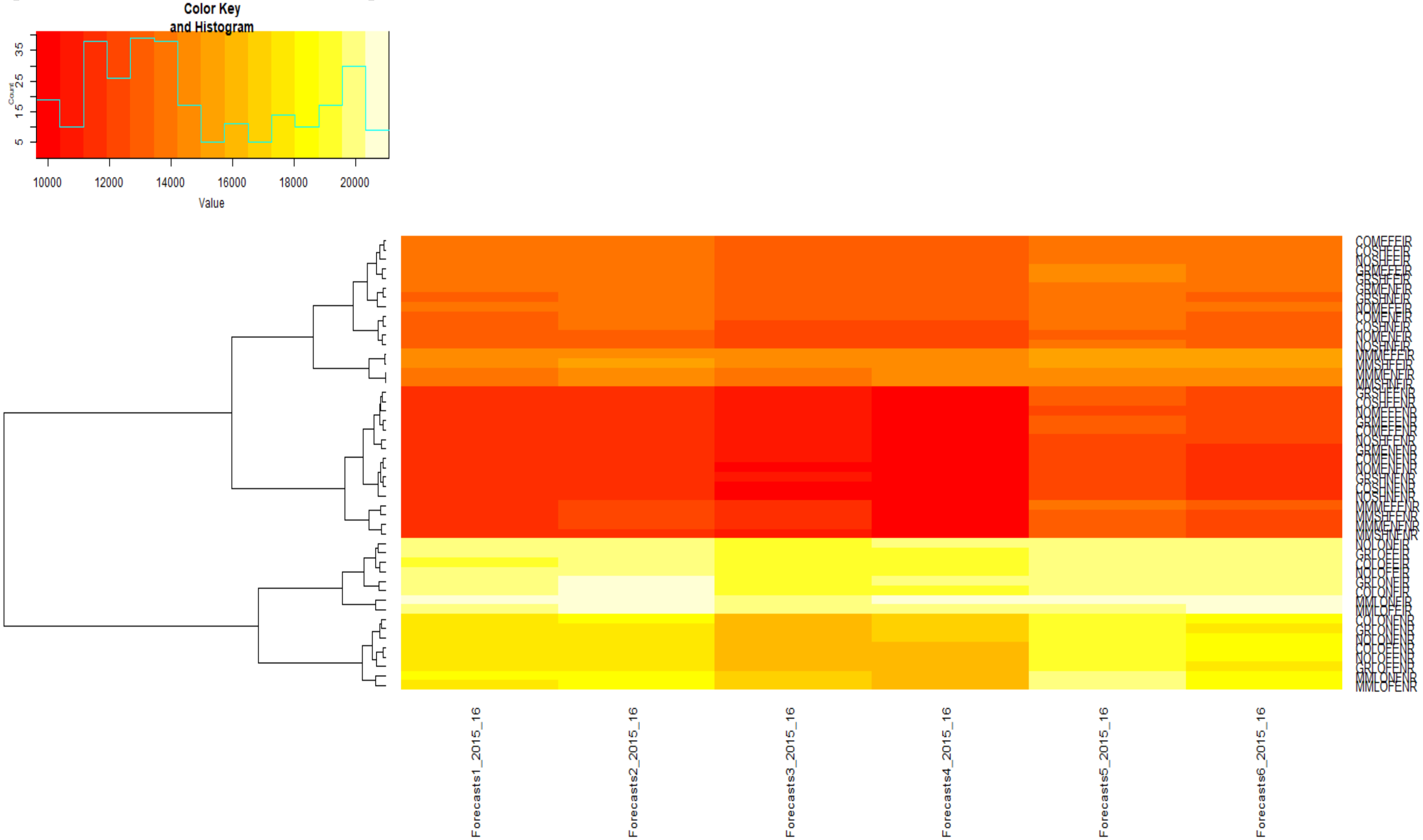
Annexure 5.63: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture dependent farmers in the Eastern Cape, South Africa for the 2013/14 season.



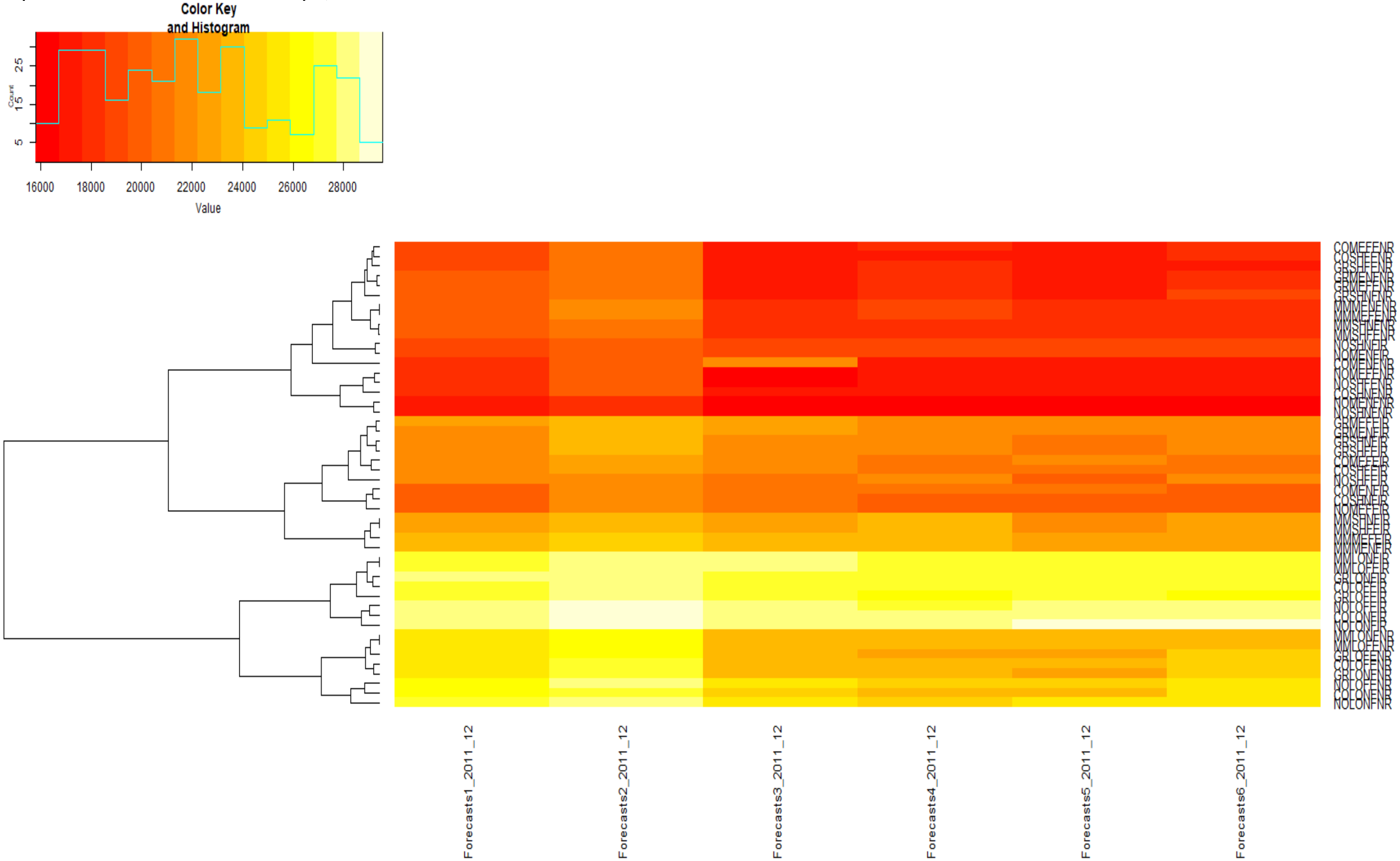
Annexure 5.64: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture dependent farmers in the Eastern Cape, South Africa for the 2014/15 season.



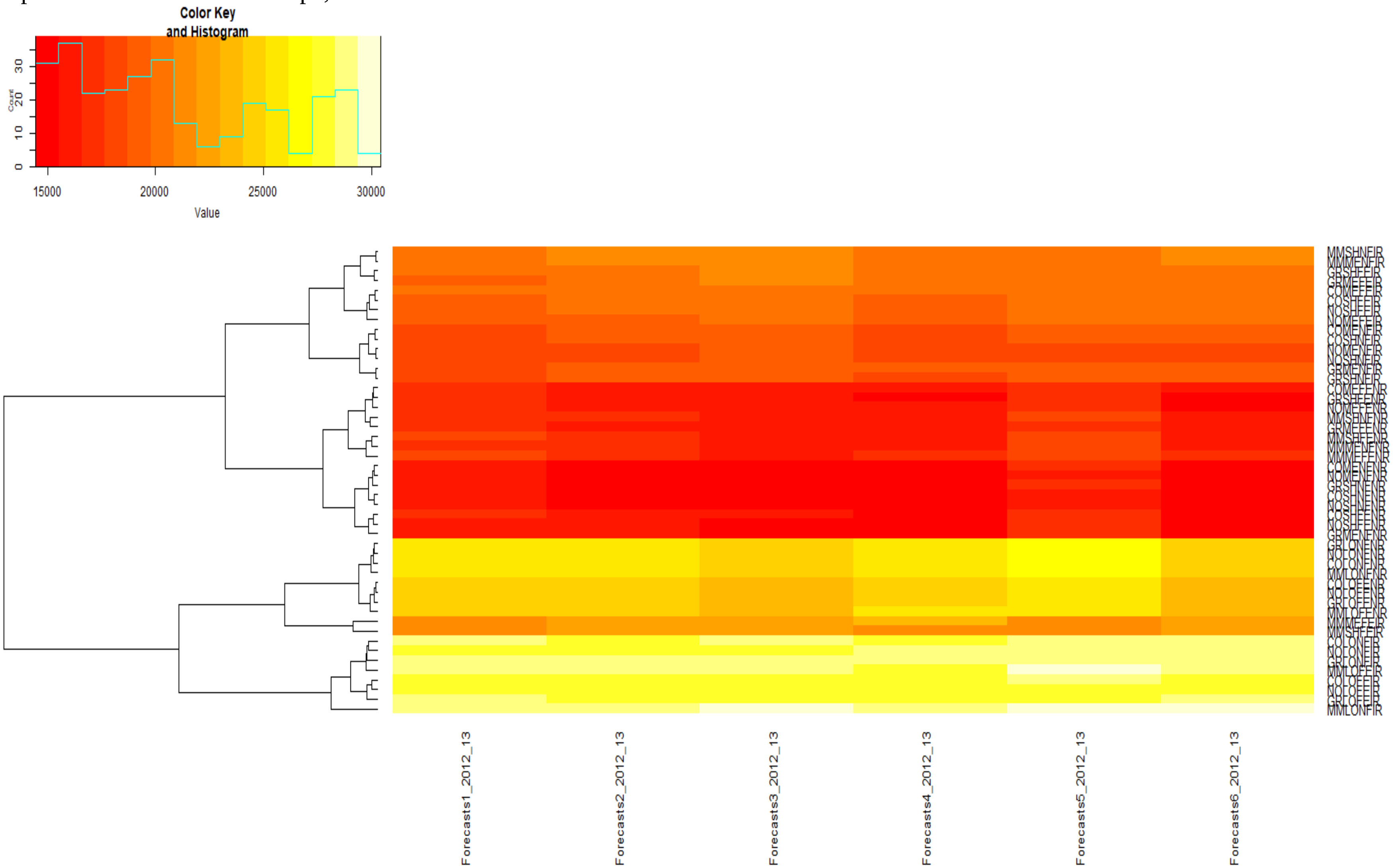
Annexure 5.65: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture dependent farmers in the Eastern Cape, South Africa for the 2015/16 season.



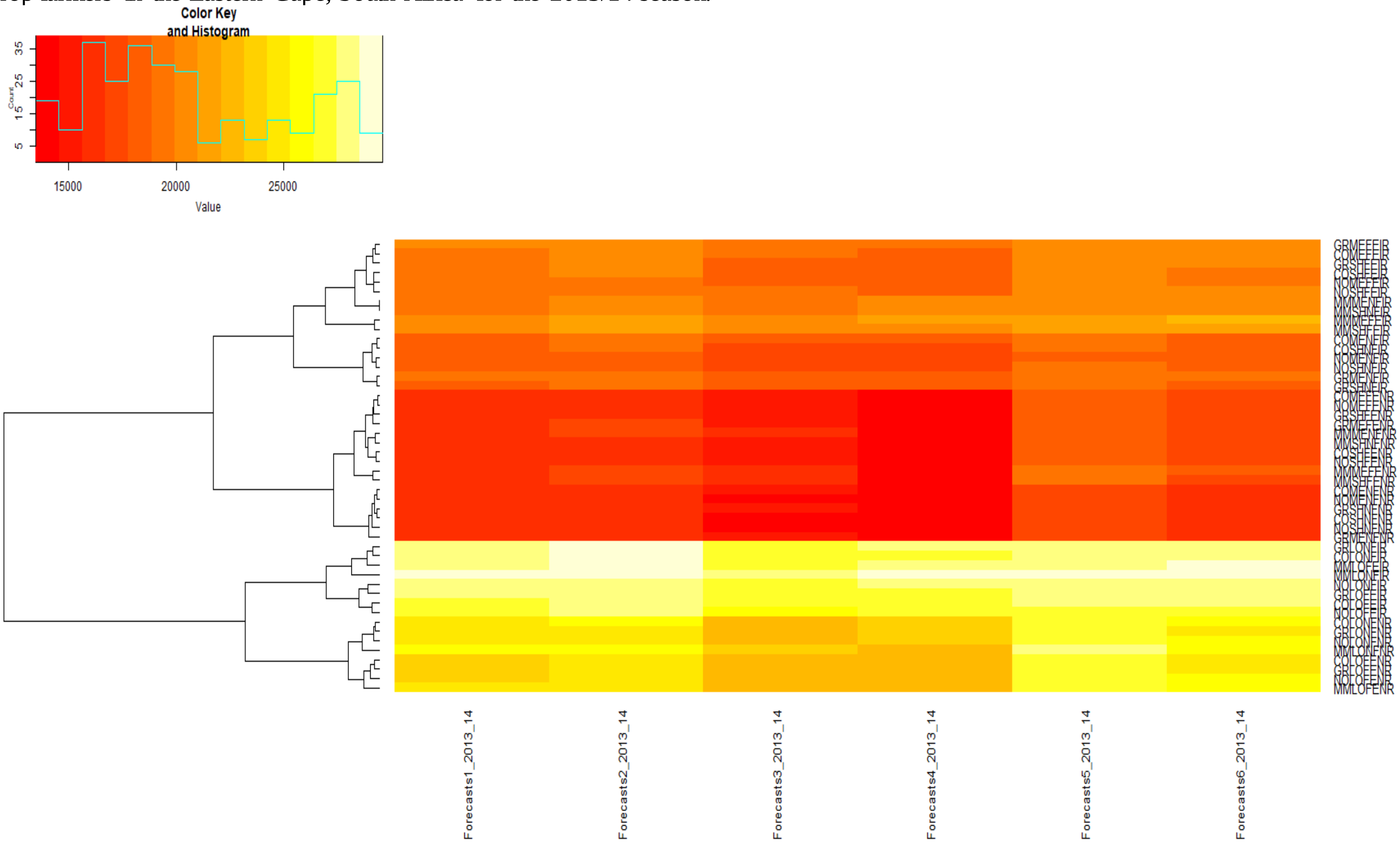
Annexure 5.66: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for cooperative crop farmers in the Eastern Cape, South Africa for the 2011/12 season.



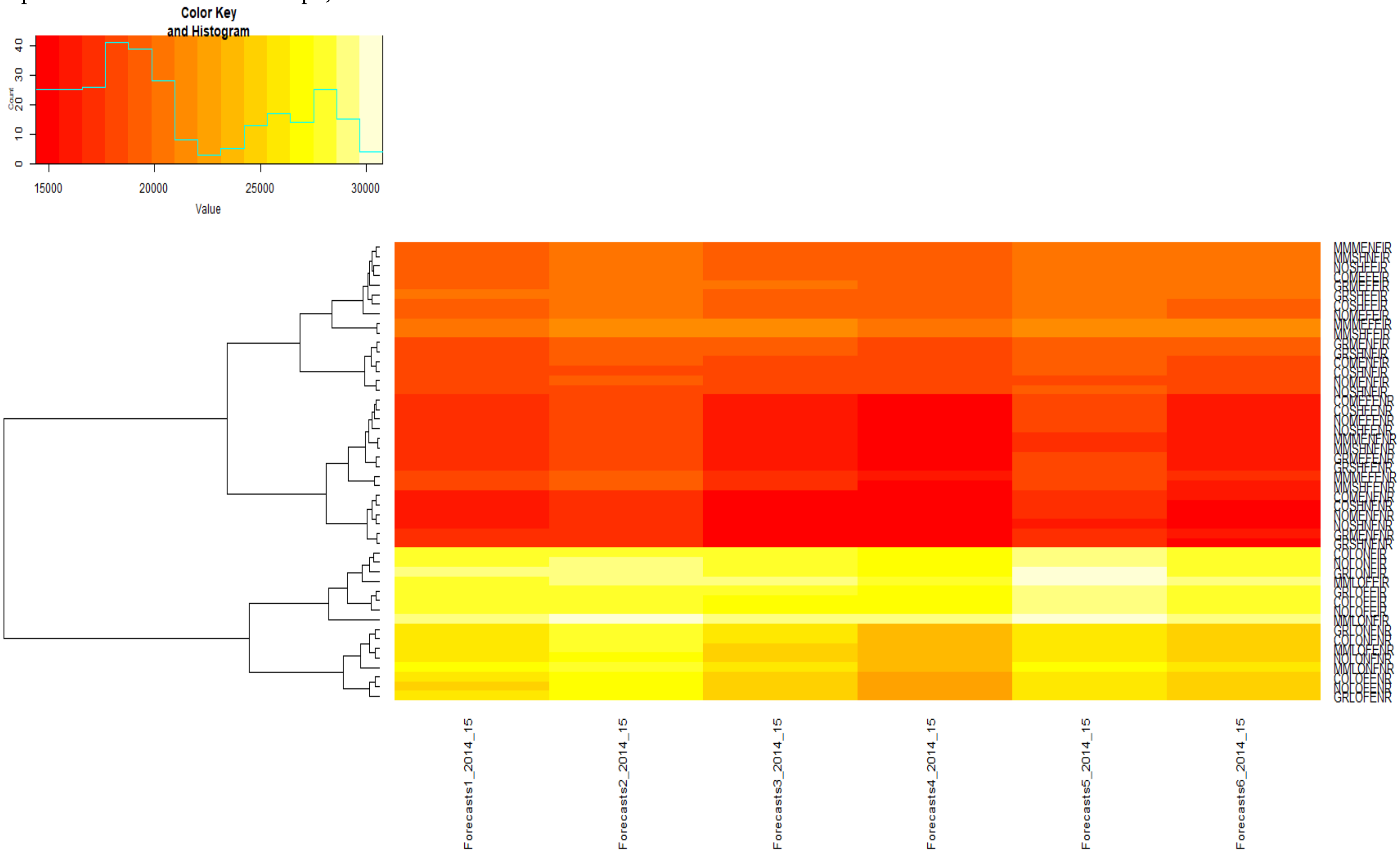
Annexure 5.67: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for cooperative crop farmers in the Eastern Cape, South Africa for the 2012/13 season.



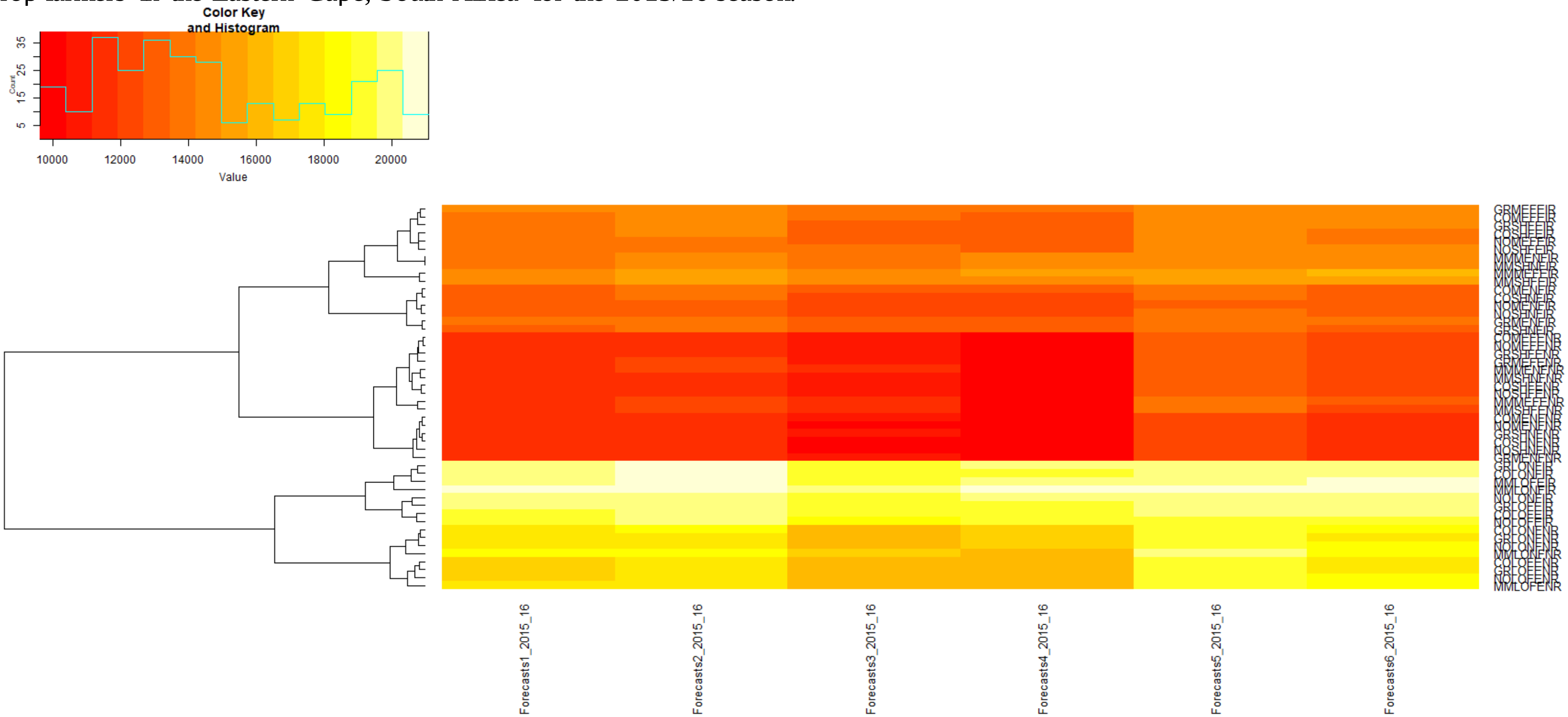
Annexure 5.68: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for cooperative crop farmers in the Eastern Cape, South Africa for the 2013/14 season.



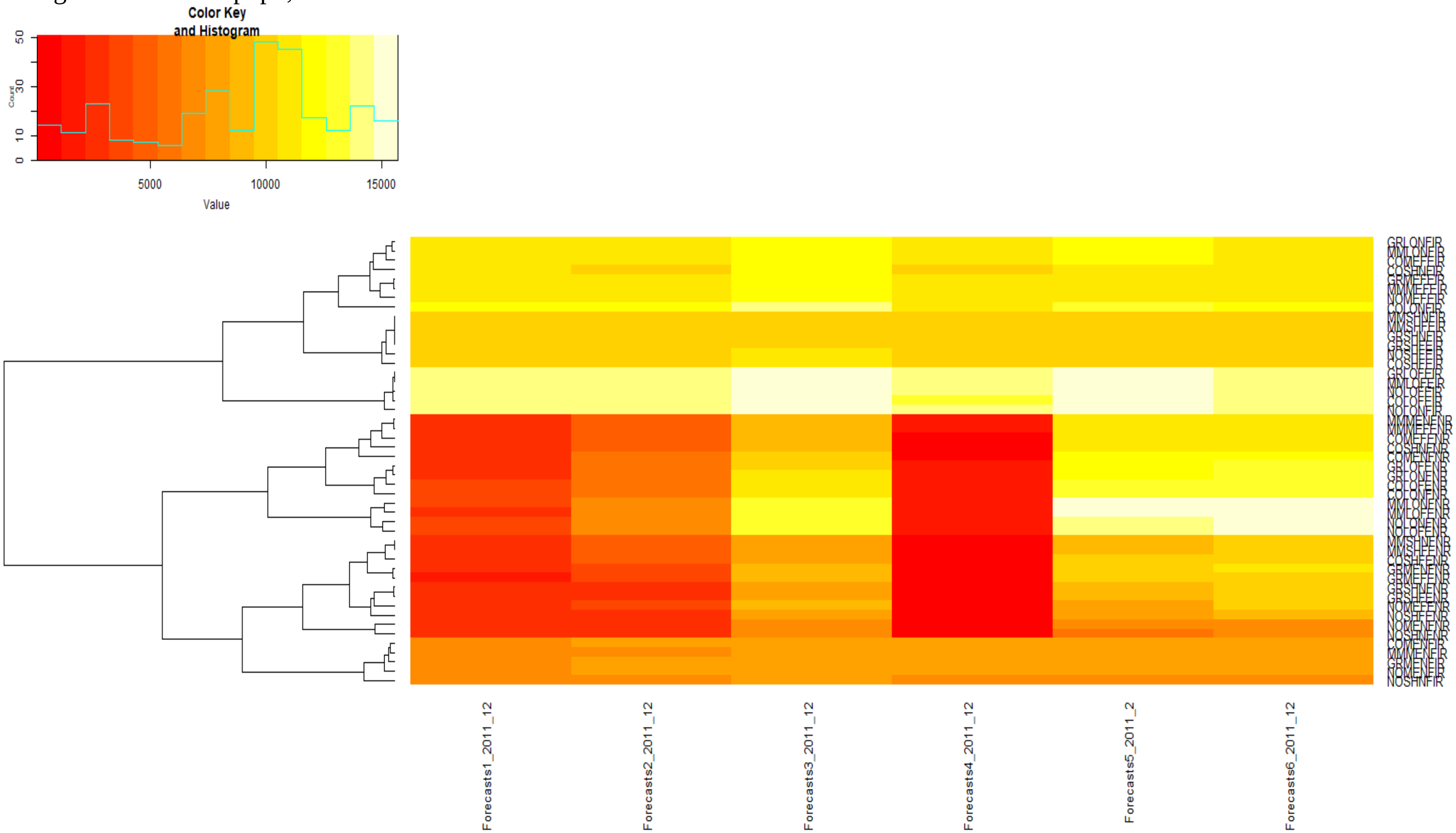
Annexure 5.69: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for cooperative crop farmers in the Eastern Cape, South Africa for the 2014/15 season.



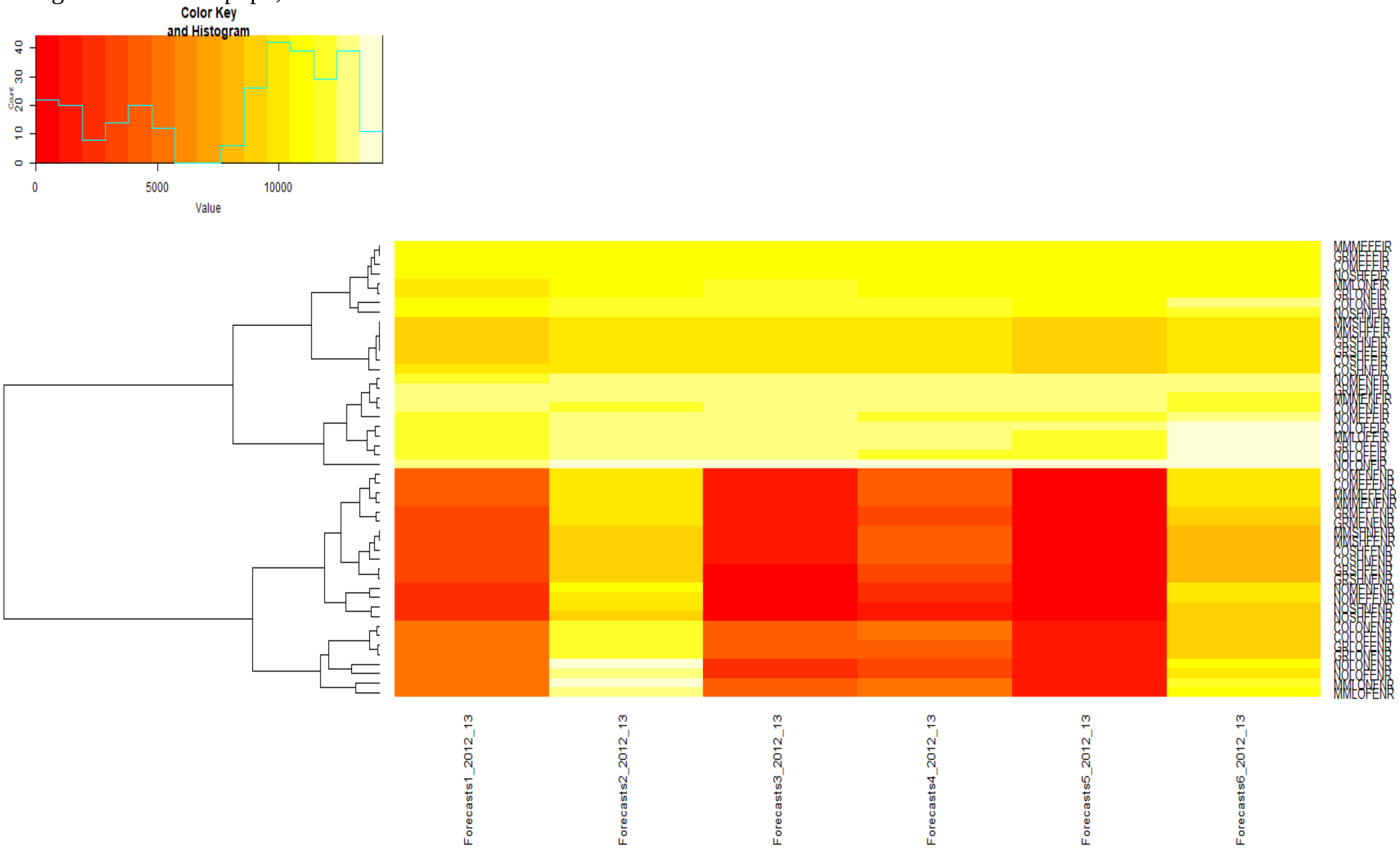
Annexure 5.70: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for cooperative crop farmers in the Eastern Cape, South Africa for the 2015/16 season.



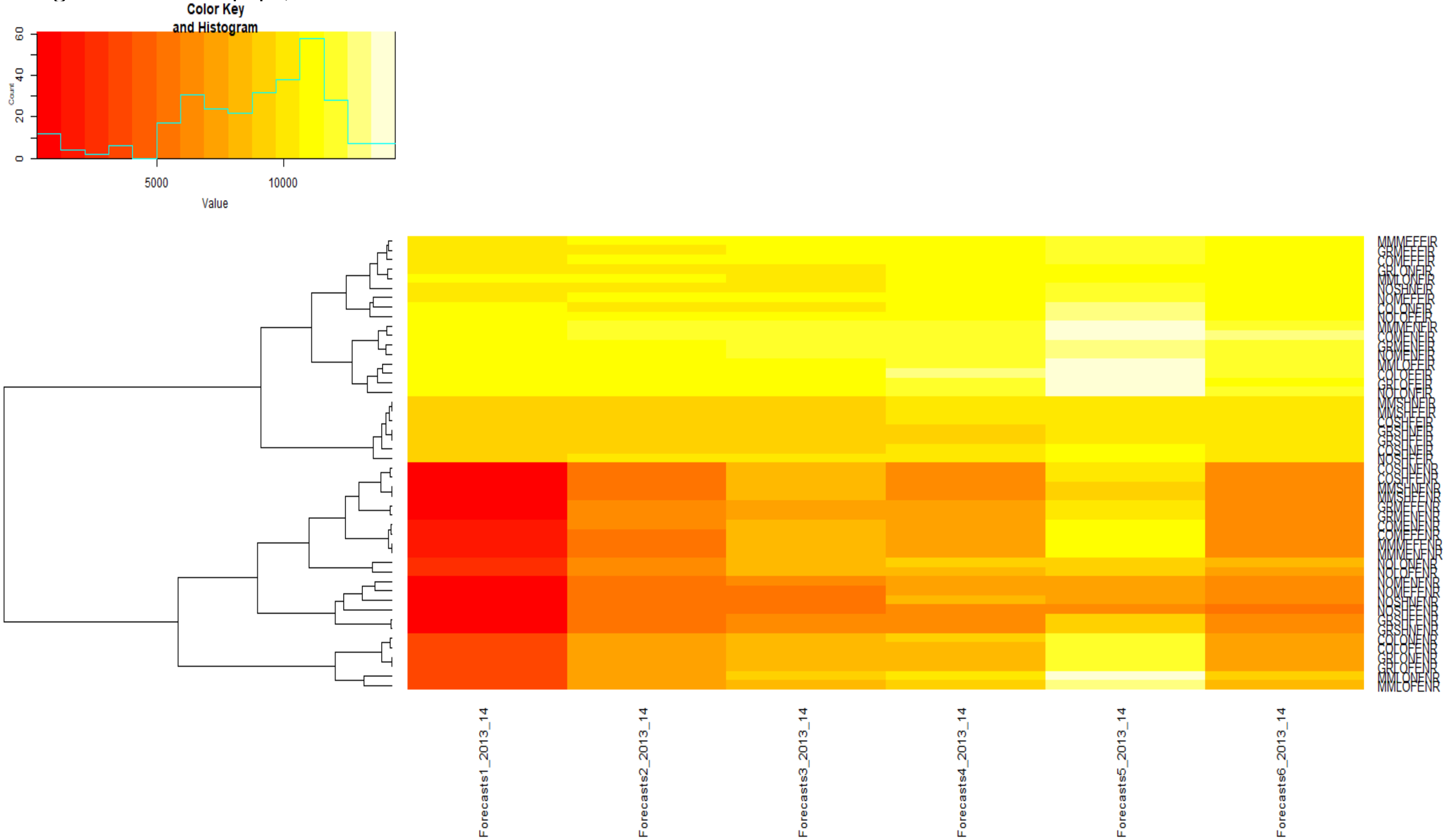
Annexure 5.71: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming farmers in Limpopo, South Africa for the 2011/12 season.



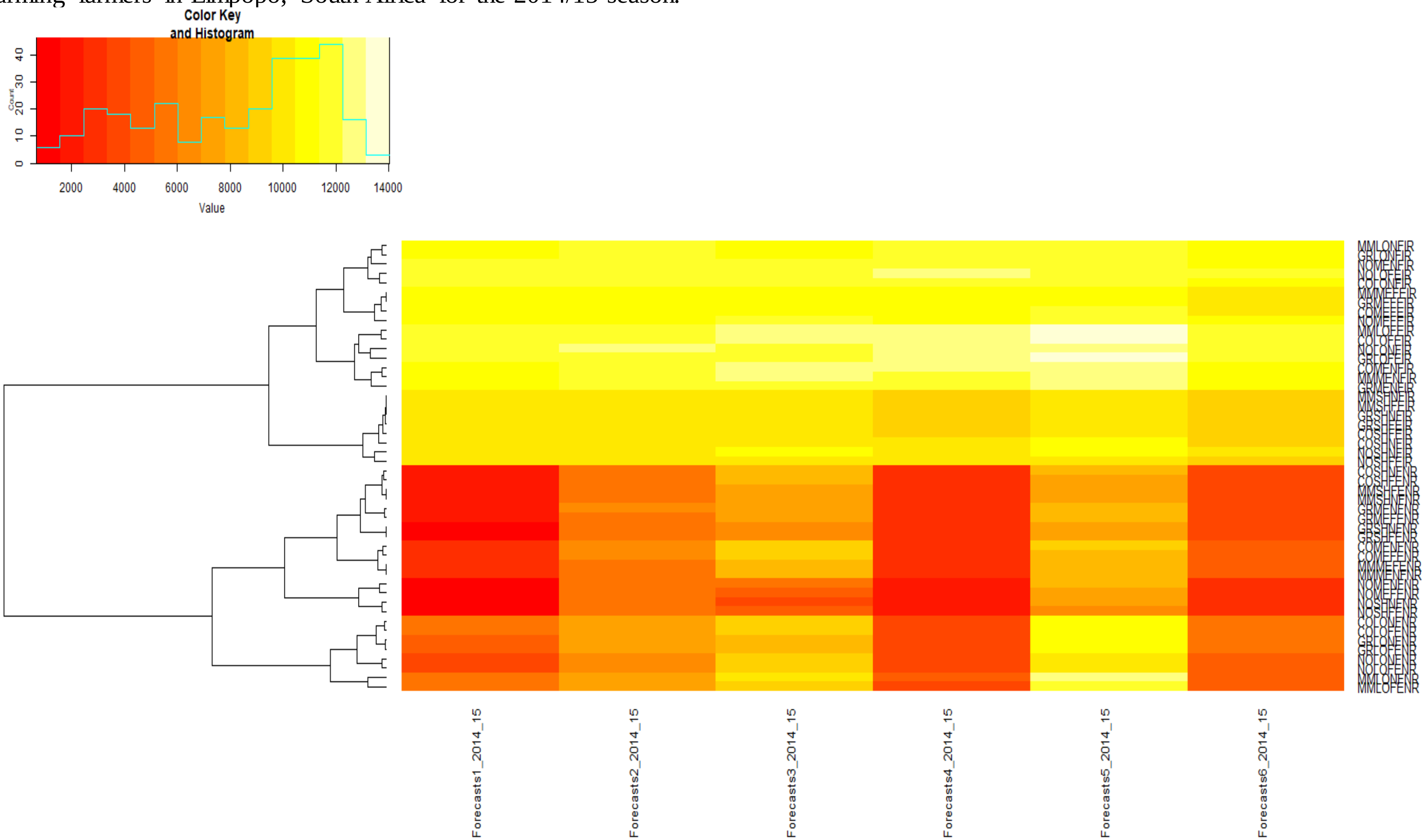
Annexure 5.72: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming farmers in Limpopo, South Africa for the 2012/13 season.



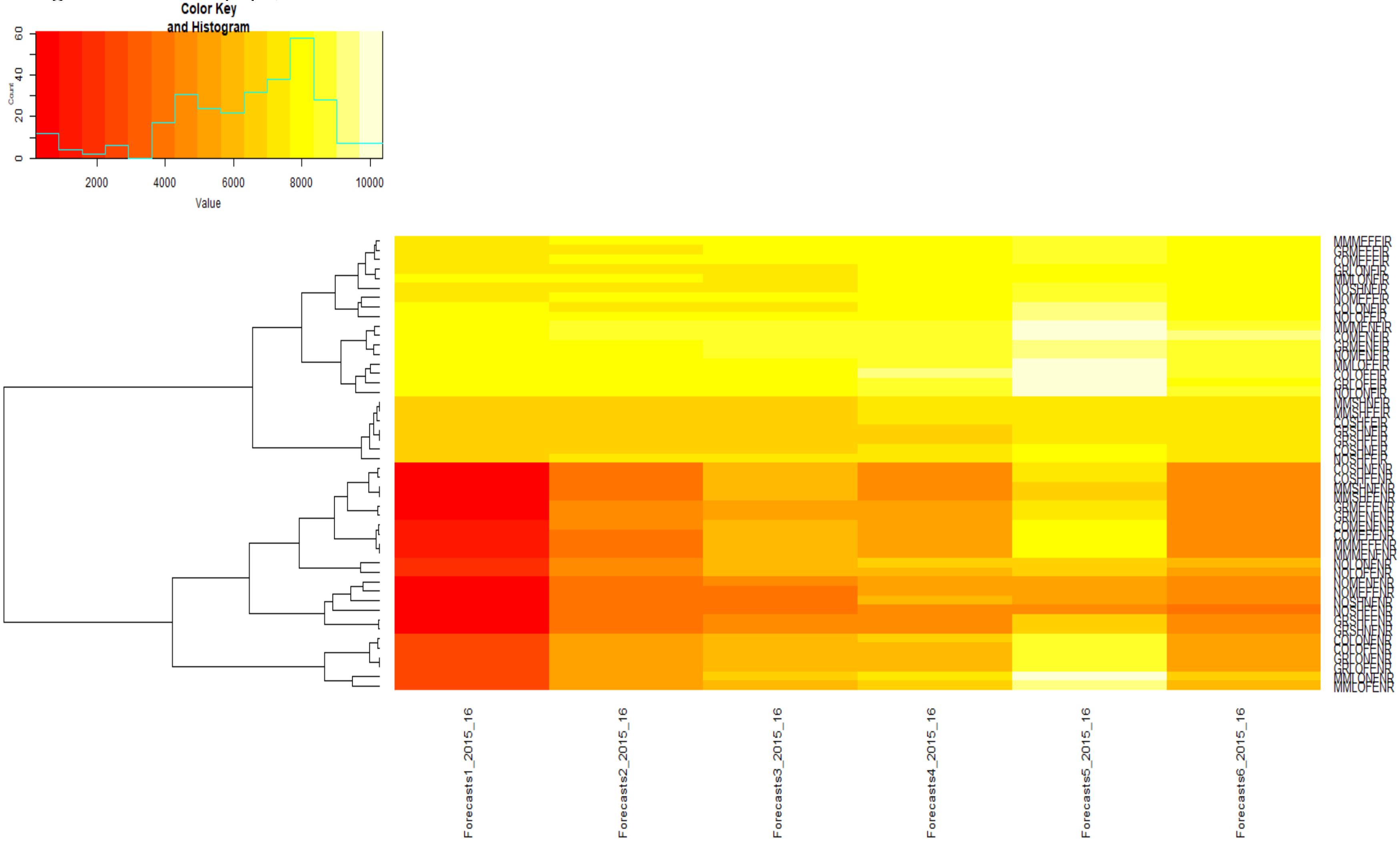
Annexure 5.73: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming farmers in Limpopo, South Africa for the 2013/14 season.



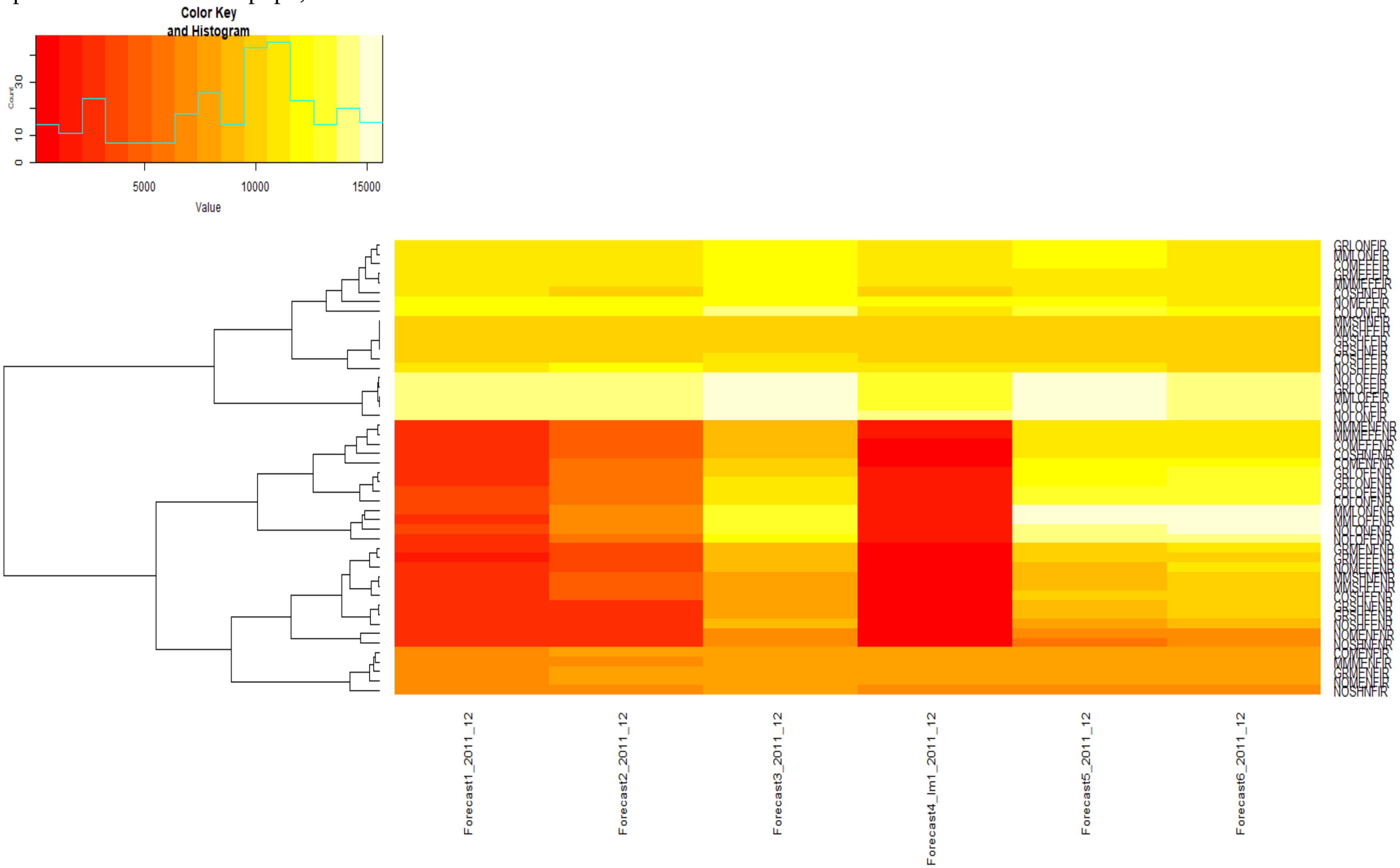
Annexure 5.74: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming farmers in Limpopo, South Africa for the 2014/15 season.



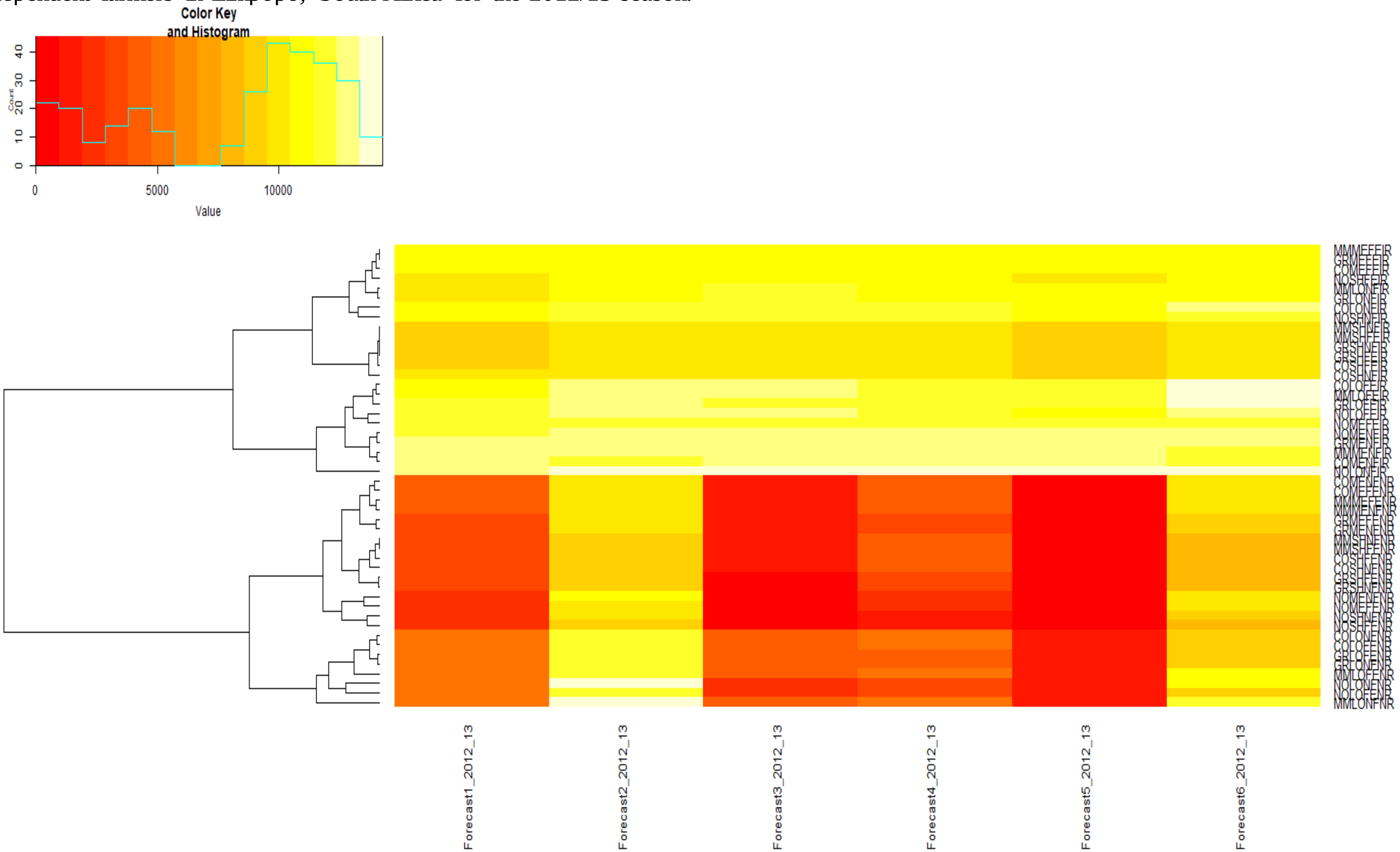
Annexure 5.75: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming farmers in Limpopo, South Africa for the 2015/16 season.



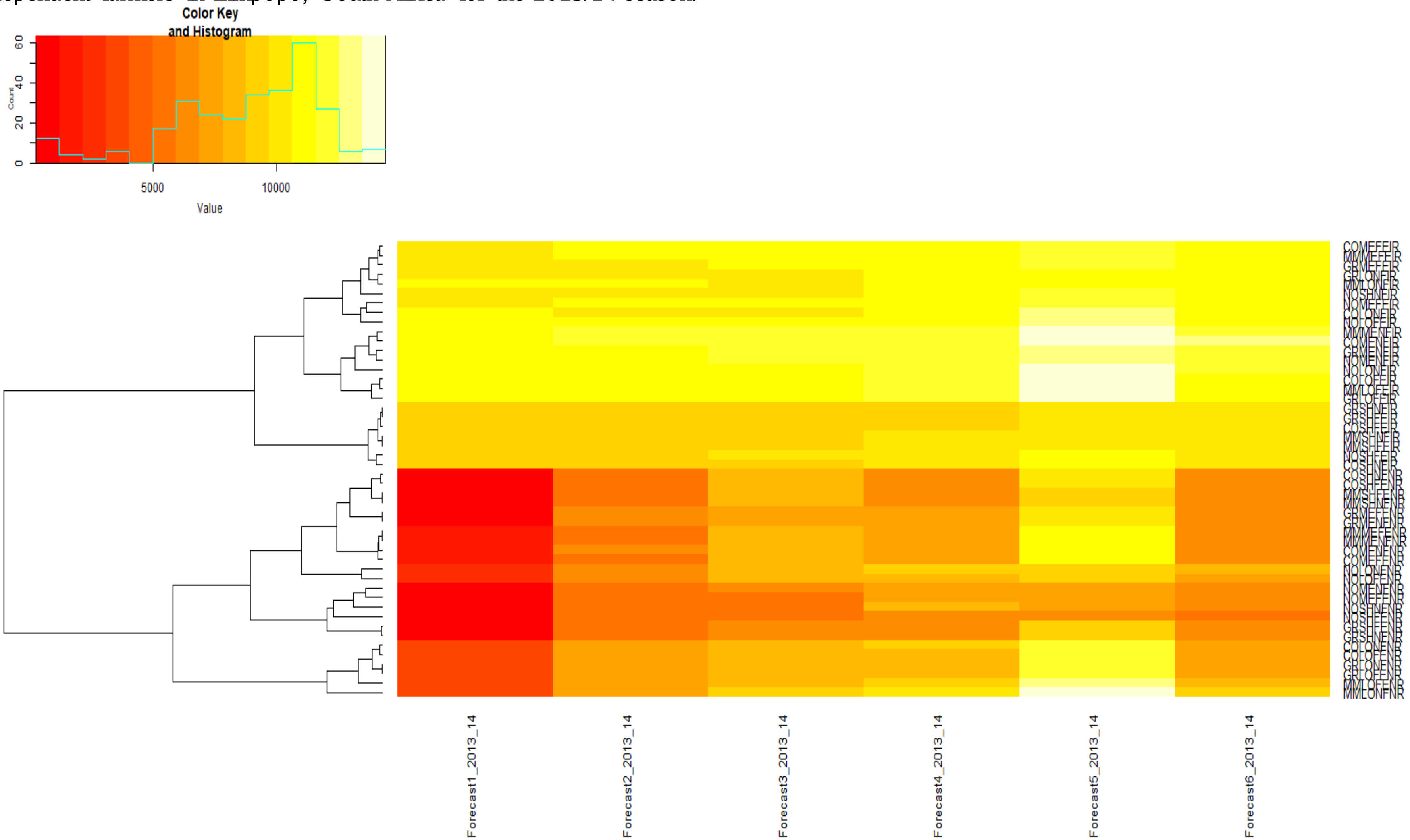
Annexure 5.76: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture dependent farmers in Limpopo, South Africa for the 2011/12 season.



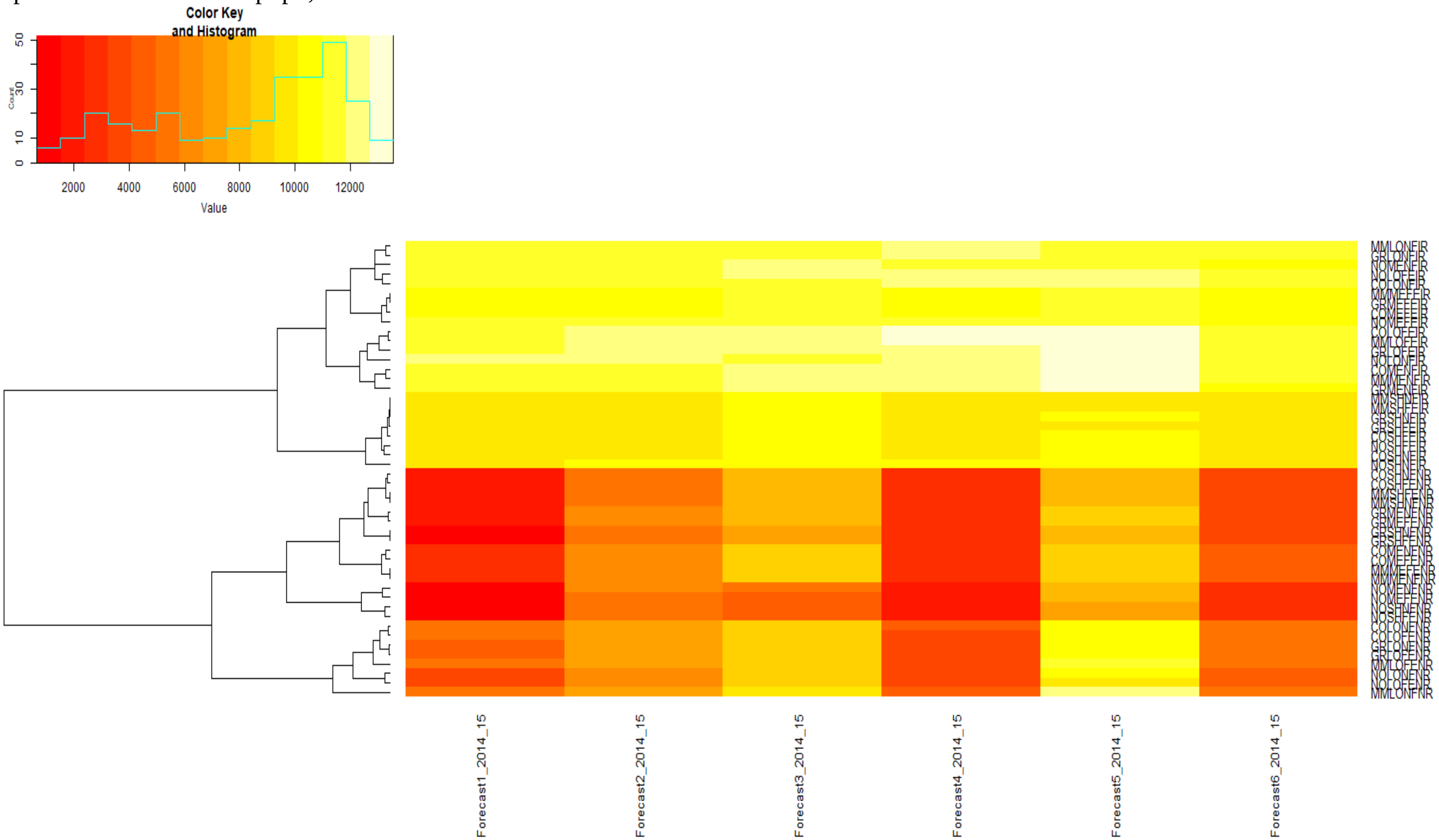
Annexure 5.77: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture dependent farmers in Limpopo, South Africa for the 2012/13 season.



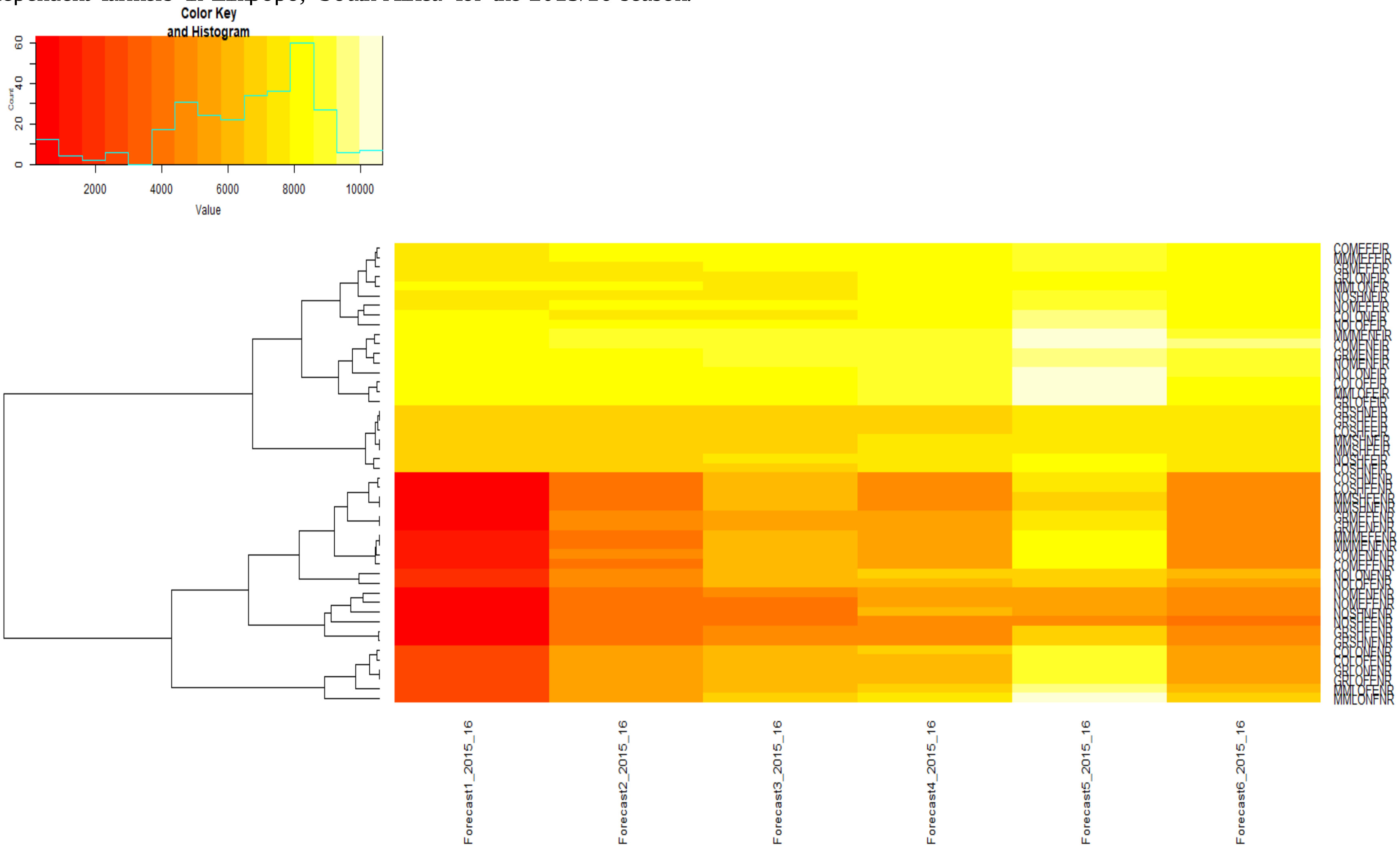
Annexure 5.78: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture dependent farmers in Limpopo, South Africa for the 2013/14 season.



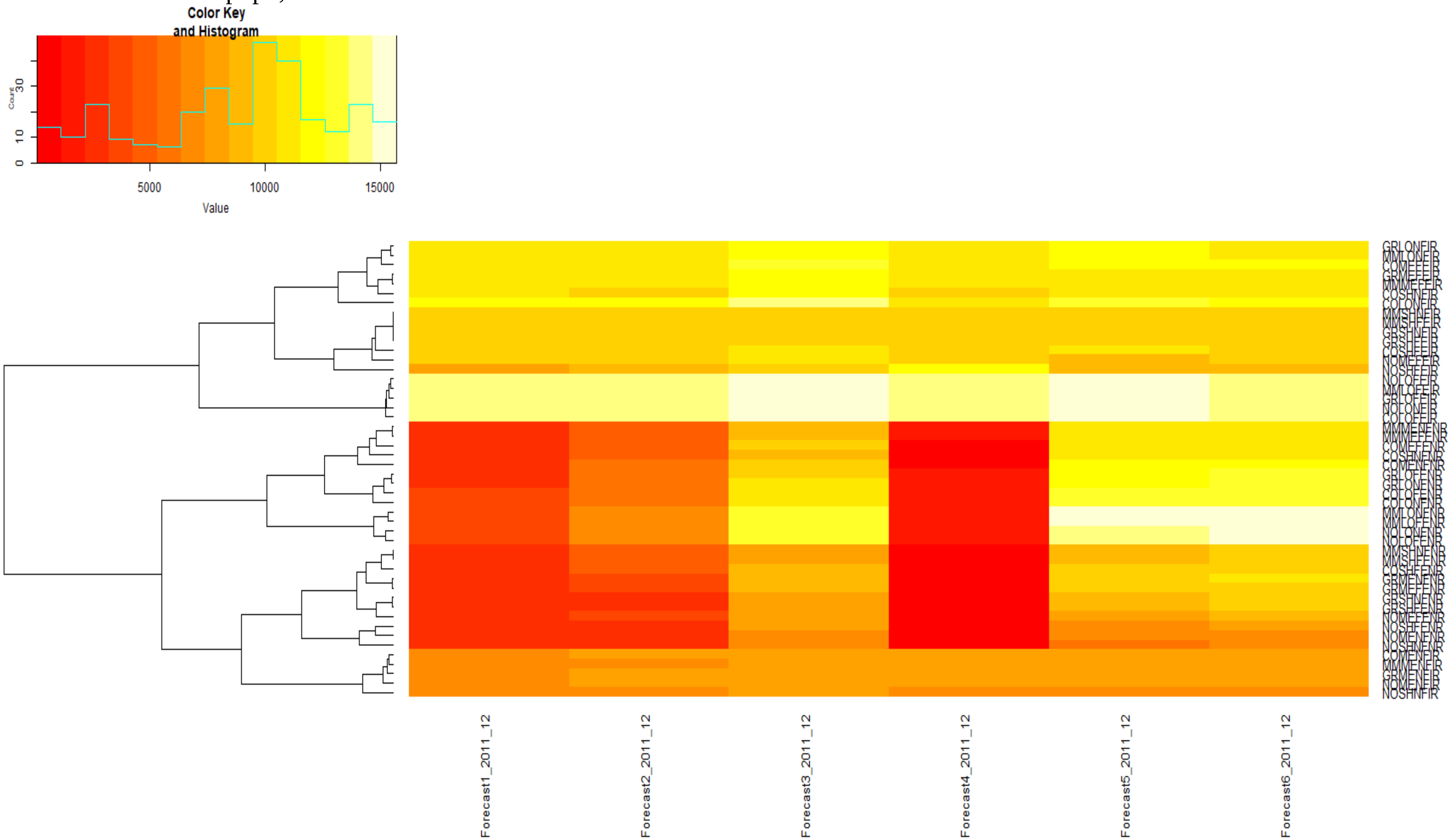
Annexure 5.79: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture dependent farmers in Limpopo, South Africa for the 2014/15 season.



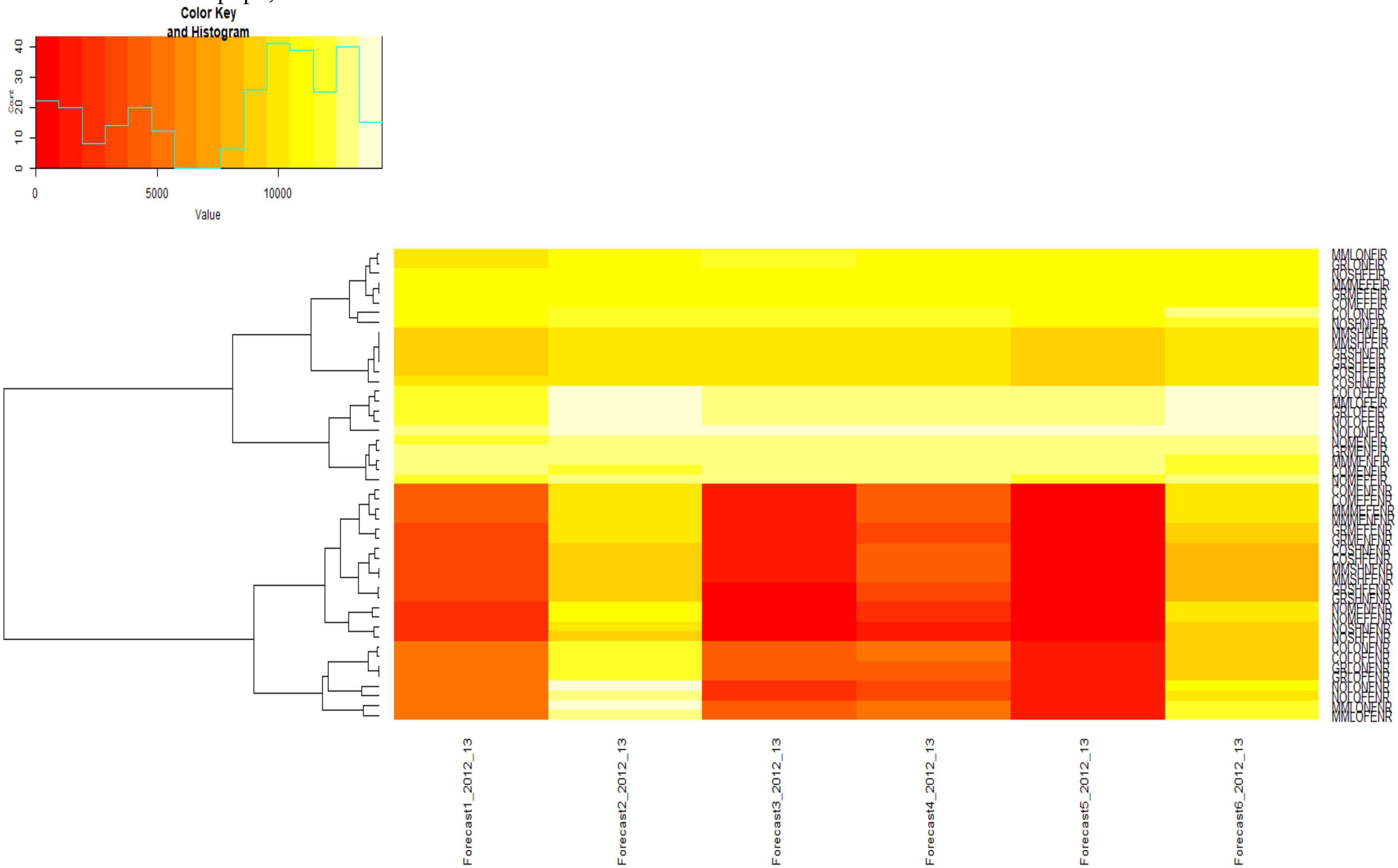
Annexure 5.80: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for horticulture dependent farmers in Limpopo, South Africa for the 2015/16 season.



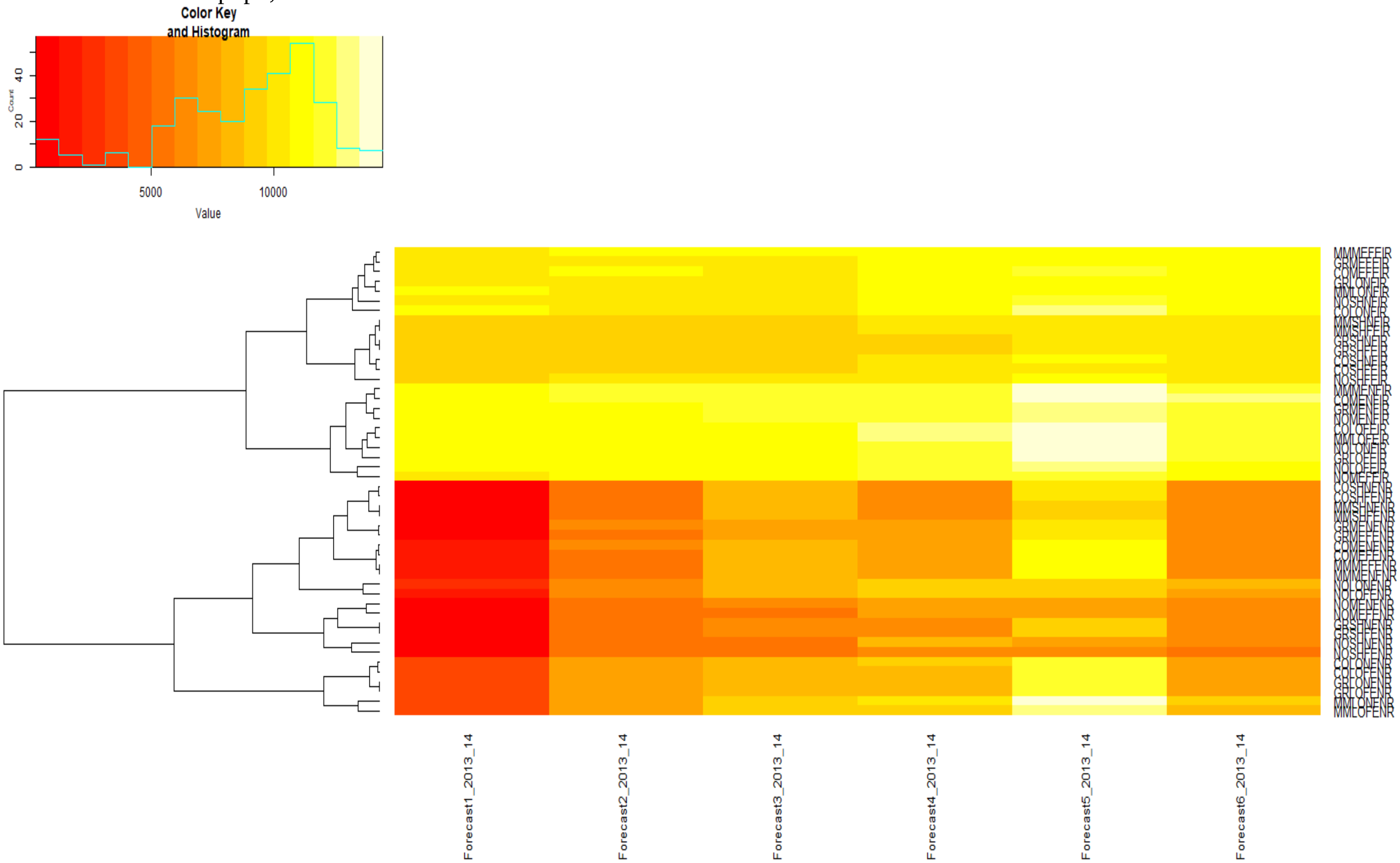
Annexure 5.81: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for off farm income farmers in Limpopo, South Africa for the 2011/12 season.



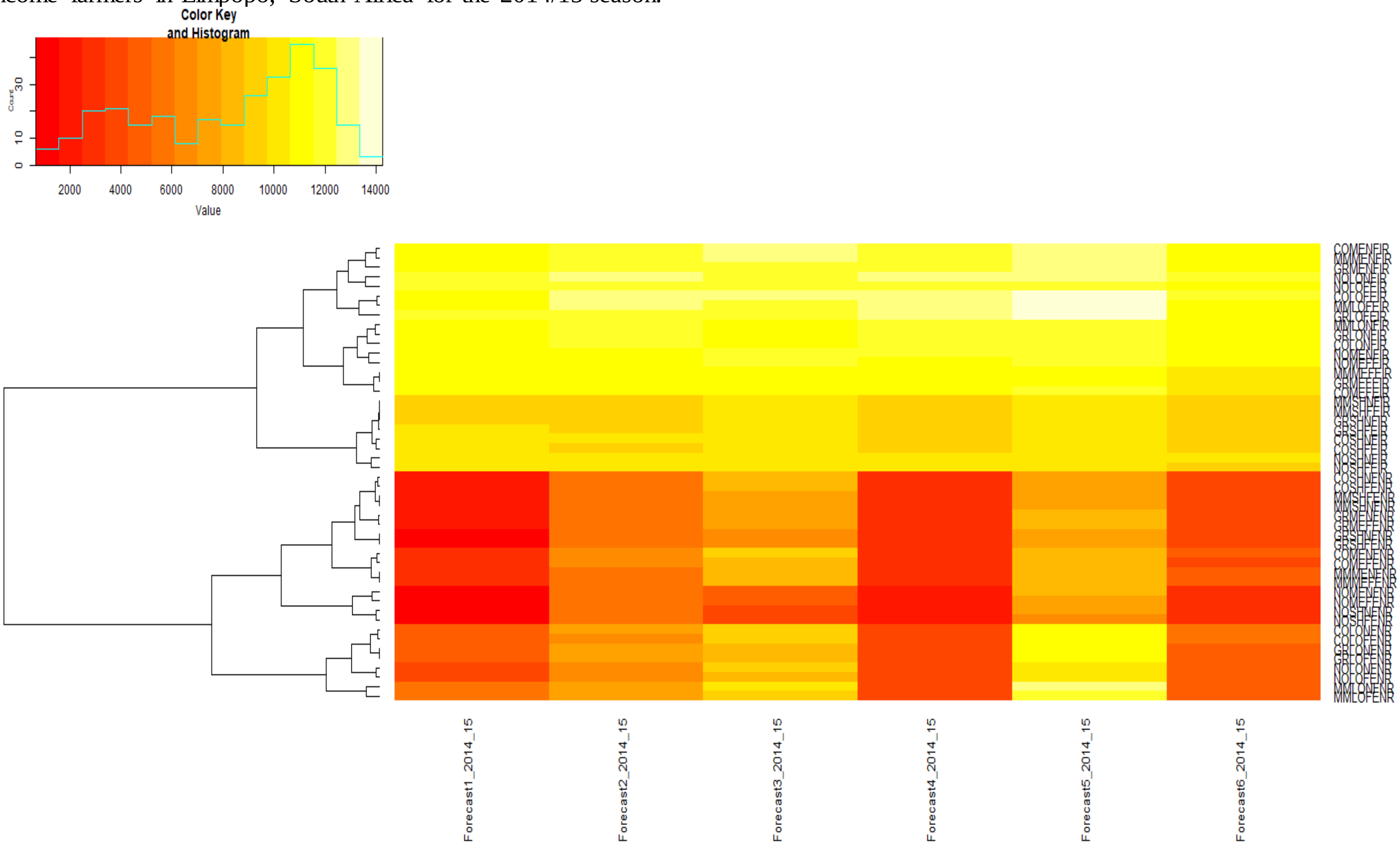
Annexure 5.82: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for off farm income farmers in Limpopo, South Africa for the 2012/13 season.



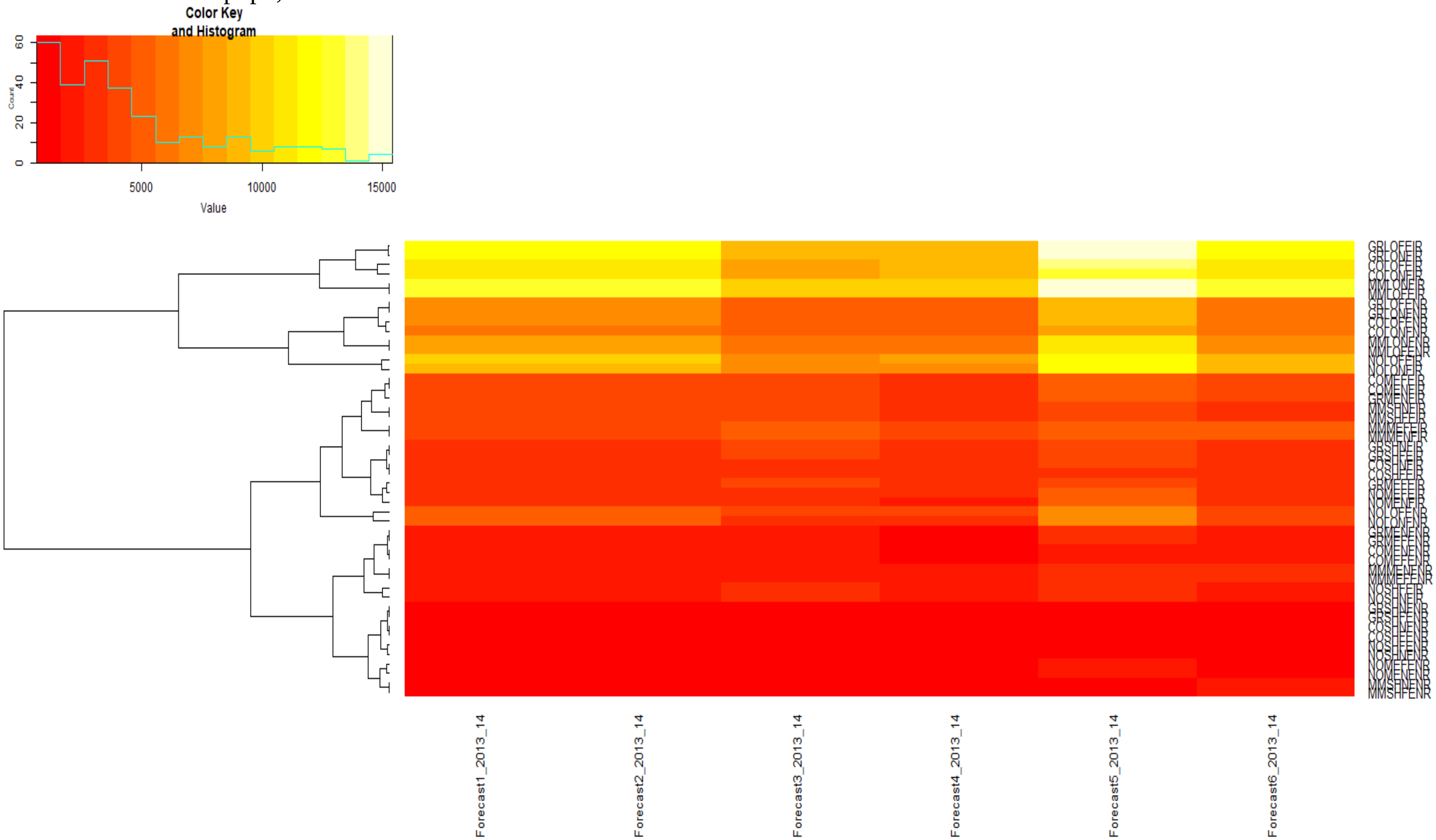
Annexure 5.83: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for off farm income farmers in Limpopo, South Africa for the 2013/14 season.



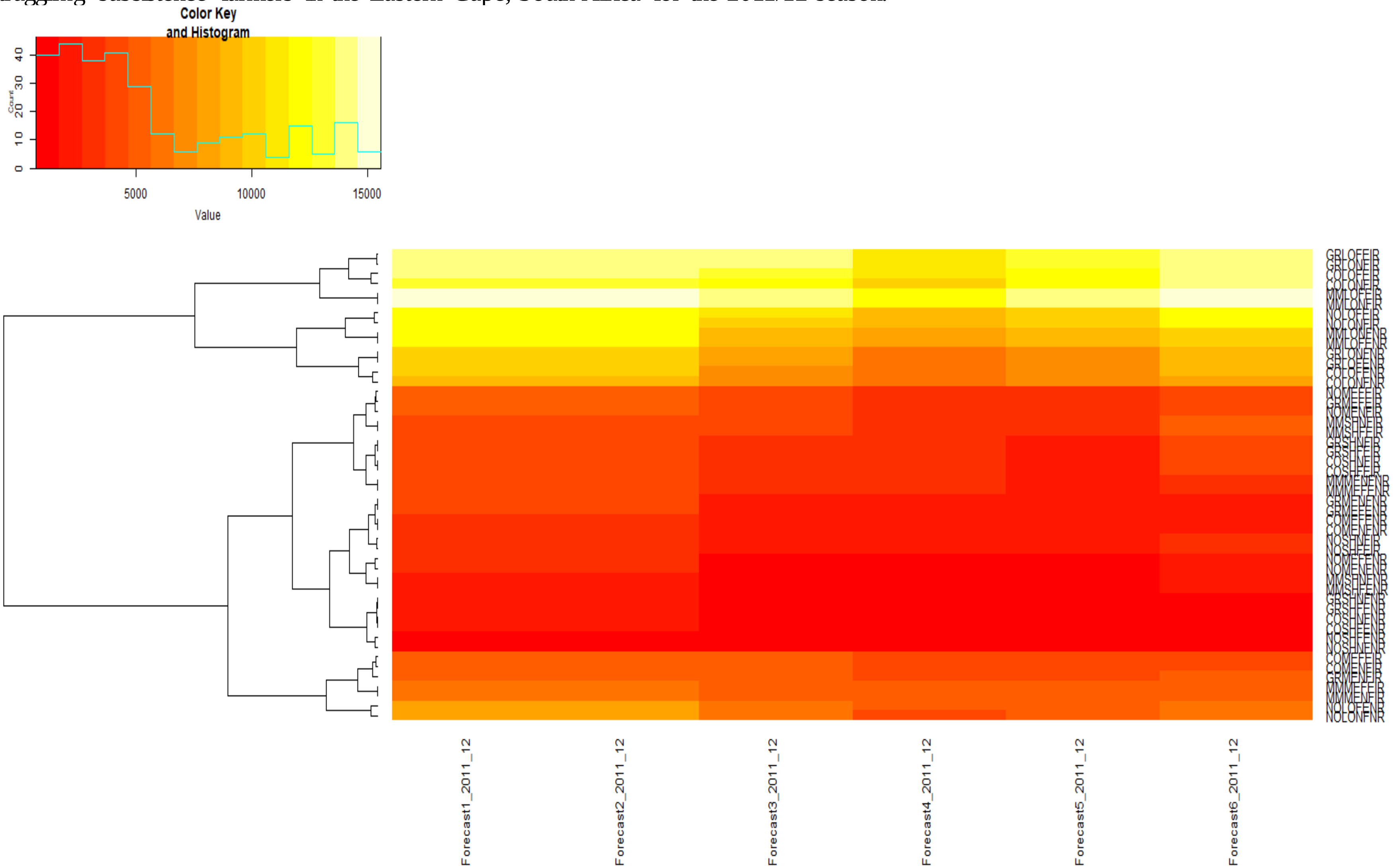
Annexure 5.84: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for off farm income farmers in Limpopo, South Africa for the 2014/15 season.



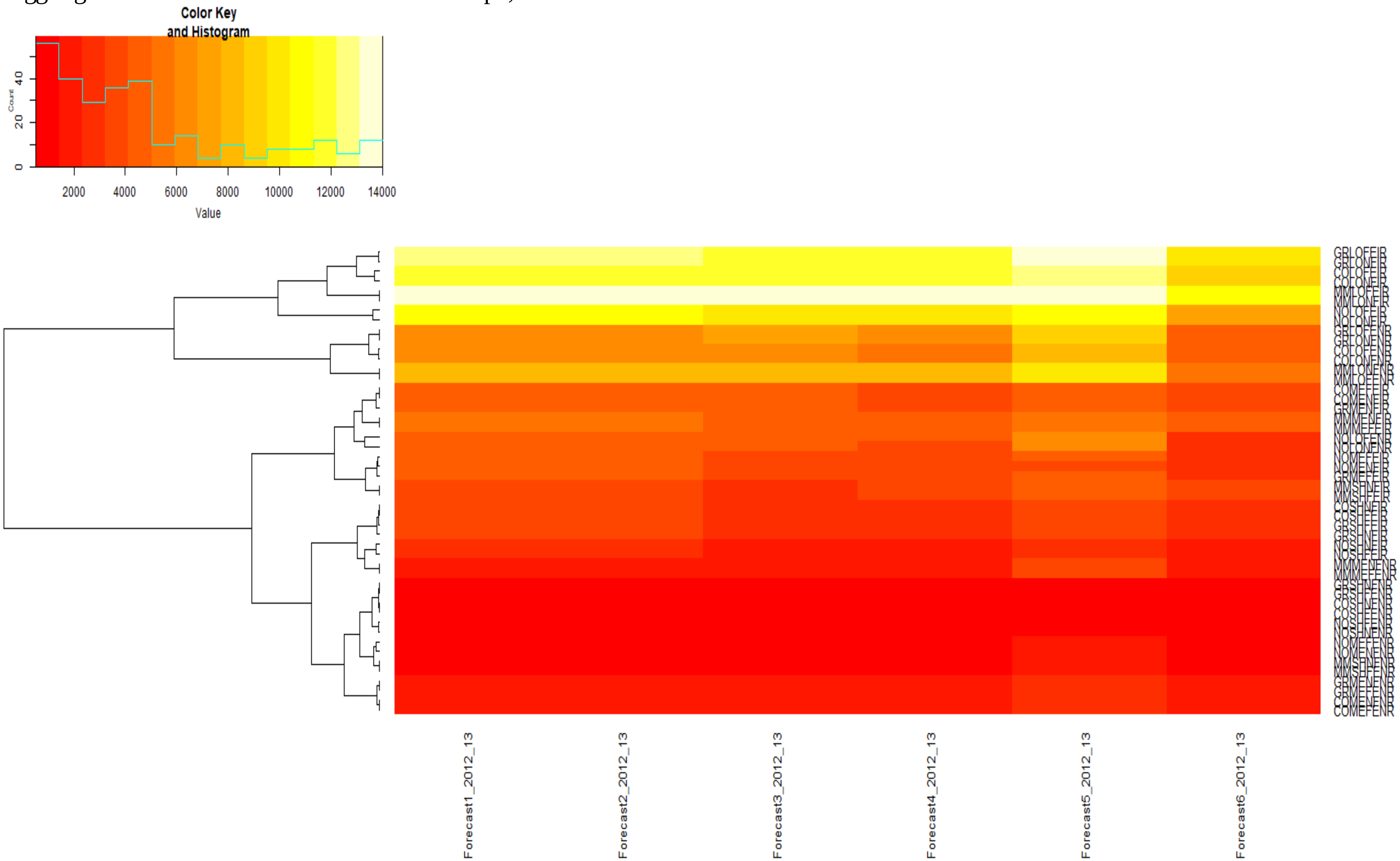
Annexure 5.85: Tomato yields amongst the different climate variability management strategies and historical seasonal forecasts for off farm income farmers in Limpopo, South Africa for the 2015/16 season.



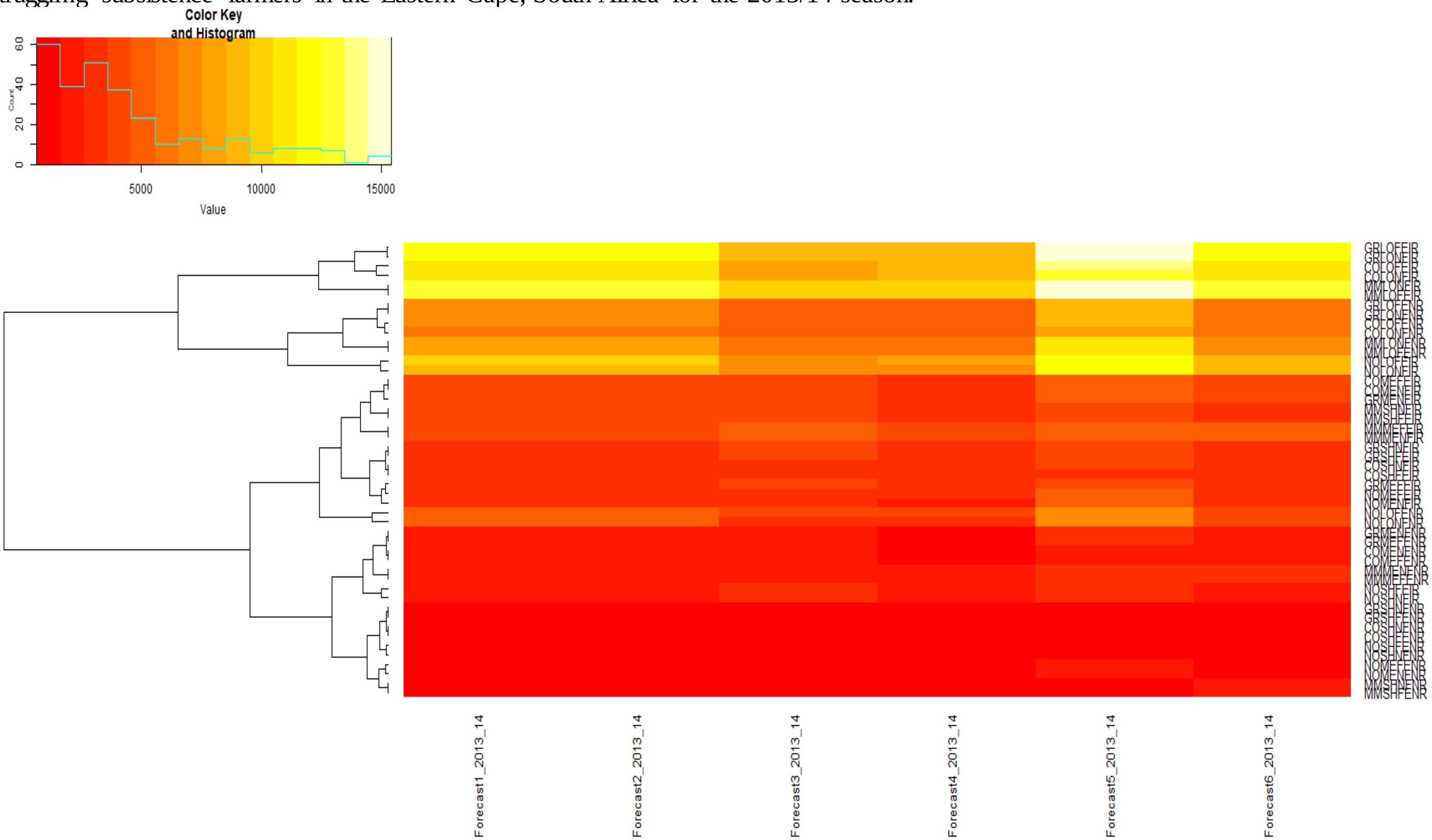
Annexure 5.86: Dry bean yields amongst the different climate variability management strategies and historical seasonal forecasts for struggling subsistence farmers in the Eastern Cape, South Africa for the 2011/12 season.



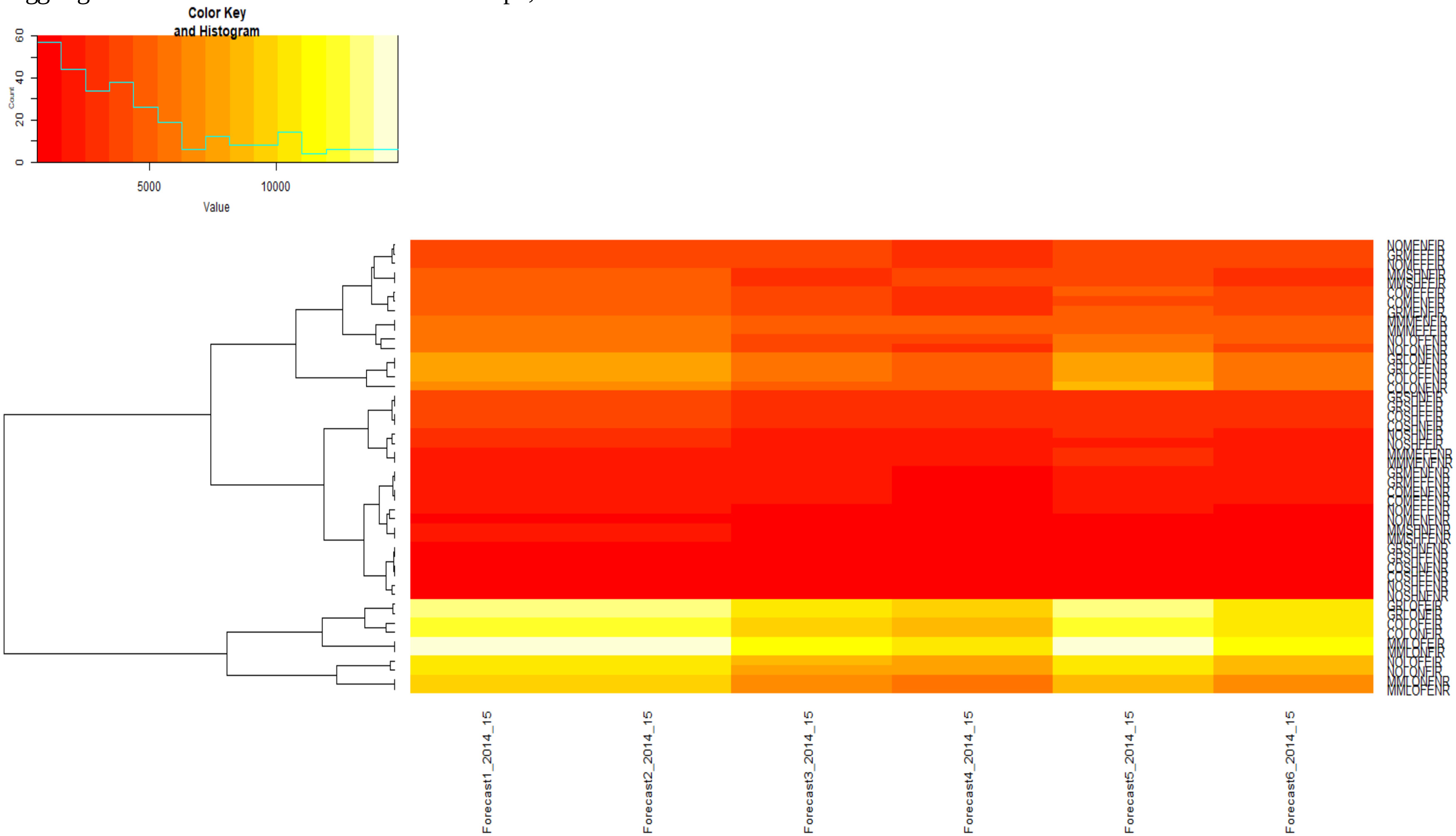
Annexure 5.87: Dry bean yields amongst the different climate variability management strategies and historical seasonal forecasts for struggling subsistence farmers in the Eastern Cape, South Africa for the 2012/13 season.



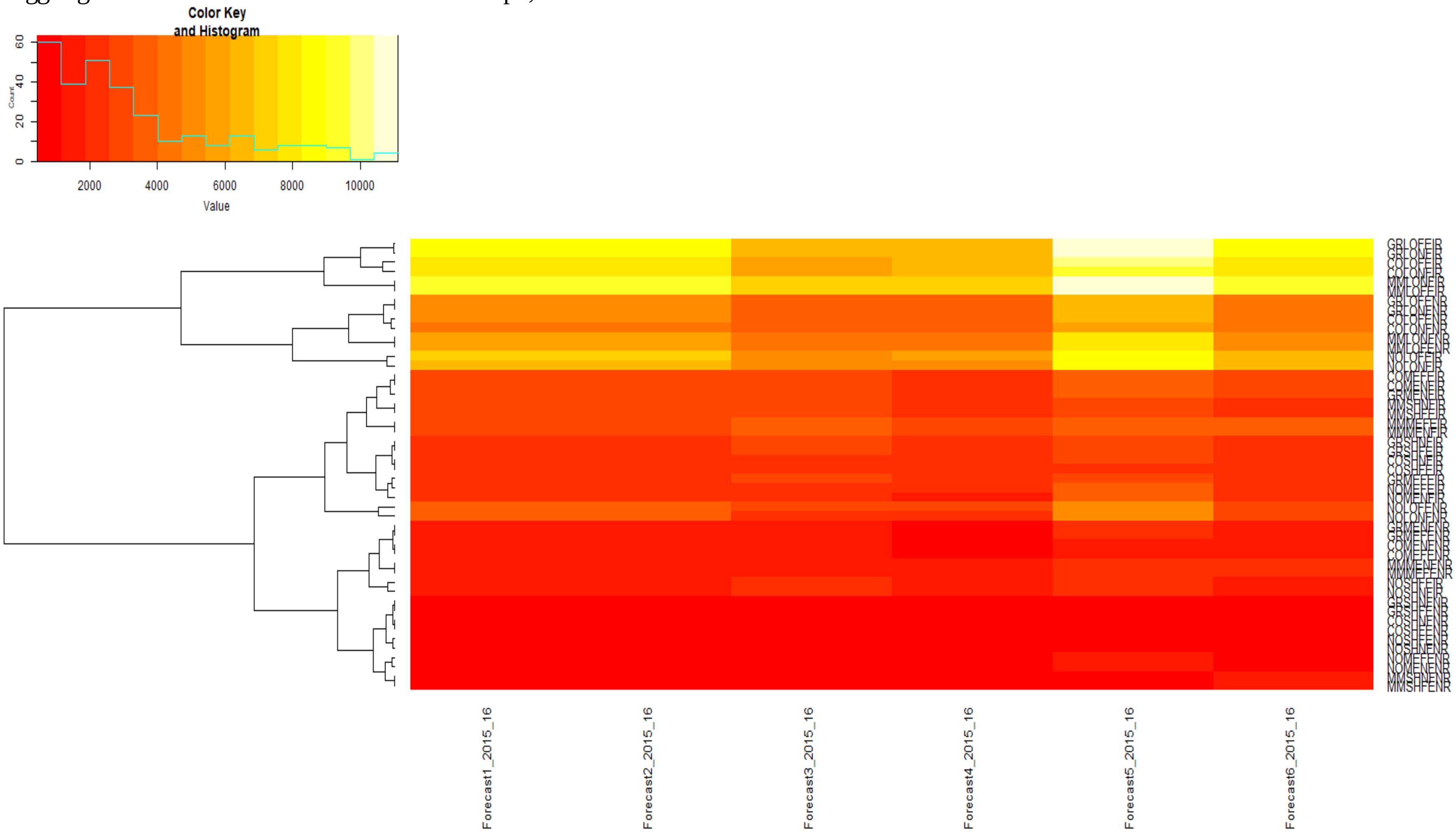
Annexure 5.88: Dry bean yields amongst the different climate variability management strategies and historical seasonal forecasts for struggling subsistence farmers in the Eastern Cape, South Africa for the 2013/14 season.



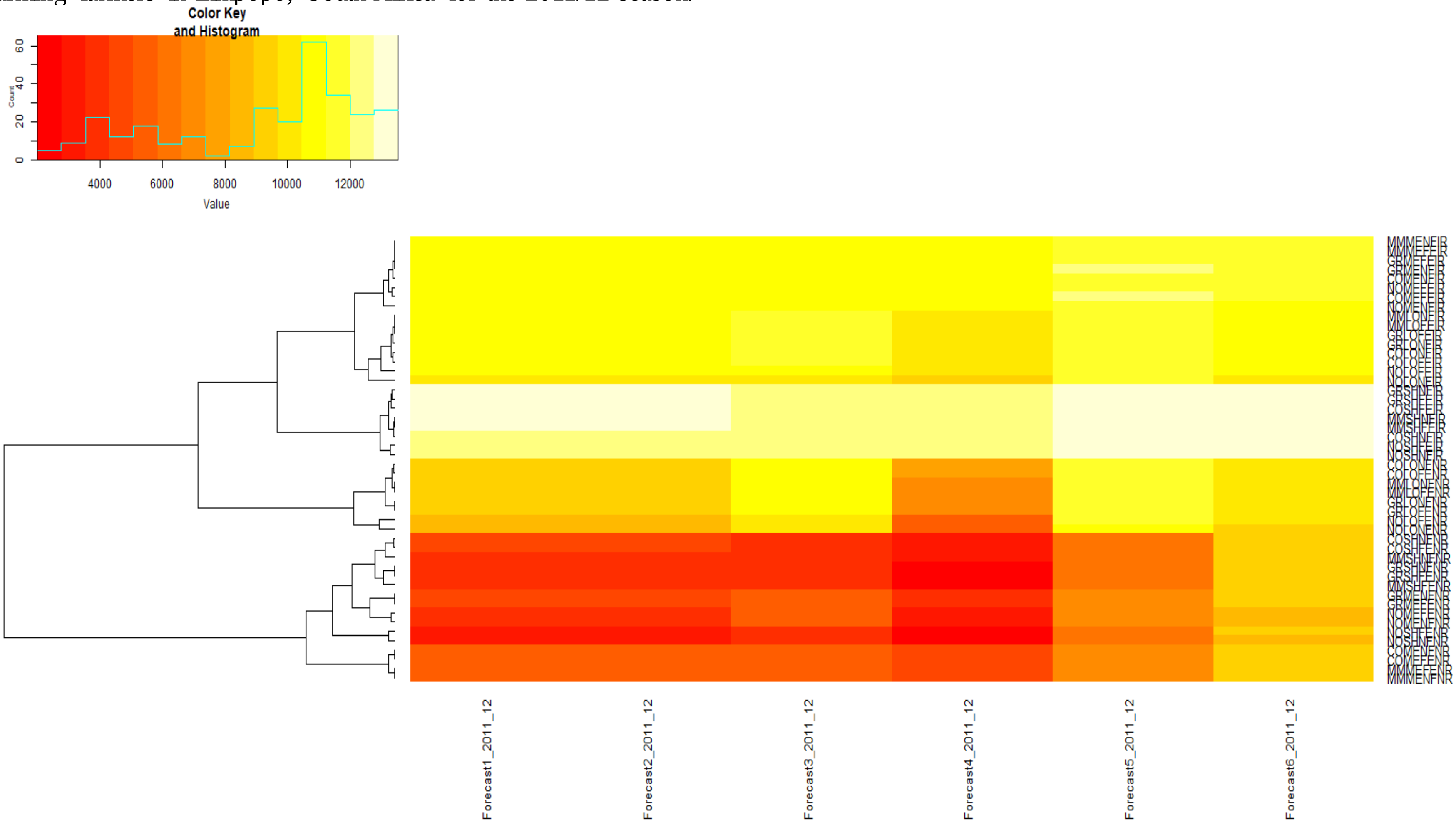
Annexure 5.89: Dry bean yields amongst the different climate variability management strategies and historical seasonal forecasts for struggling subsistence farmers in the Eastern Cape, South Africa for the 2014/15 season.



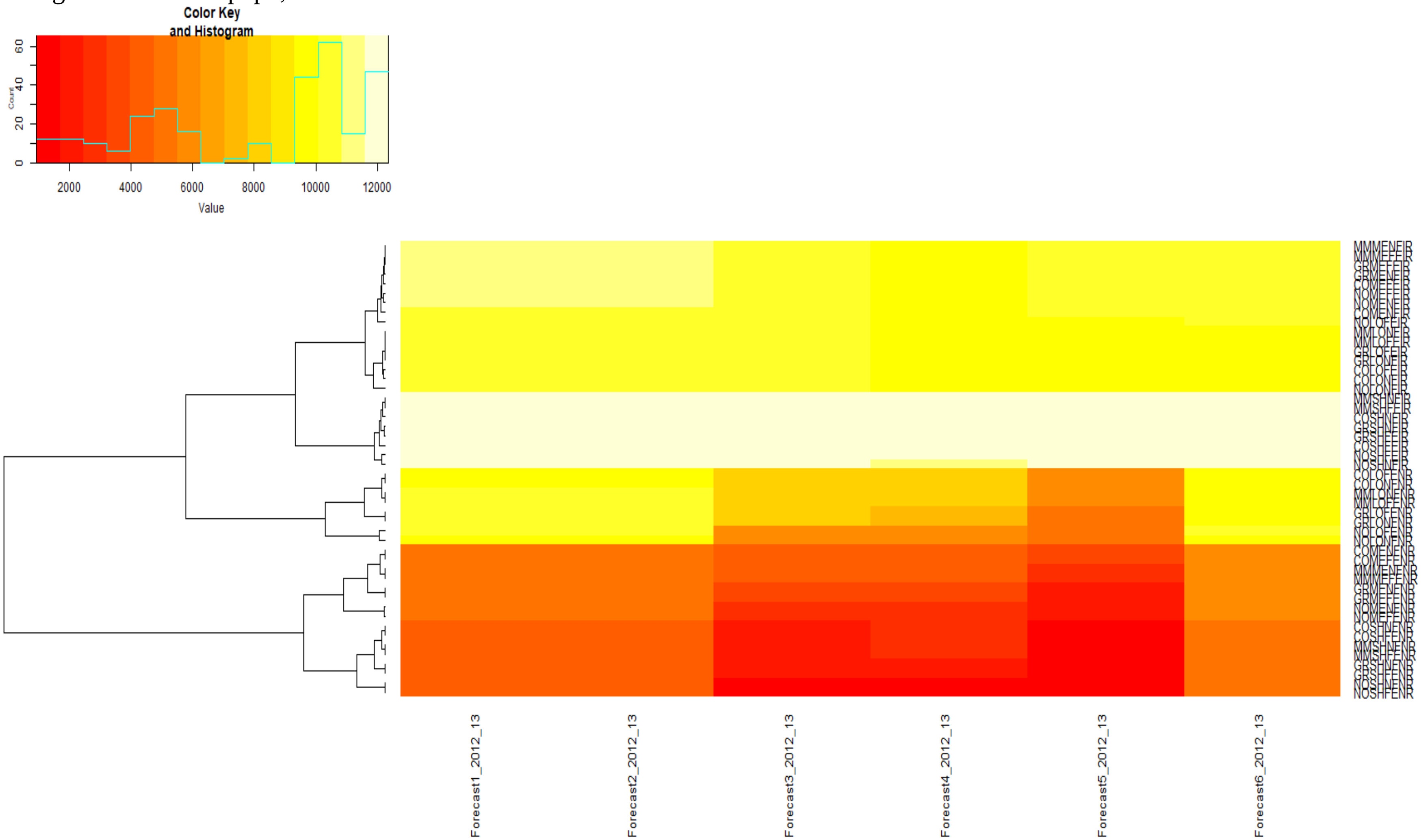
Annexure 5.90: Dry bean yields amongst the different climate variability management strategies and historical seasonal forecasts for struggling subsistence farmers in the Eastern Cape, South Africa for the 2015/16 season.



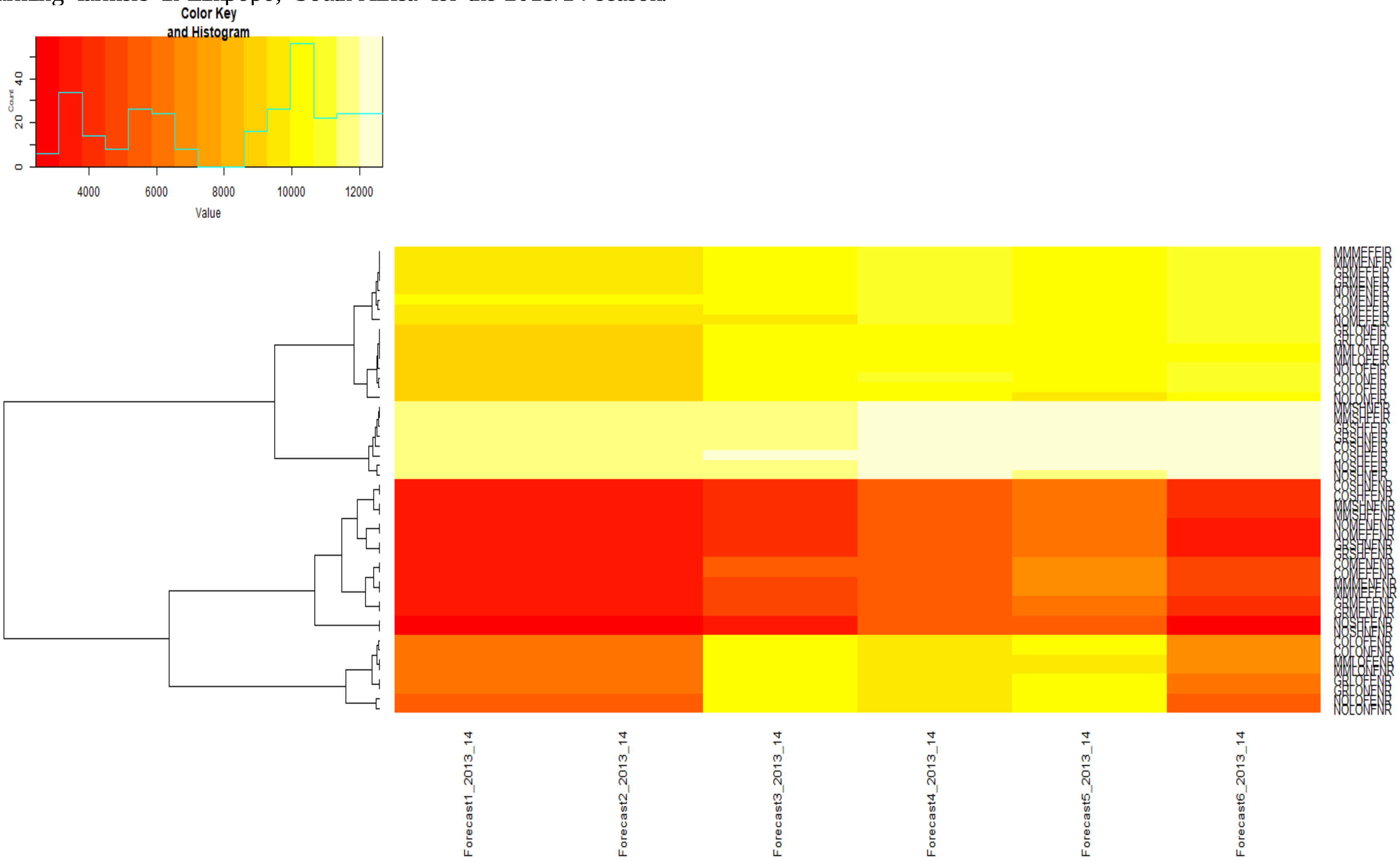
Annexure 5.91: Dry bean yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming farmers in Limpopo, South Africa for the 2011/12 season.



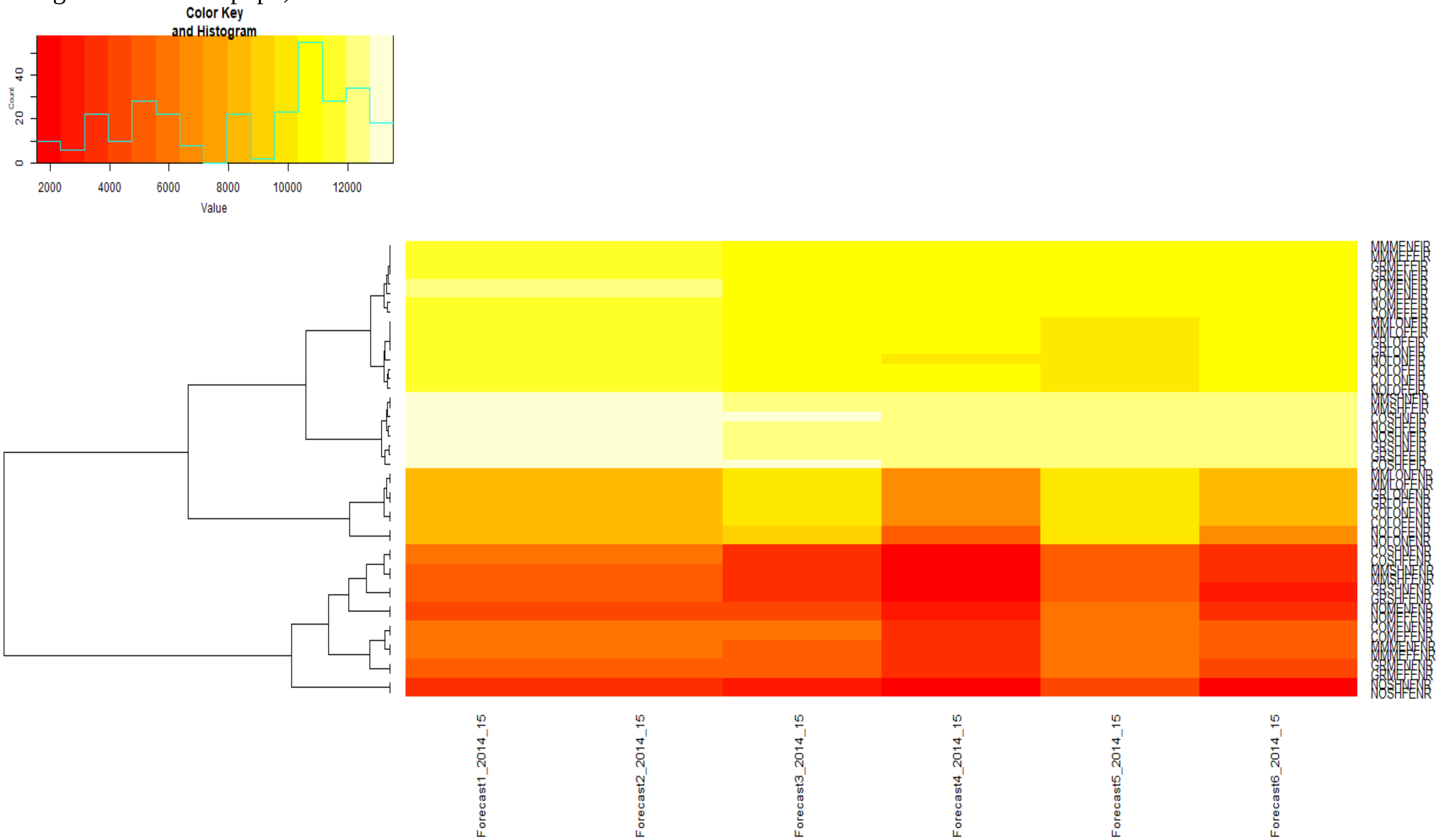
Annexure 5.92: Dry bean yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming farmers in Limpopo, South Africa for the 2012/13 season.



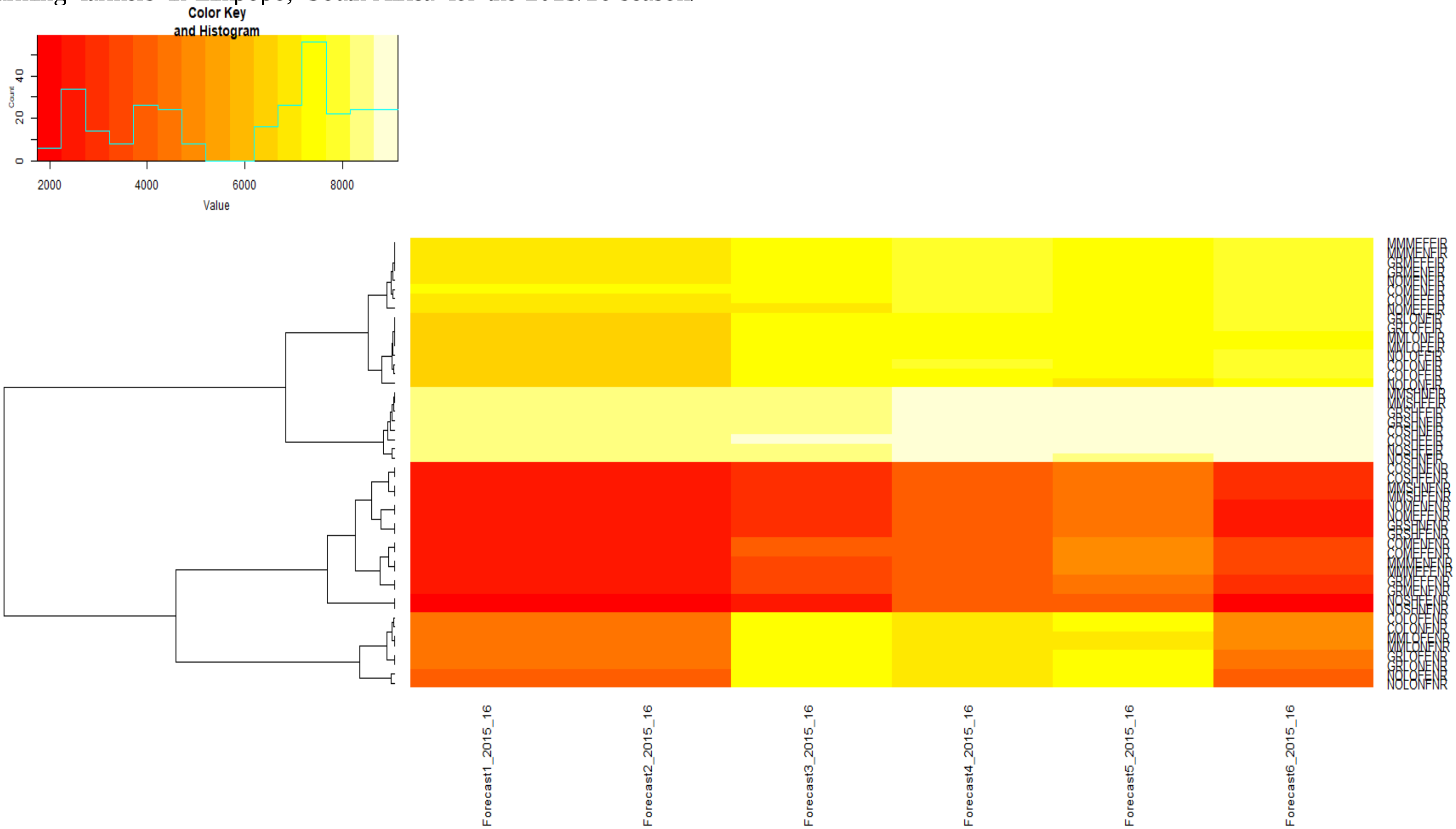
Annexure 5.93: Dry bean yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming farmers in Limpopo, South Africa for the 2013/14 season.



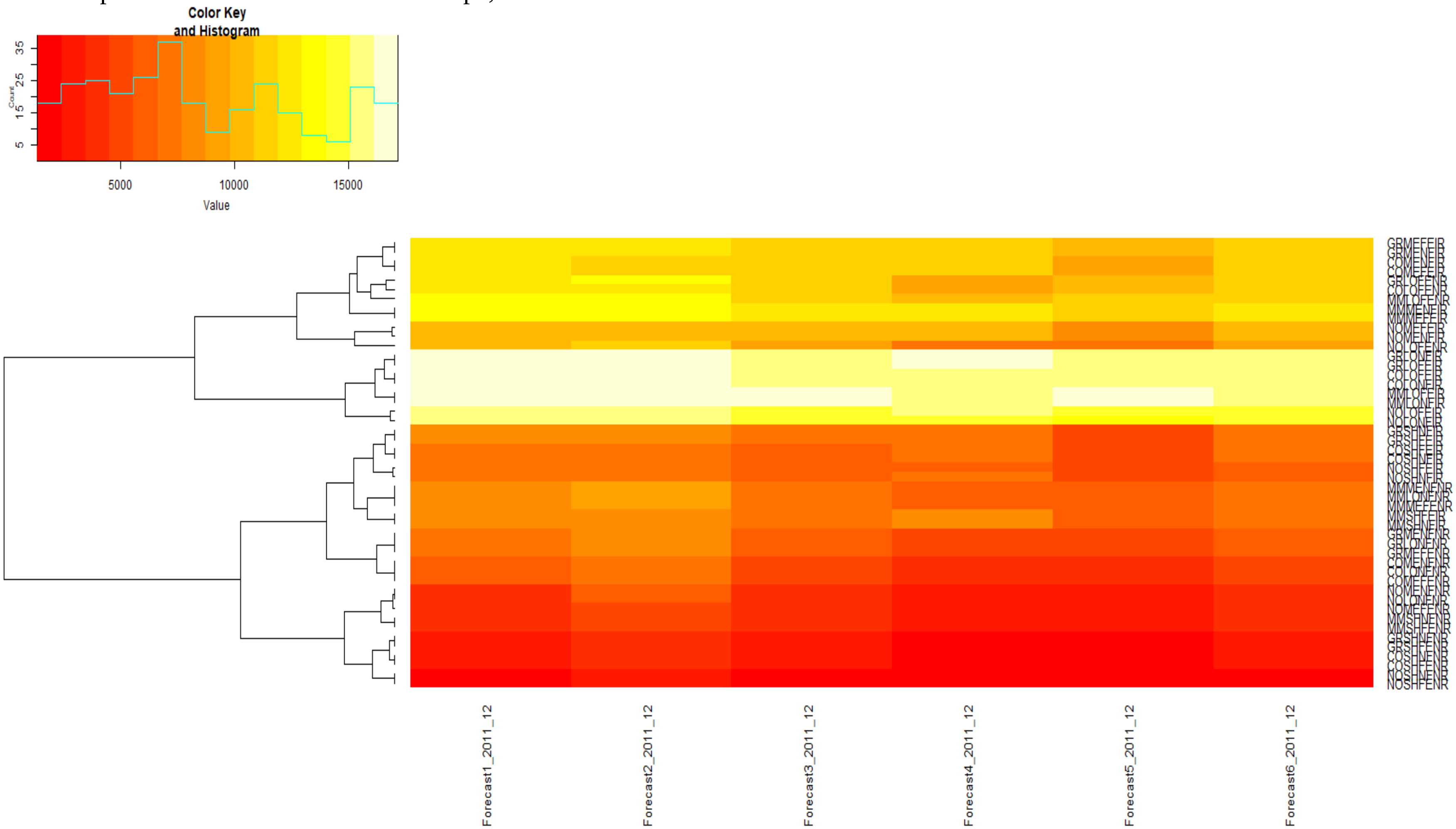
Annexure 5.94: Dry bean yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming farmers in Limpopo, South Africa for the 2014/15 season.



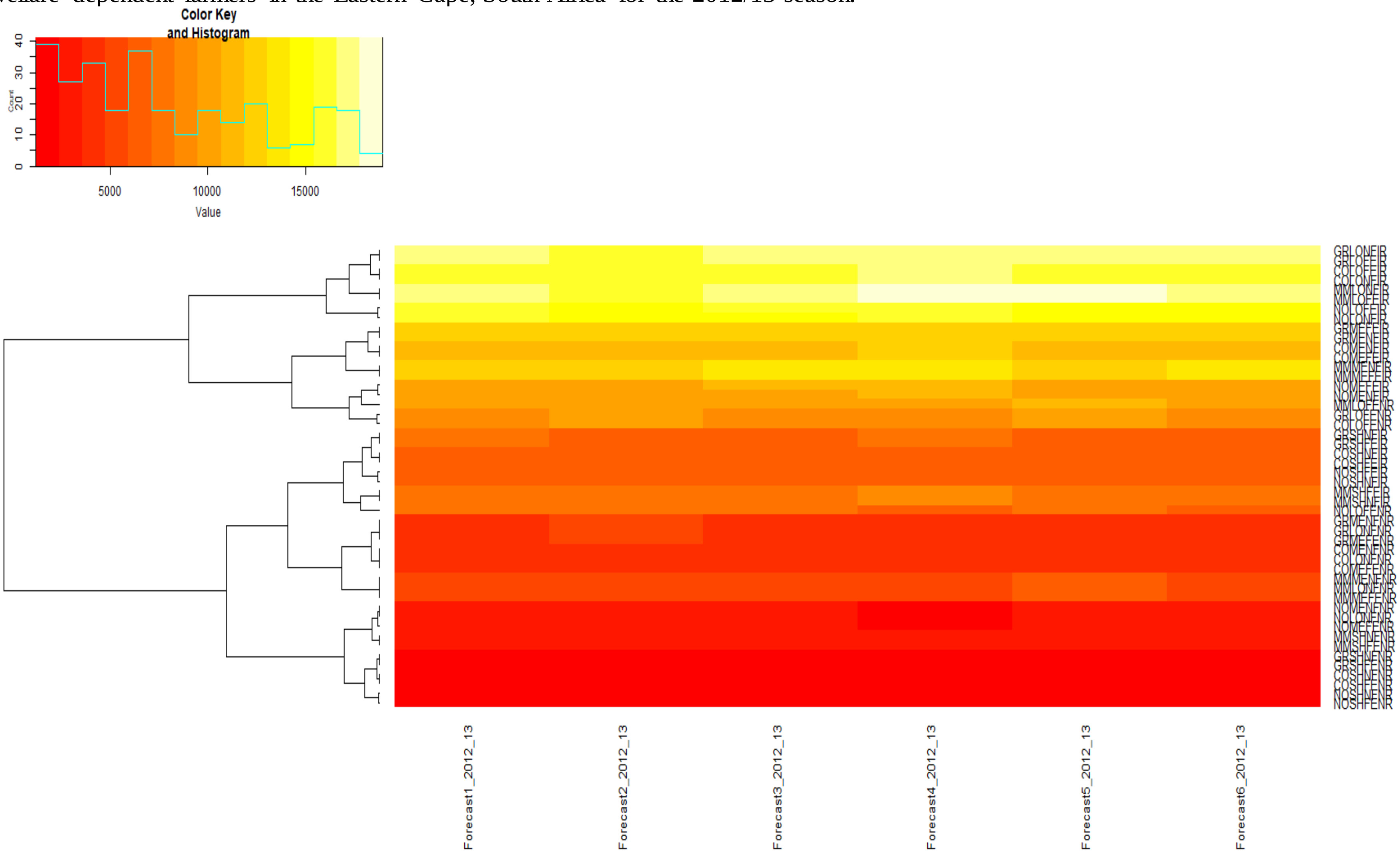
Annexure 5.95: Dry bean yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming farmers in Limpopo, South Africa for the 2015/16 season.



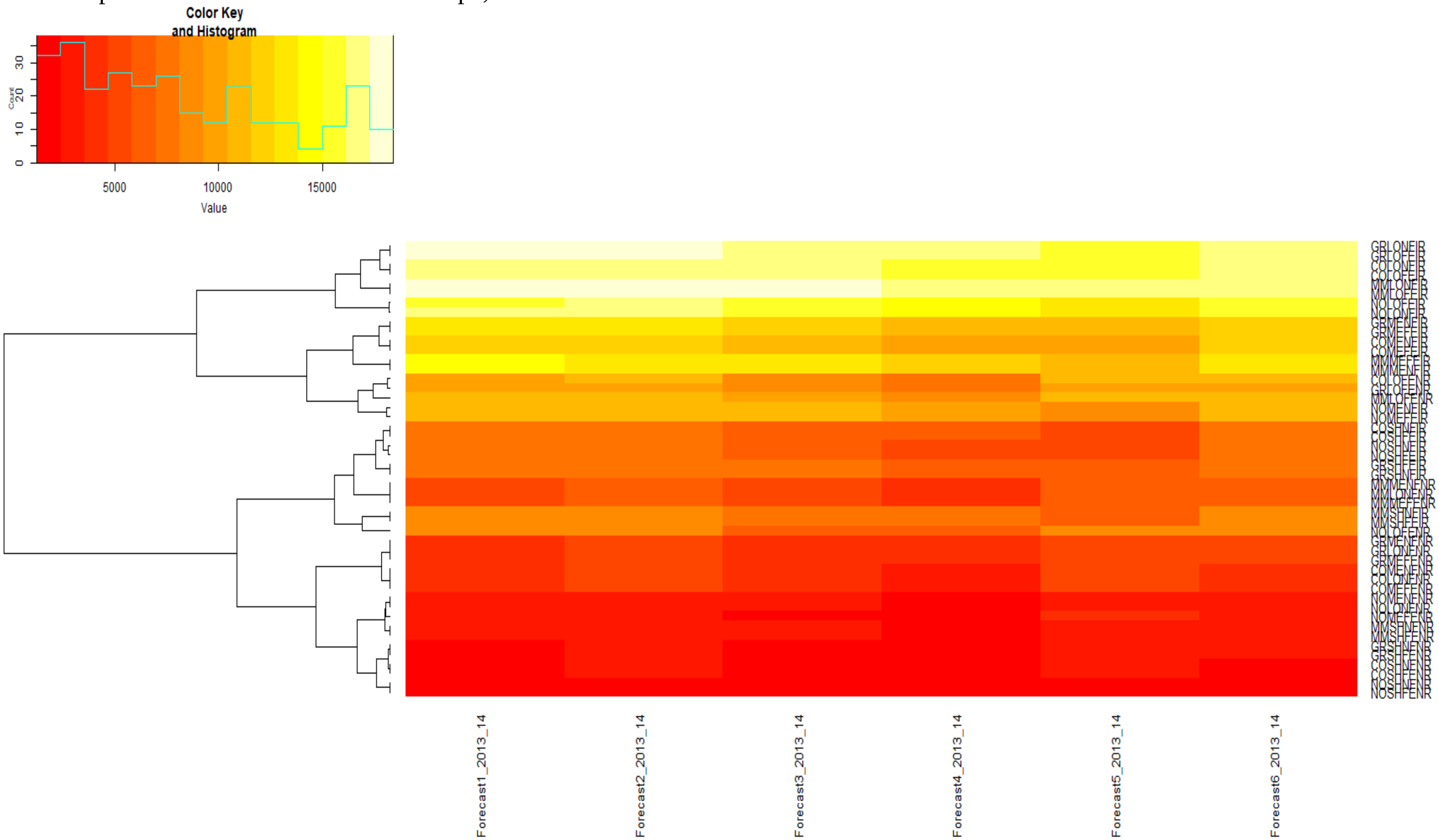
Annexure 5.96: Peanut yields amongst the different climate variability management strategies and historical seasonal forecasts for social welfare dependent farmers in the Eastern Cape, South Africa for the 2011/12 season.



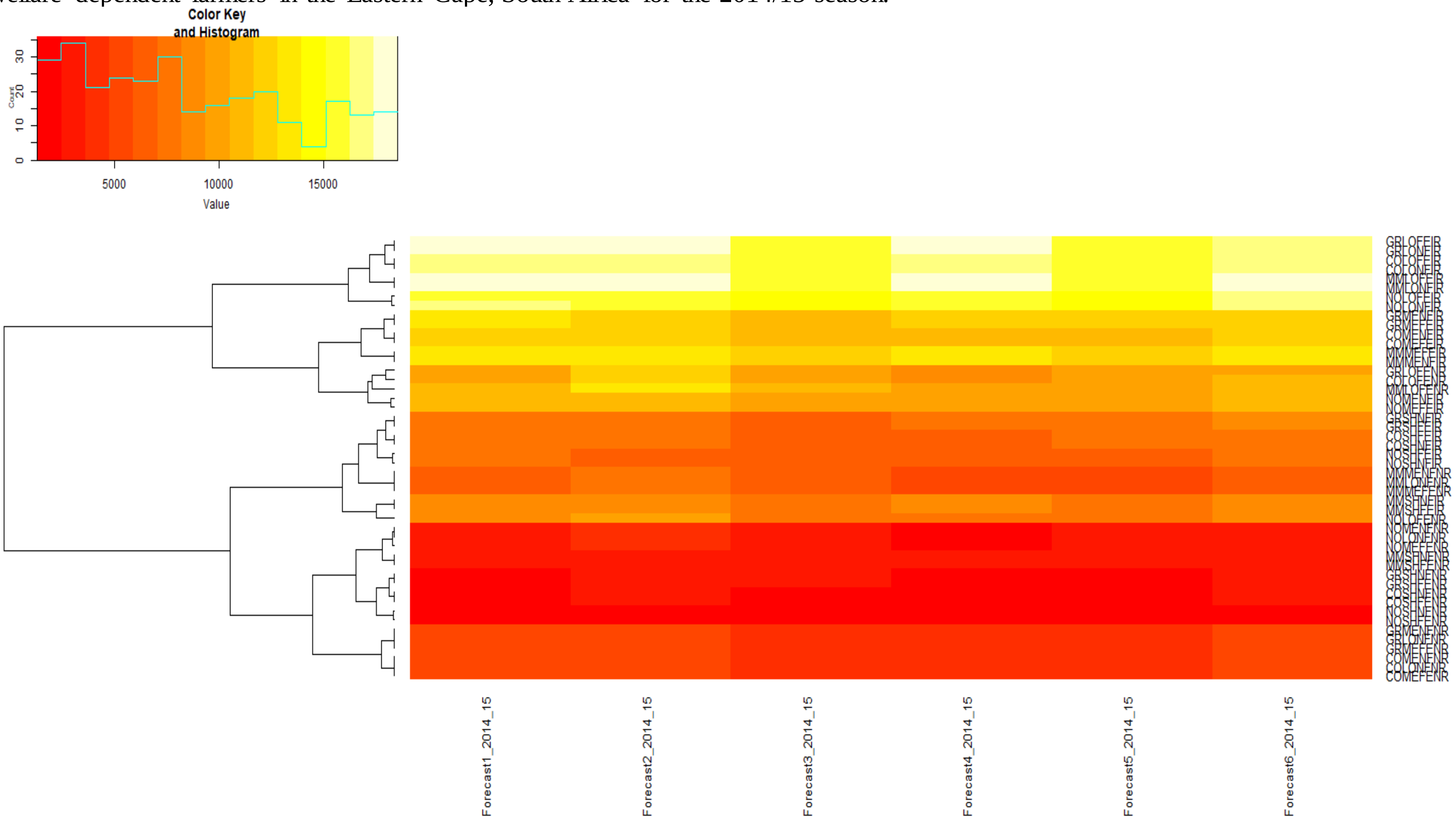
Annexure 5.97: Peanut yields amongst the different climate variability management strategies and historical seasonal forecasts for social welfare dependent farmers in the Eastern Cape, South Africa for the 2012/13 season.



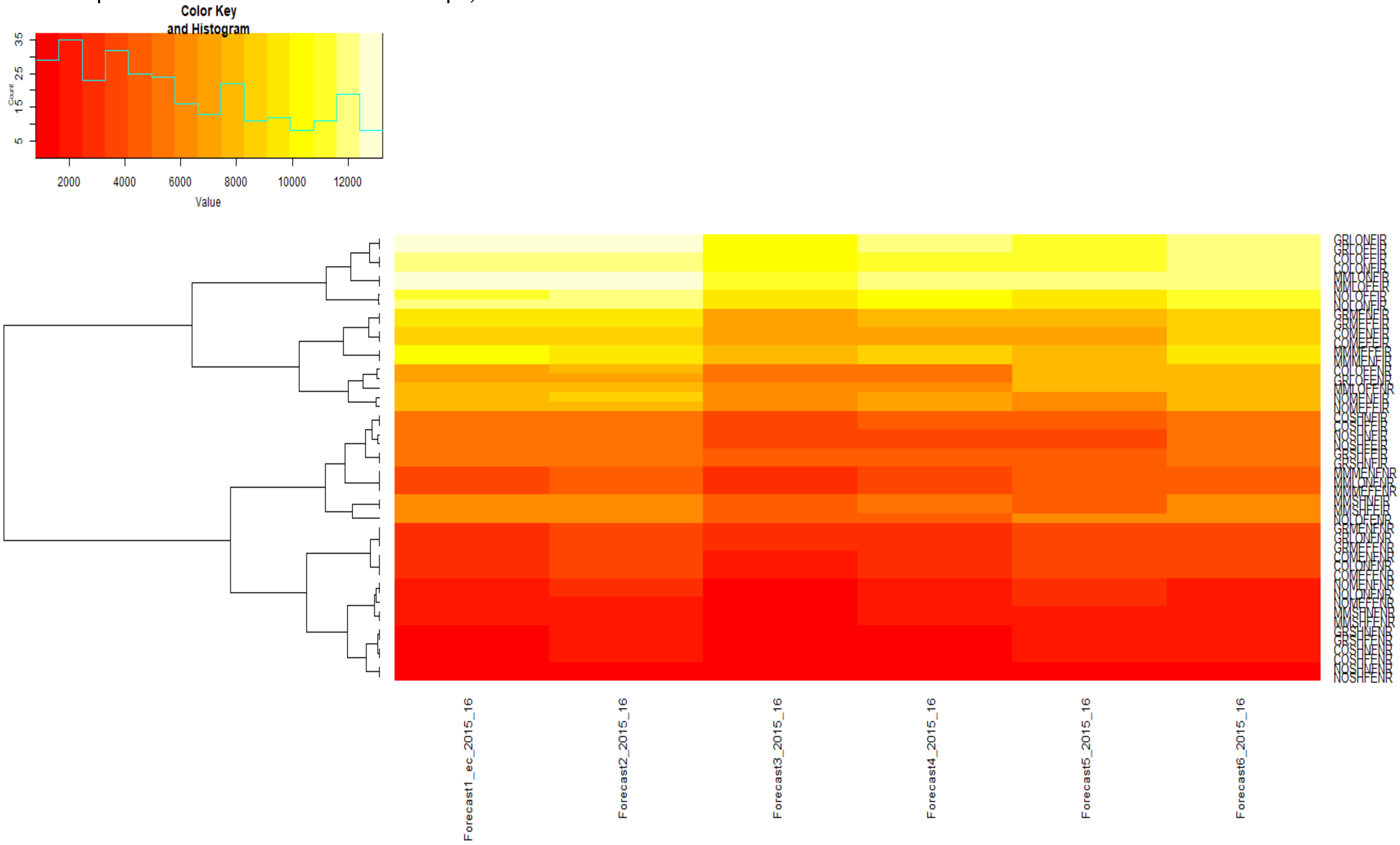
Annexure 5.98: Peanut yields amongst the different climate variability management strategies and historical seasonal forecasts for social welfare dependent farmers in the Eastern Cape, South Africa for the 2013/14 season.



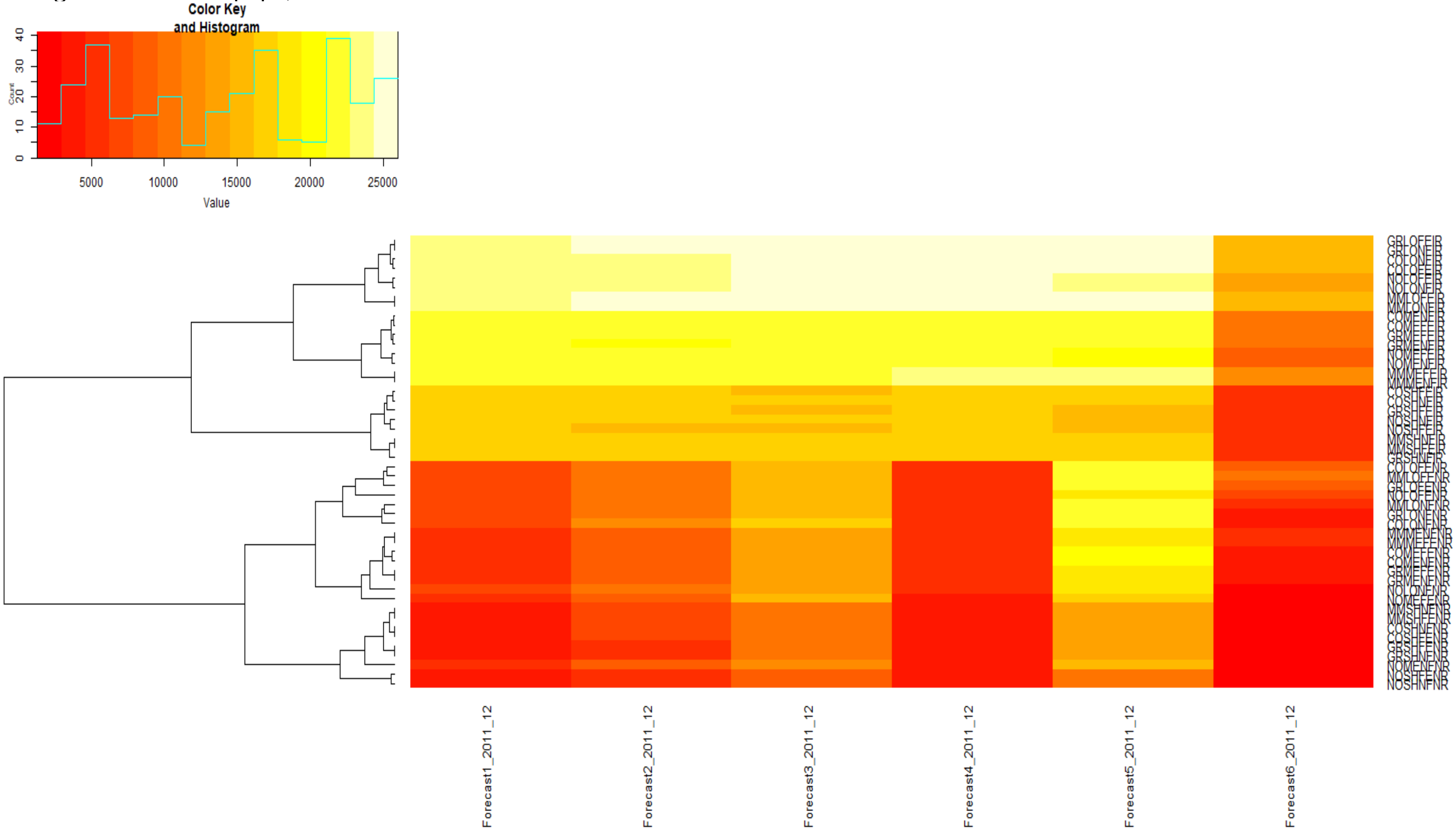
Annexure 5.99: Peanut yields amongst the different climate variability management strategies and historical seasonal forecasts for social welfare dependent farmers in the Eastern Cape, South Africa for the 2014/15 season.



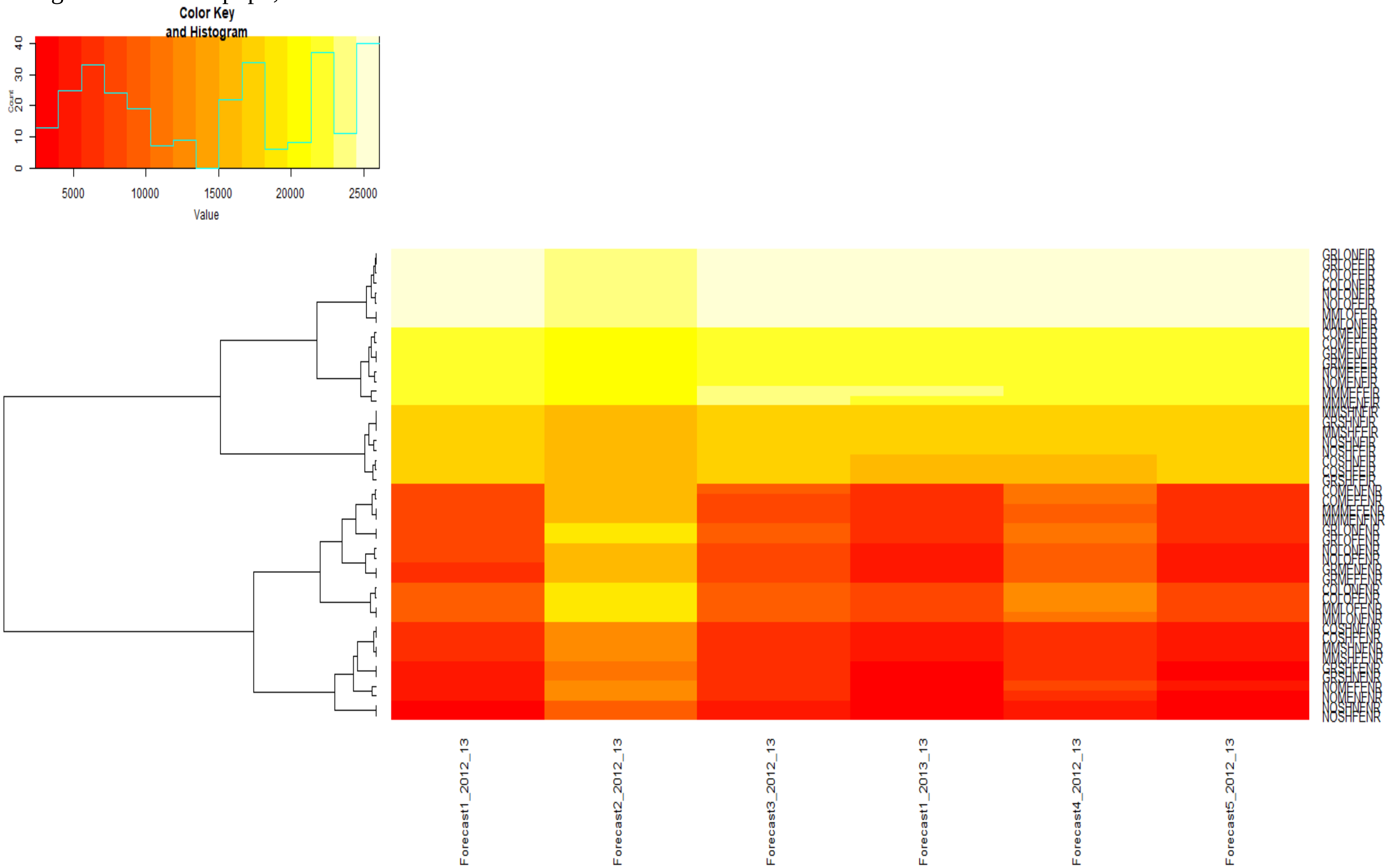
Annexure 5.100: **P**eanut yields amongst the different climate variability management strategies and historical seasonal forecasts for social welfare dependent farmers in the Eastern Cape, South Africa for the 2015/16 season.



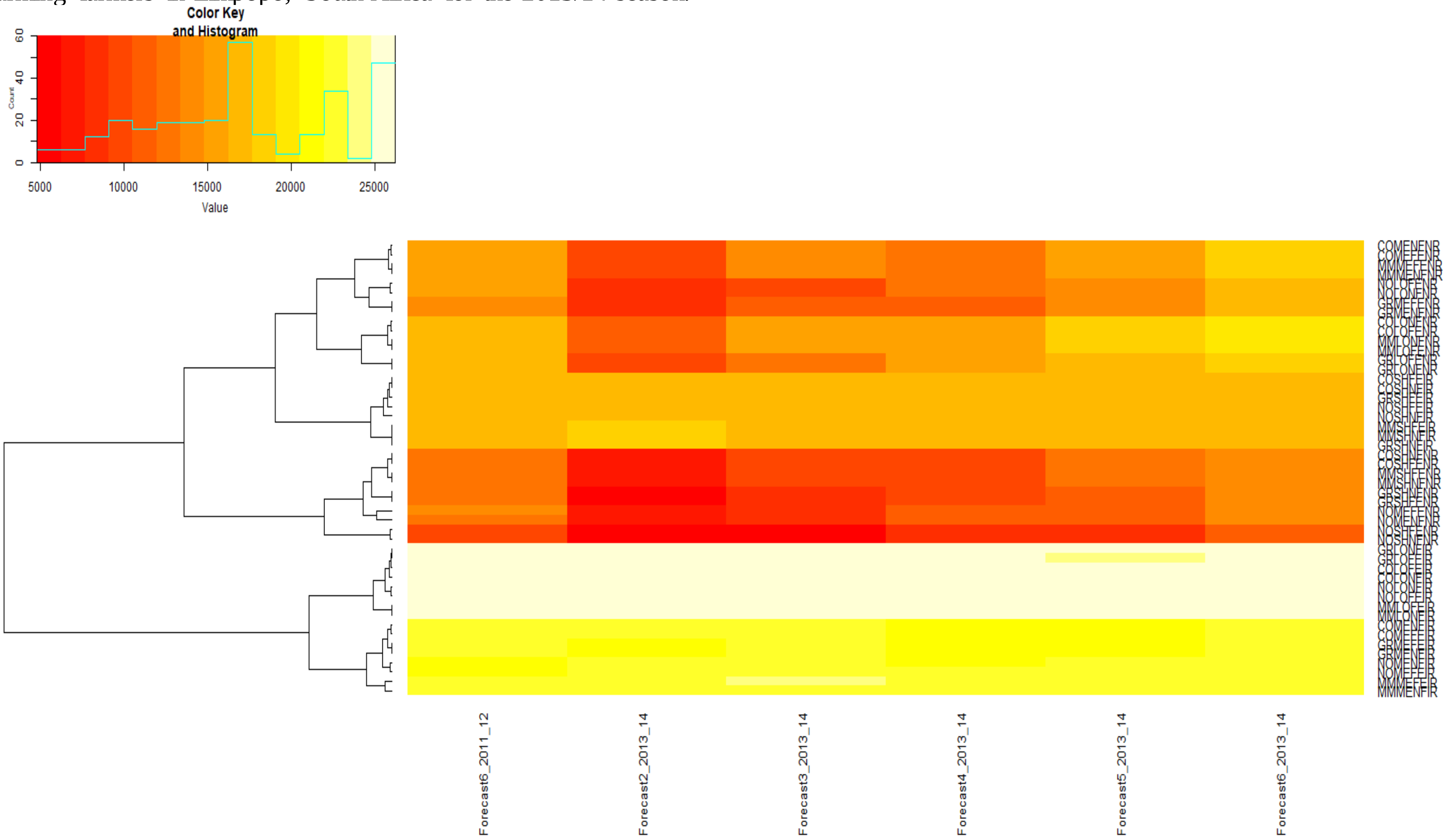
Annexure 5.101: **P**eanut yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming farmers in Limpopo, South Africa for the 2011/12 season.



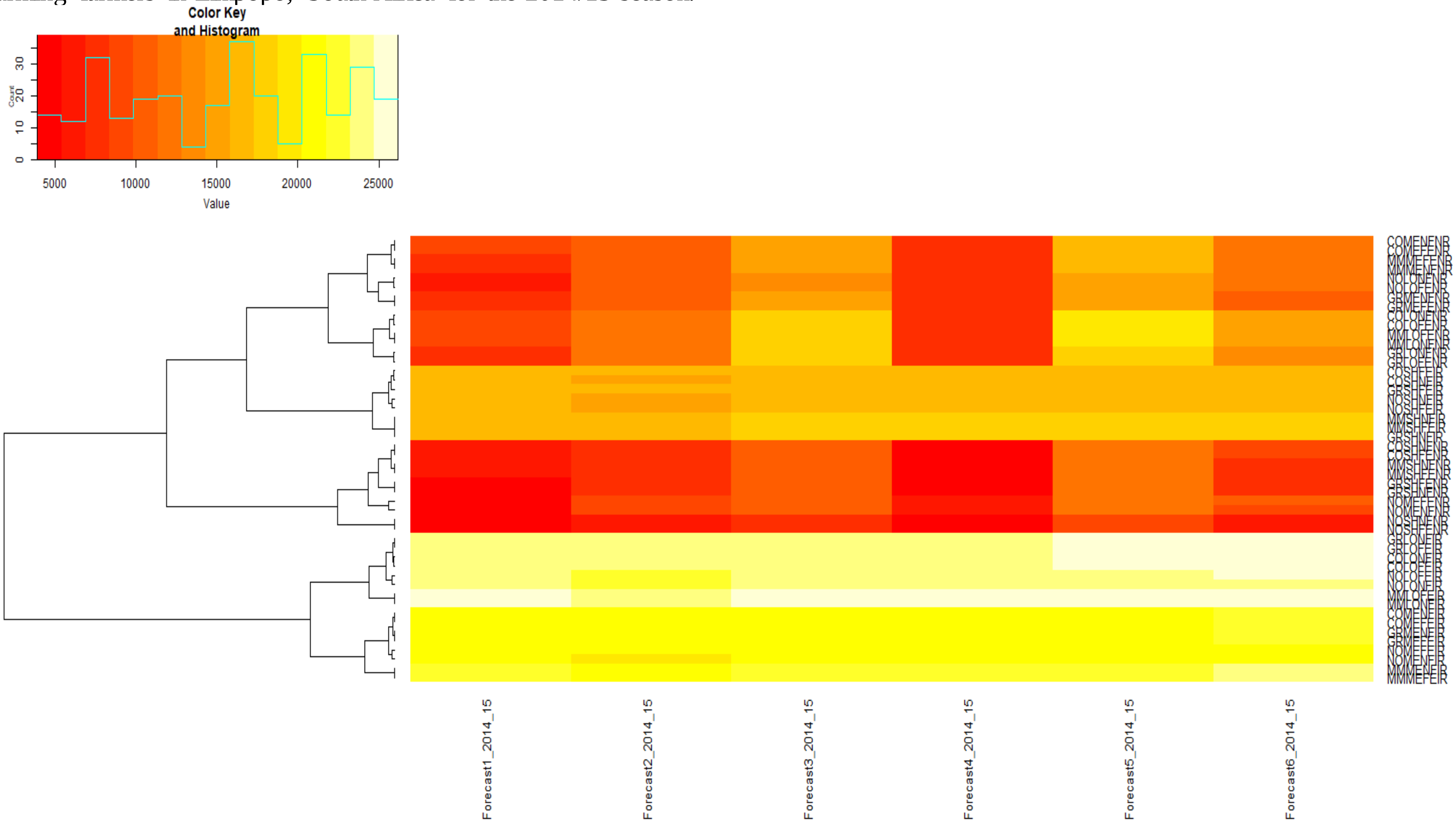
Annexure 5.102: Peanut yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming farmers in Limpopo, South Africa for the 2012/13 season.



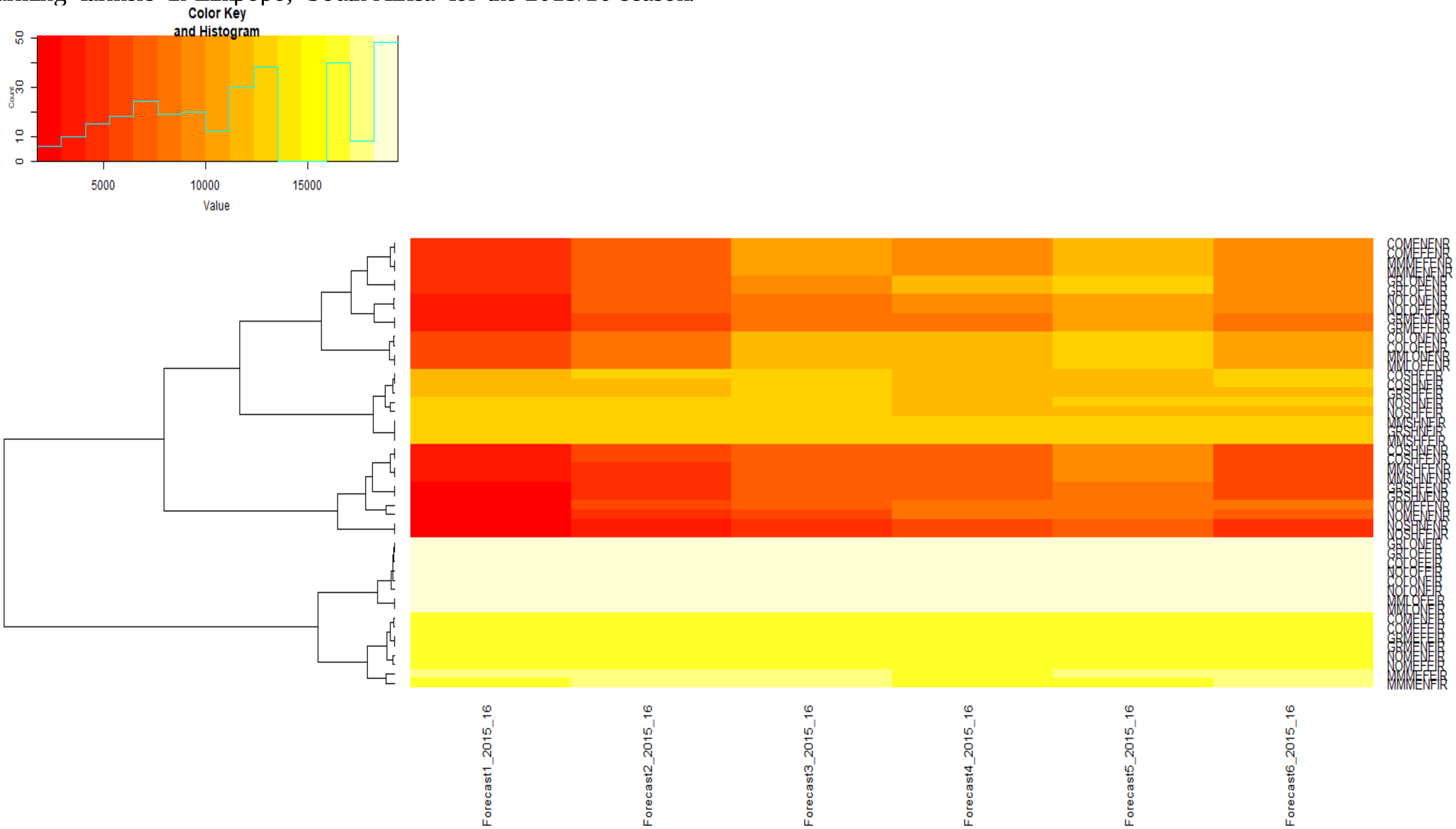
Annexure 5.103: Peanut yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming farmers in Limpopo, South Africa for the 2013/14 season.



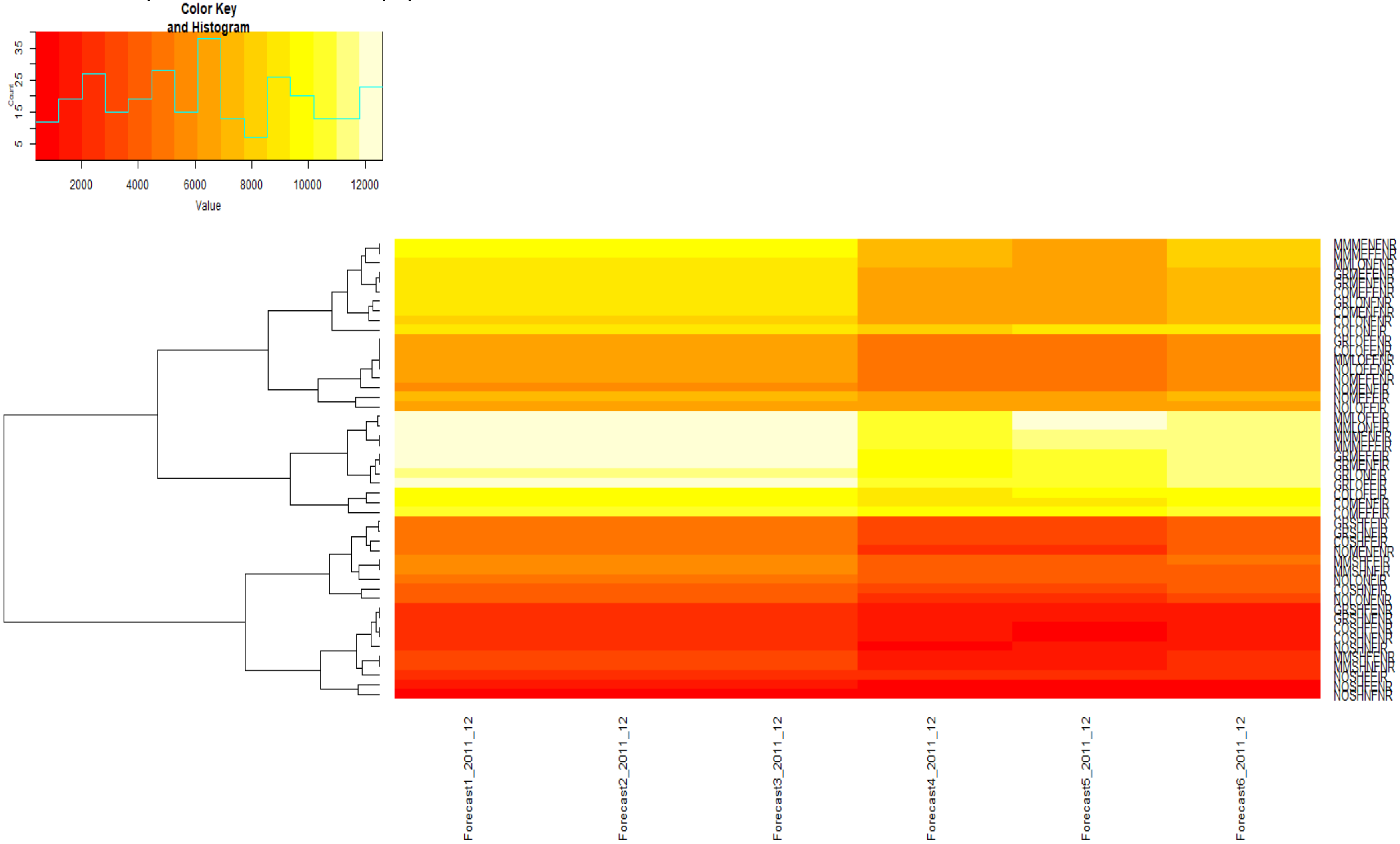
Annexure 5.104: Peanut yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming farmers in Limpopo, South Africa for the 2014/15 season.



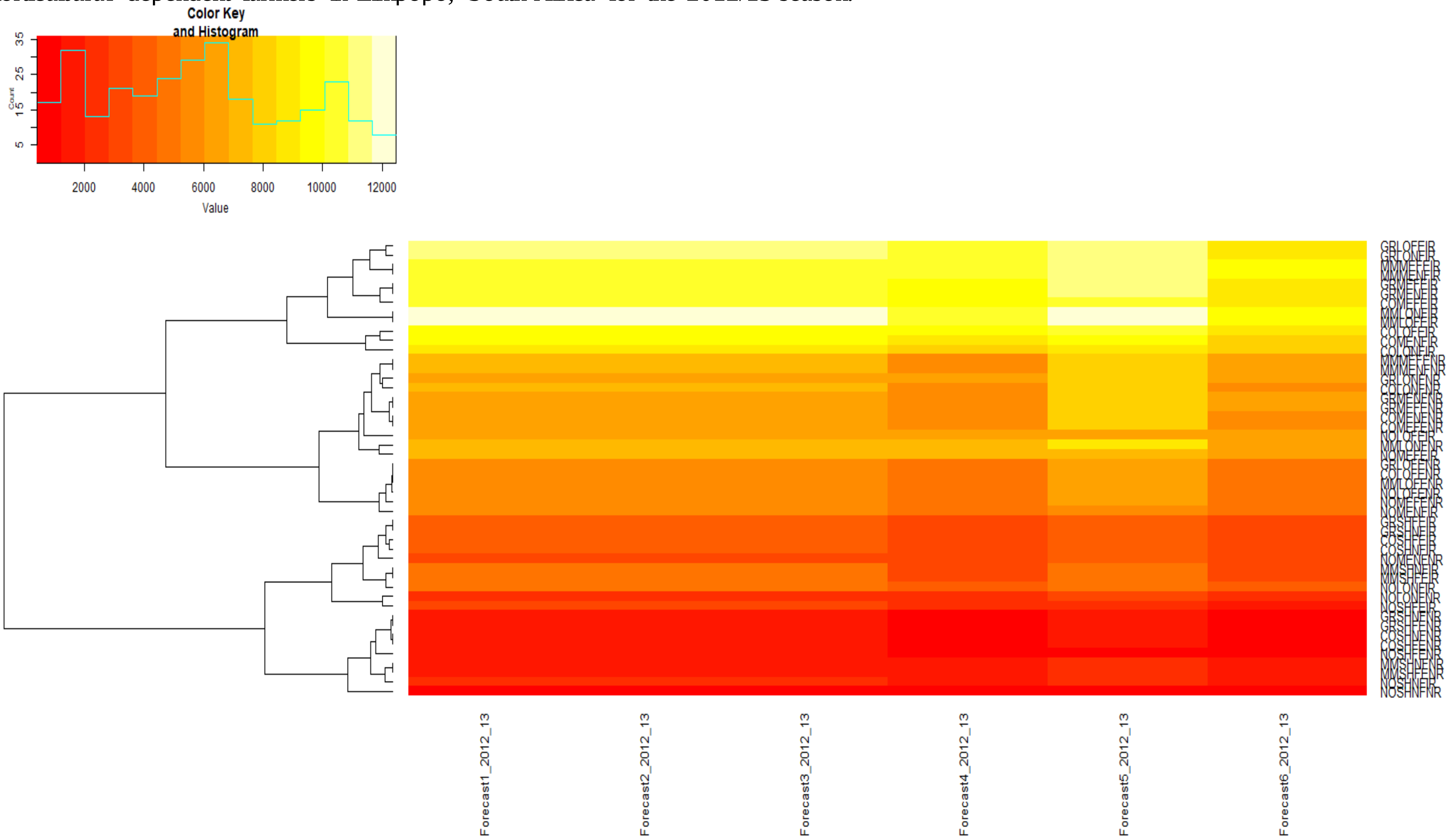
Annexure 5.105: Peanut yields amongst the different climate variability management strategies and historical seasonal forecasts for mixed farming farmers in Limpopo, South Africa for the 2015/16 season.



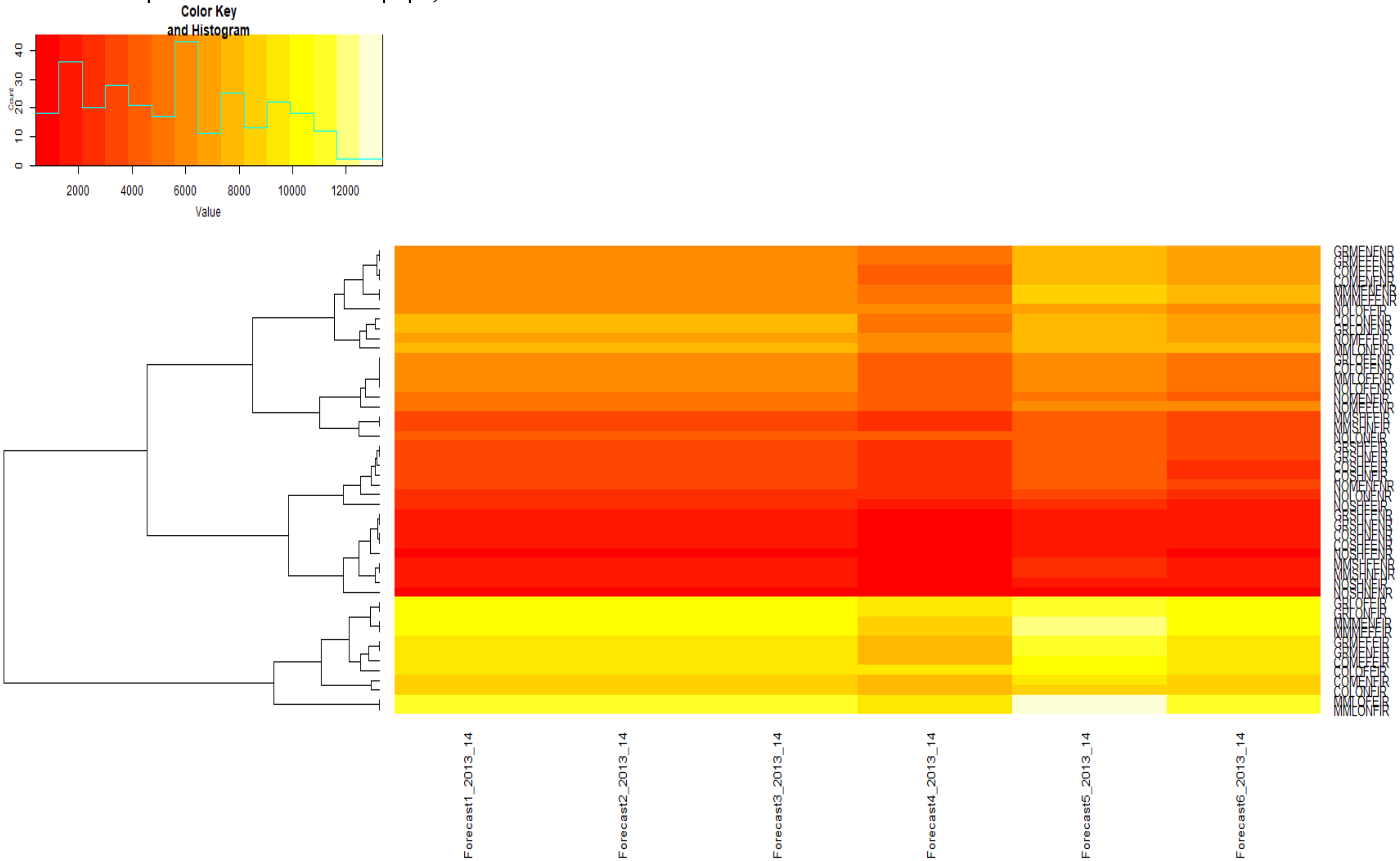
Annexure 5.106: Green bean yields amongst the different climate variability management strategies and historical seasonal forecasts for horticultural dependent farmers in Limpopo, South Africa for the 2011/12 season.



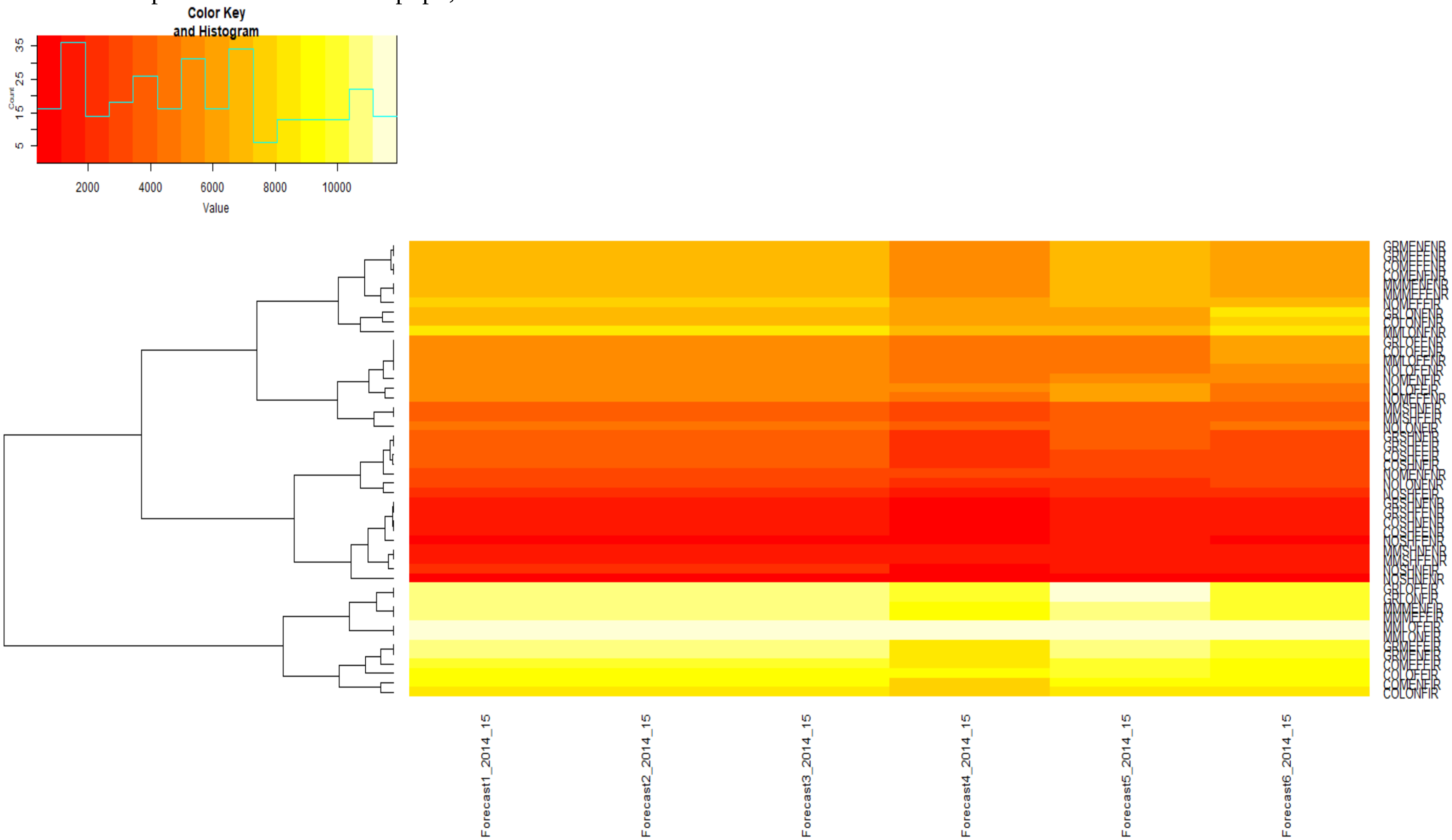
Annexure 5.107: Green bean yields amongst the different climate variability management strategies and historical seasonal forecasts for horticultural dependent farmers in Limpopo, South Africa for the 2012/13 season.



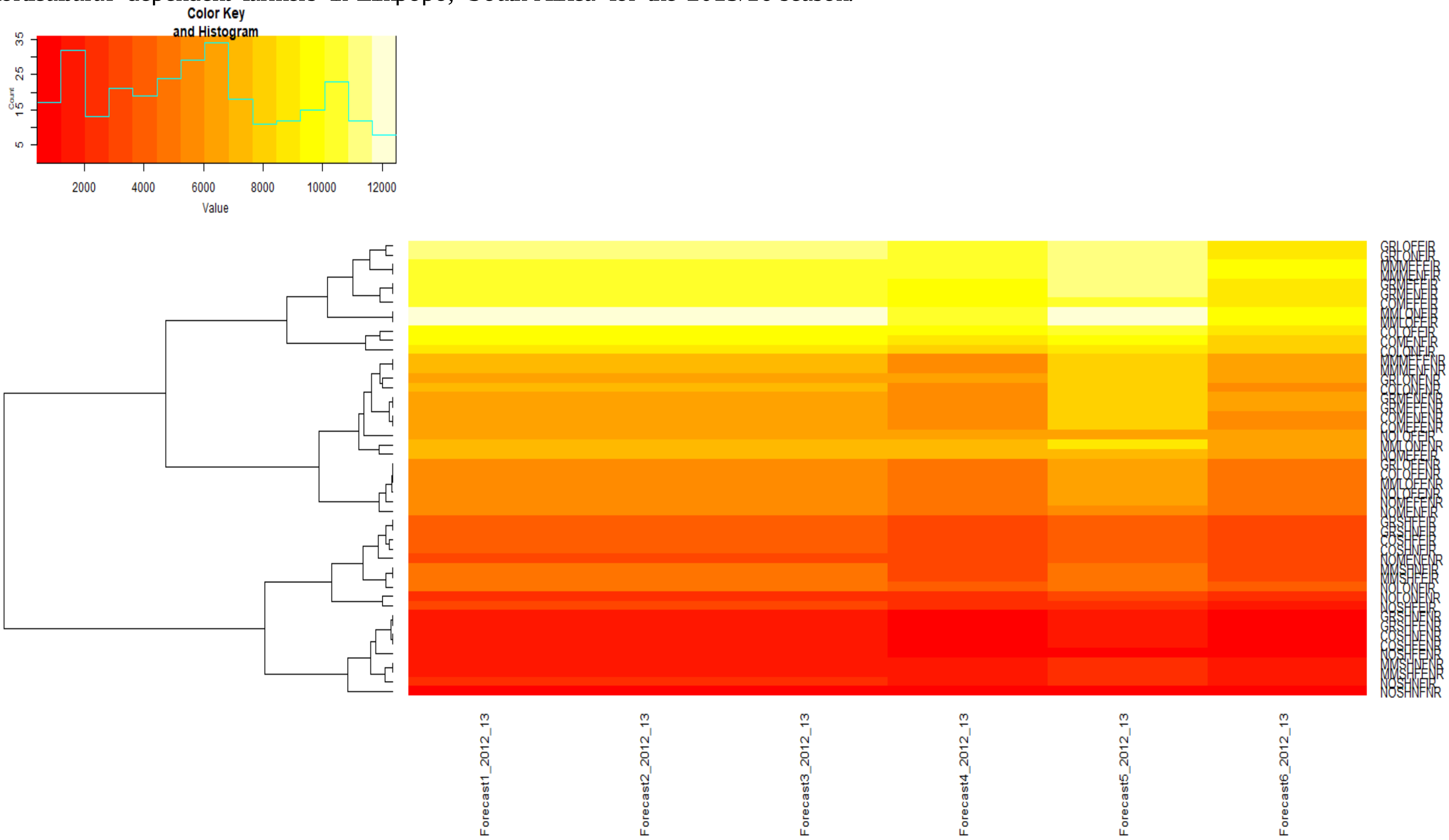
Annexure 5.108: Green bean yields amongst the different climate variability management strategies and historical seasonal forecasts for horticultural dependent farmers in Limpopo, South Africa for the 2013/14 season.



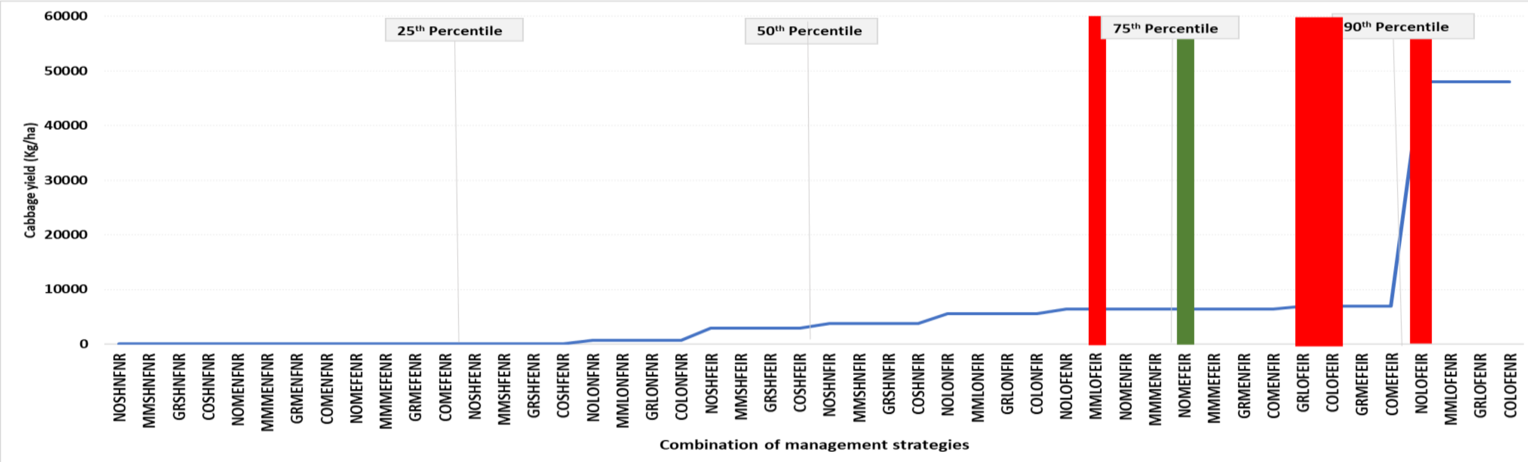
Annexure 5.109: Green bean yields amongst the different climate variability management strategies and historical seasonal forecasts for horticultural dependent farmers in Limpopo, South Africa for the 2014/15 season.



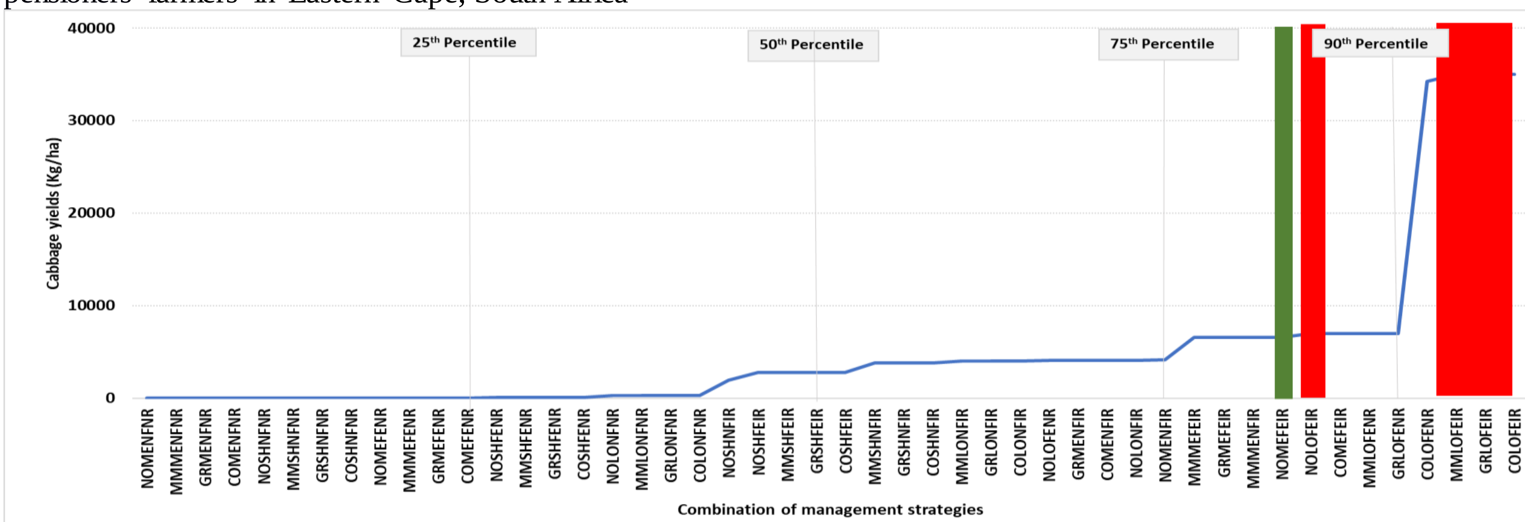
Annexure 5.110: Green bean yields amongst the different climate variability management strategies and historical seasonal forecasts for horticultural dependent farmers in Limpopo, South Africa for the 2015/16 season.



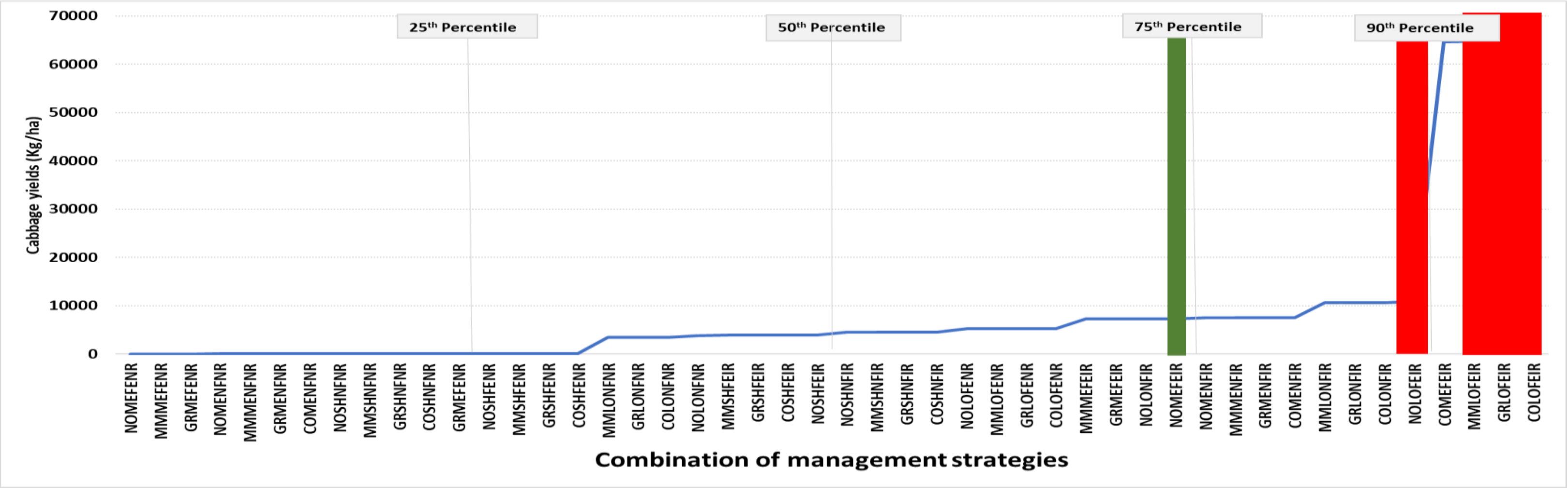
Annexure 5.111: Cabbage yield amongst the different crop management strategies based on station data for the 2011/12 season for enterprising pensioners farmers in Eastern Cape, South Africa.



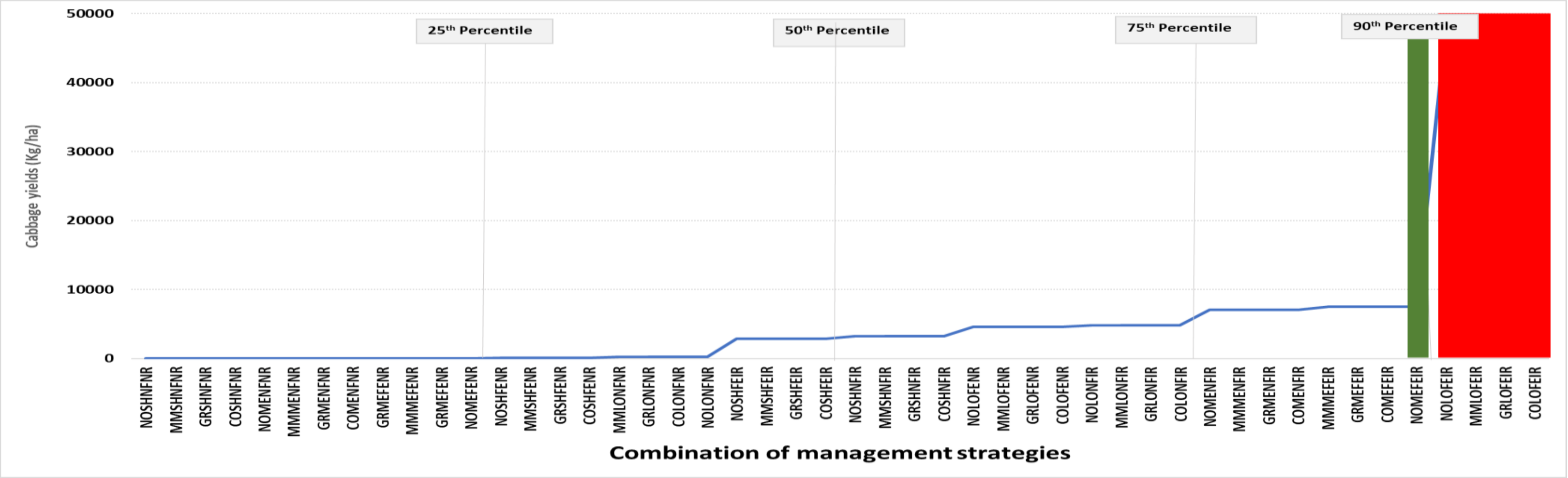
Annexure 5.112: Cabbage yield amongst the different crop management strategies based on station data for the 2012/13 season for enterprising pensioners farmers in Eastern Cape, South Africa



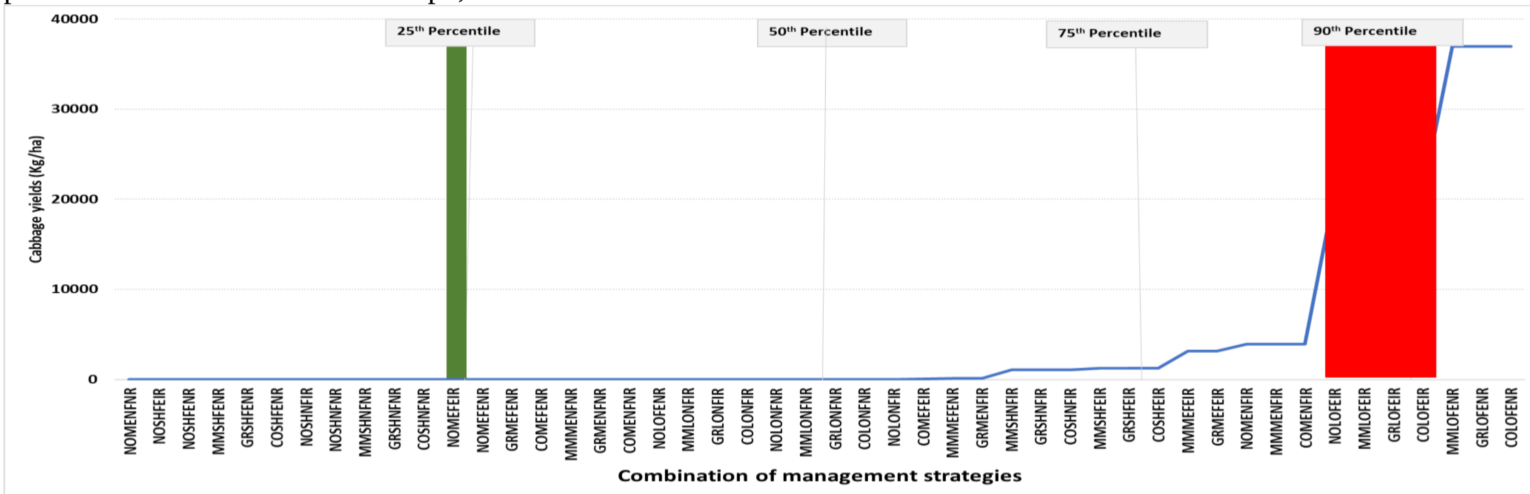
Annexure 5.113: Cabbage yield amongst the different crop management strategies based on station data for the 2013/14 season for enterprising pensioners farmers in Eastern Cape, South Africa



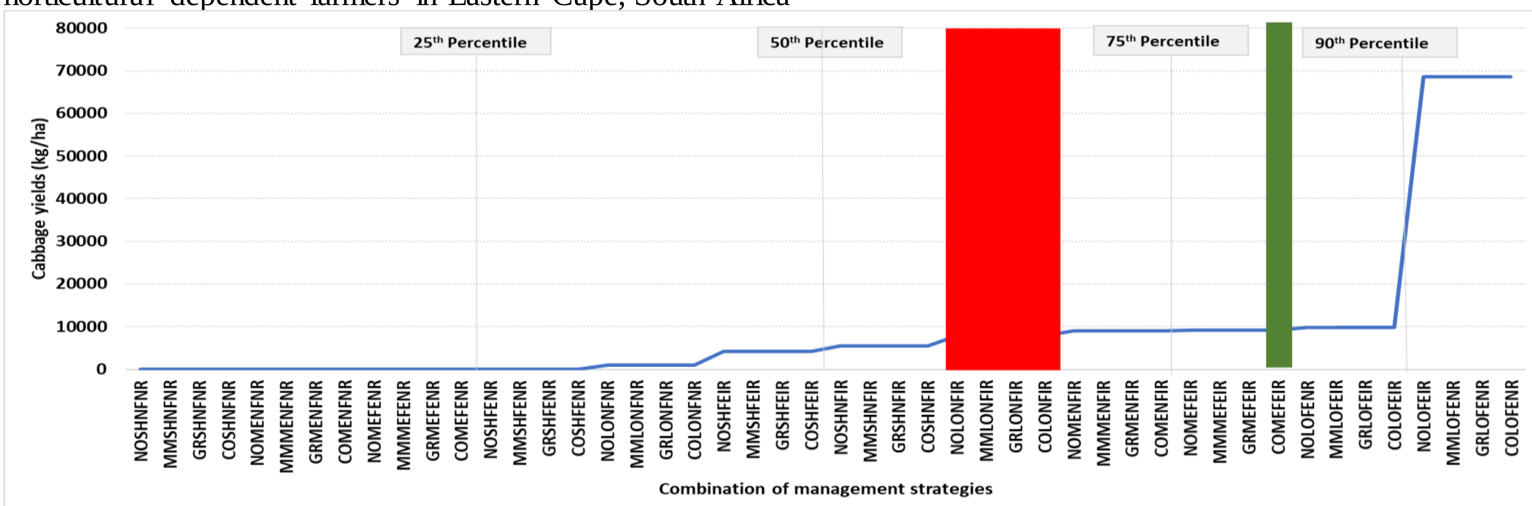
Annexure 5.114: Cabbage yield amongst the different crop management strategies based on station data for the 2014/15 season for enterprising pensioners farmers in Eastern Cape, South Africa



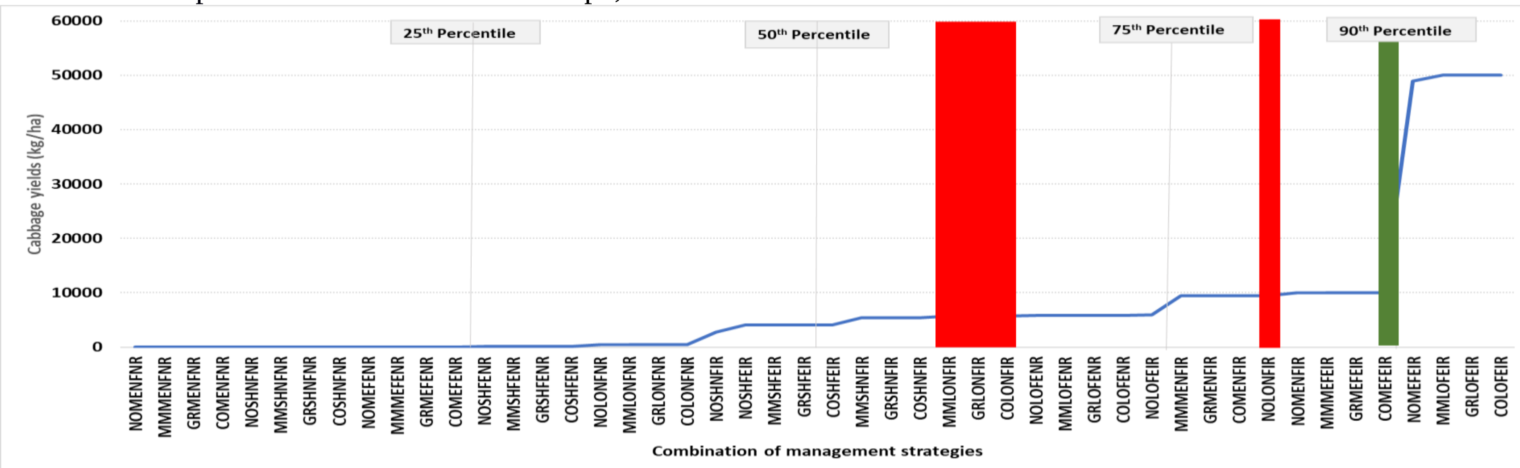
Annexure 5.115: Cabbage yield amongst the different crop management strategies based on station data for the 2015/16 season for enterprising pensioners farmers in Eastern Cape, South Africa



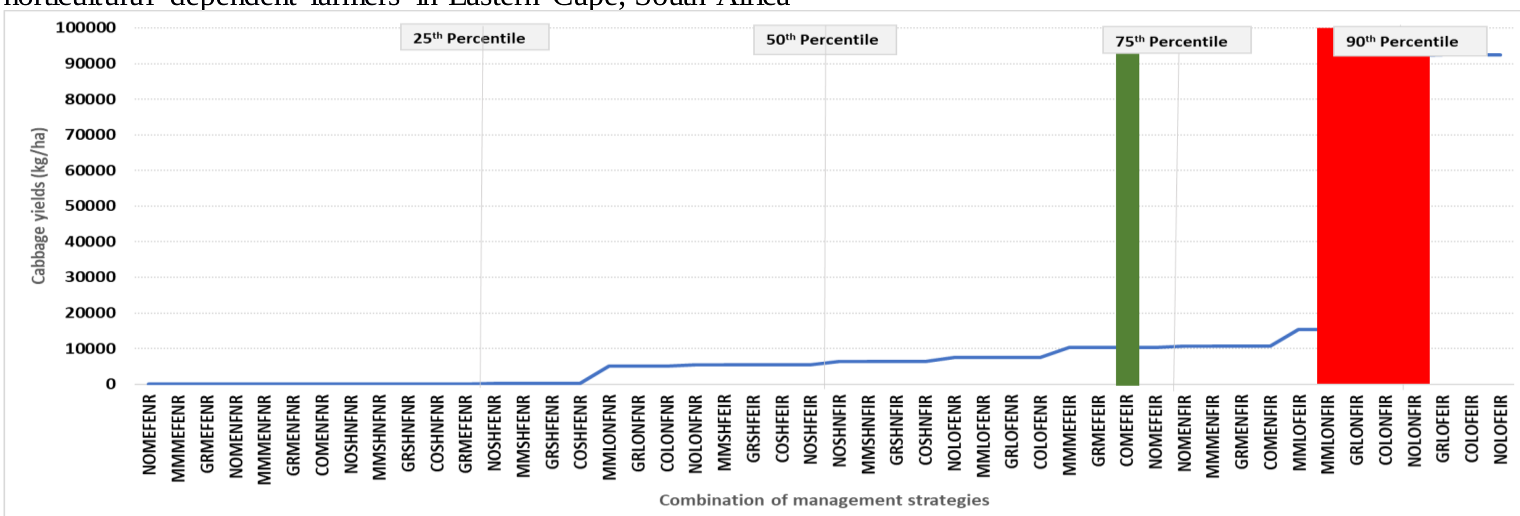
Annexure 5.116: Cabbage yield amongst the different crop management strategies based on station data for the 2011/12 season for horticultural dependent farmers in Eastern Cape, South Africa



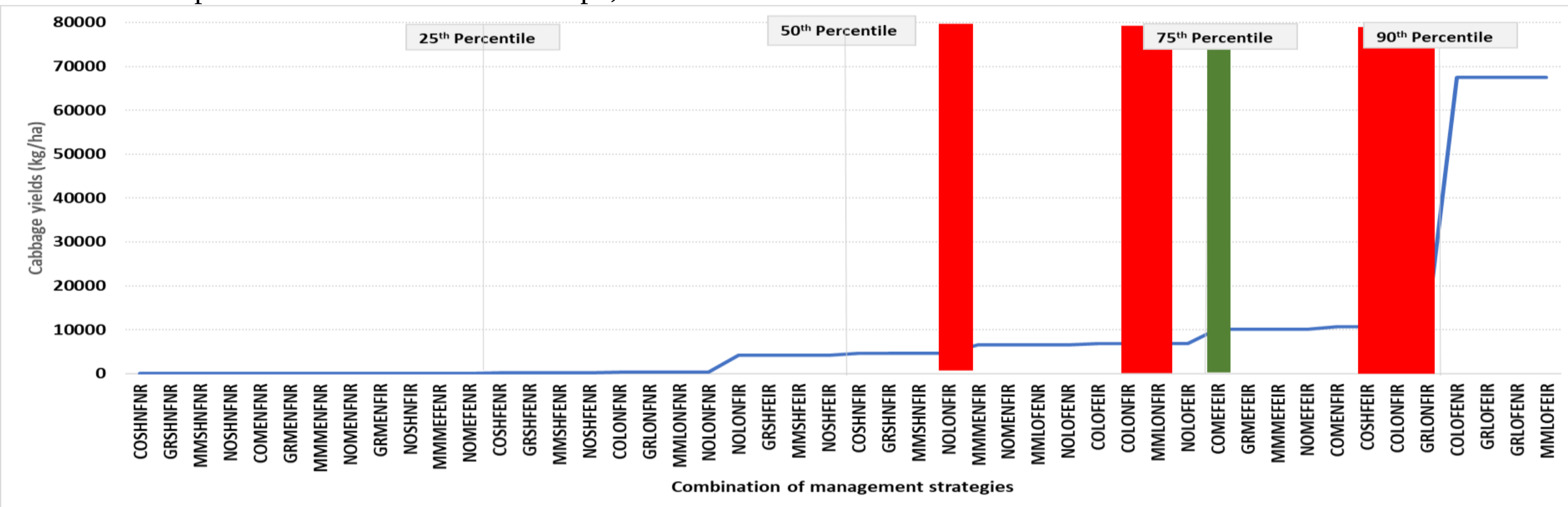
Annexure 5.117: Cabbage yield amongst the different crop management strategies based on station data for the 2012/13 season for horticultural dependent farmers in Eastern Cape, South Africa.



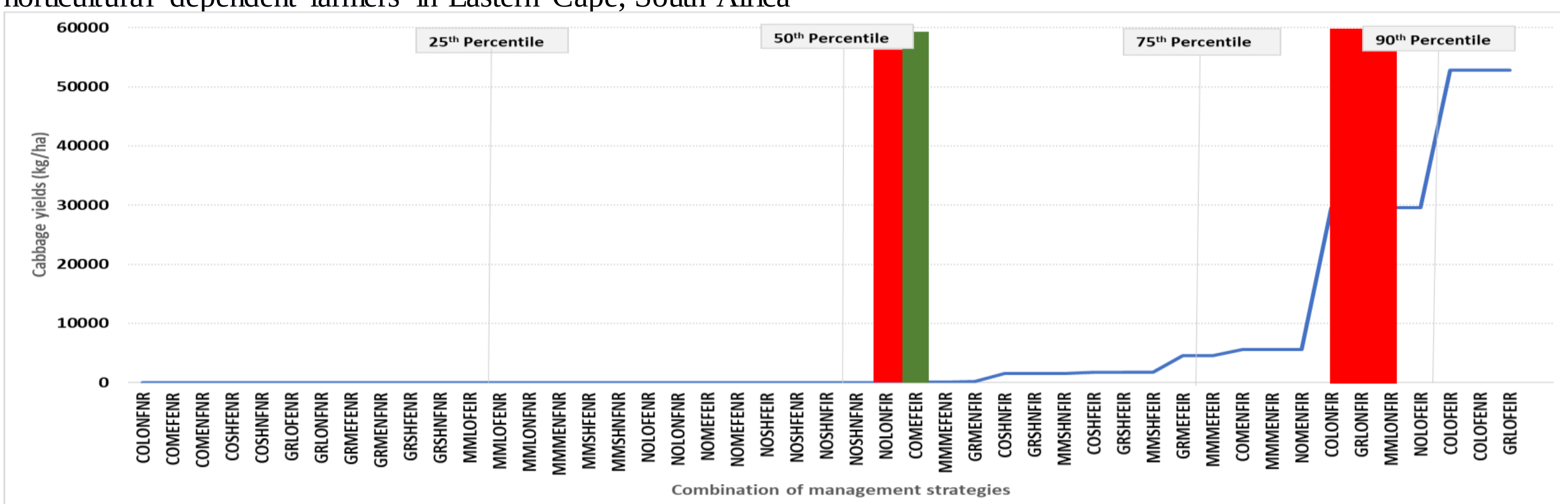
Annexure 5.118: Cabbage yield amongst the different crop management strategies based on station data for the 2013/14 season for horticultural dependent farmers in Eastern Cape, South Africa



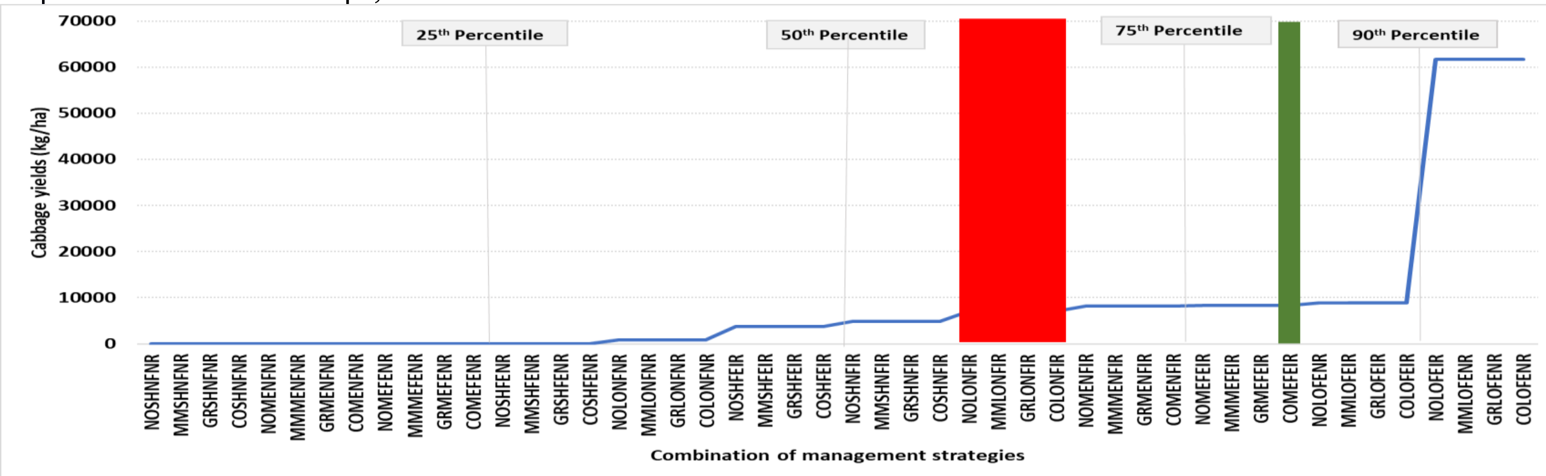
Annexure 5.119: Cabbage yield amongst the different crop management strategies based on station data for the 2014/15 season for horticultural dependent farmers in Eastern Cape, South Africa.



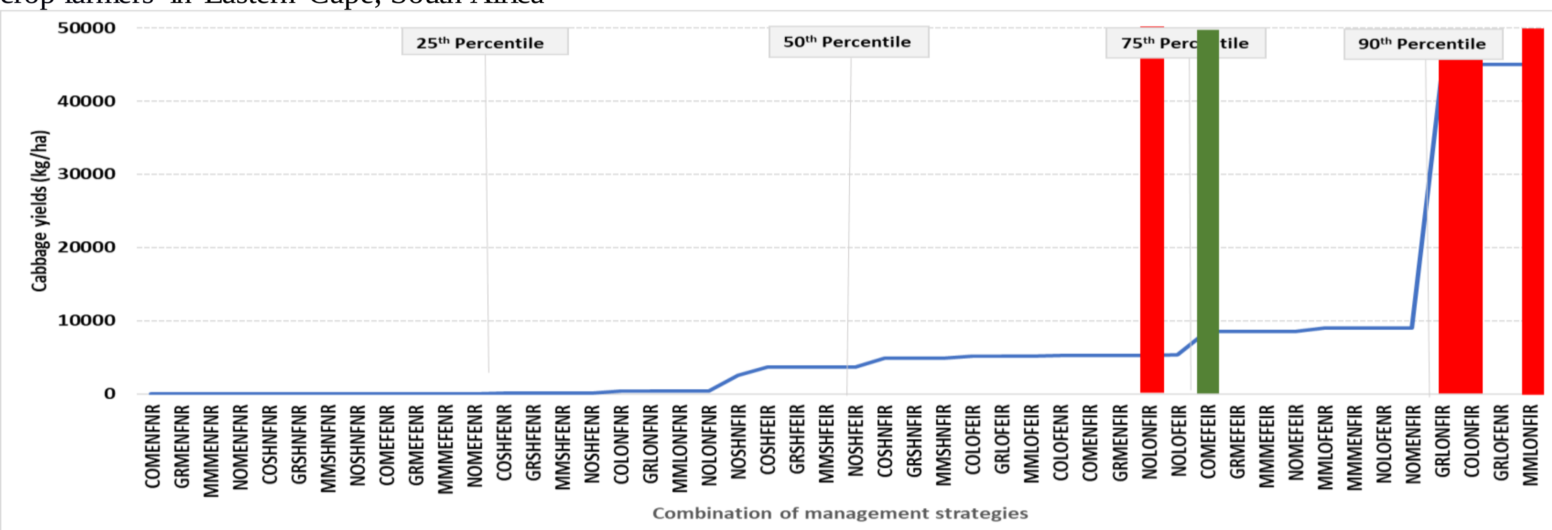
Annexure 5.120: Cabbage yield amongst the different crop management strategies based on station data for the 2015/16 season for horticultural dependent farmers in Eastern Cape, South Africa



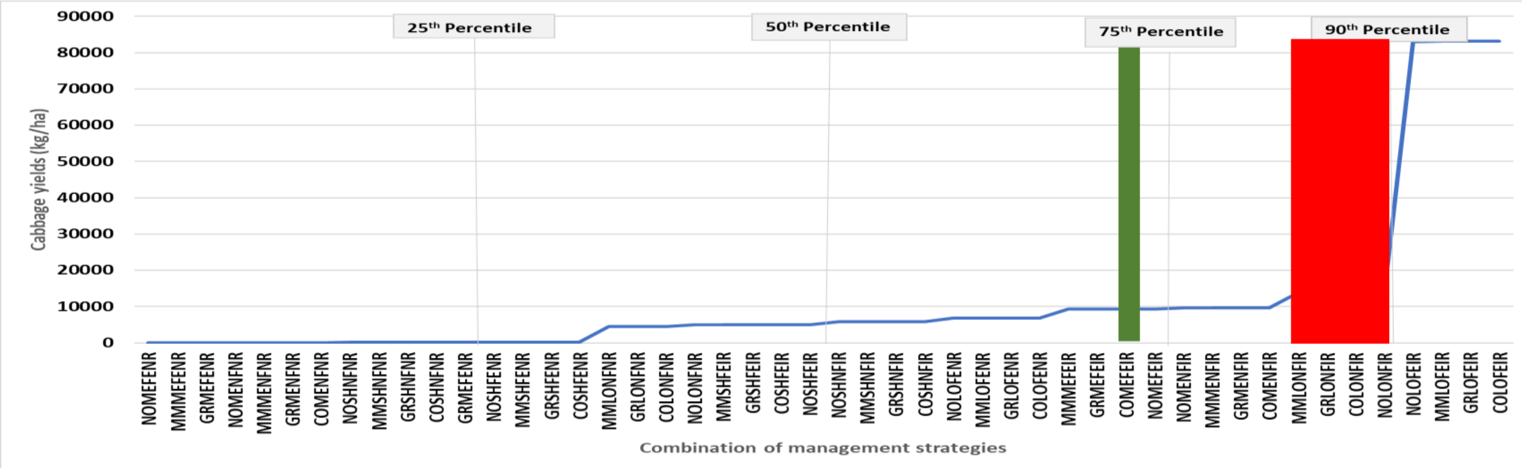
Annexure 5.121: Cabbage yield amongst the different crop management strategies based on station data for the 2011/12 season for cooperative crop farmers in Eastern Cape, South Africa



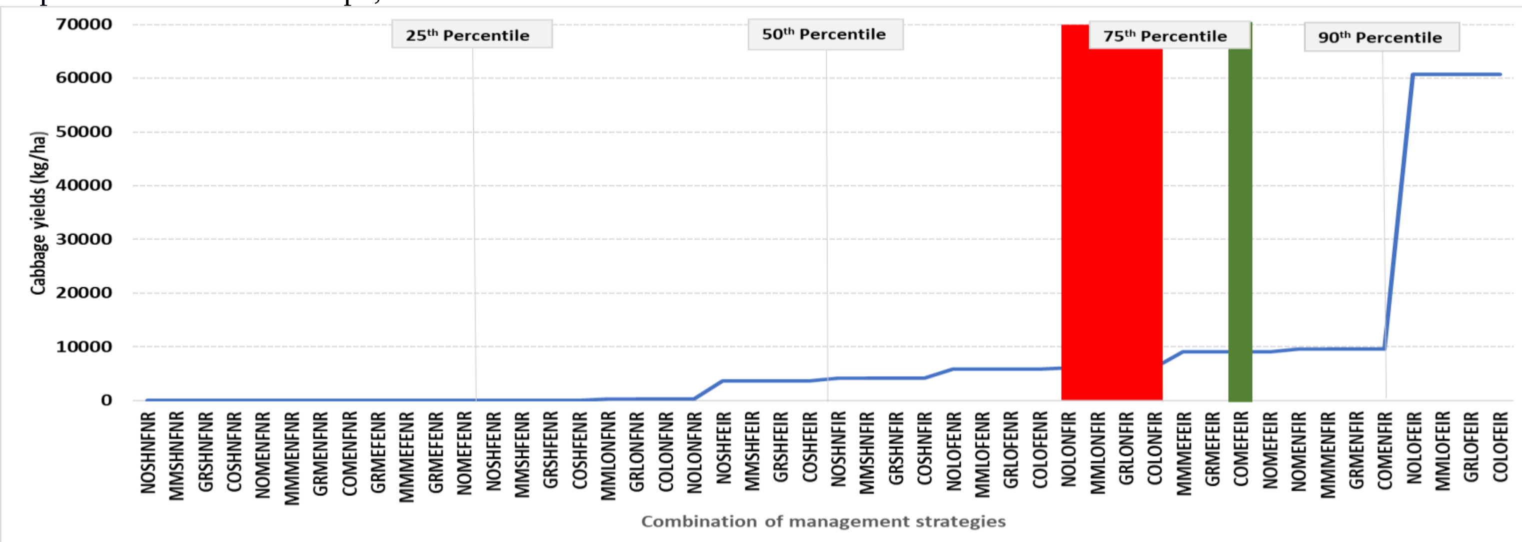
Annexure 5.122: Cabbage yield amongst the different crop management strategies based on station data for the 2012/13 season for cooperative crop farmers in Eastern Cape, South Africa



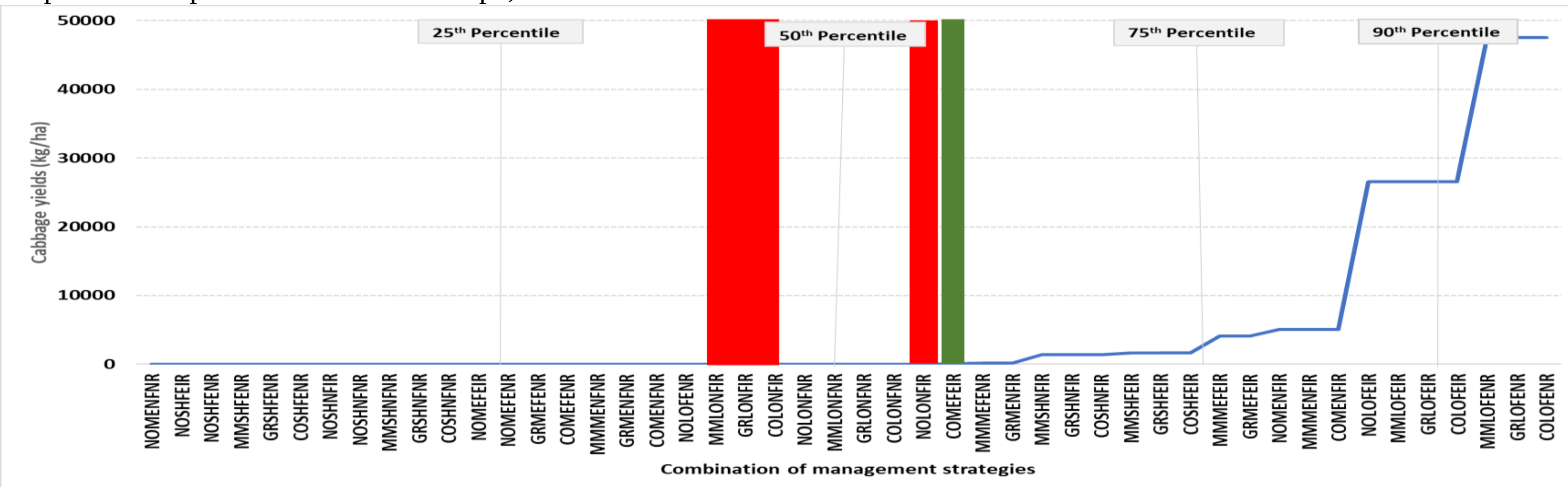
Annexure 5.123: Cabbage yield amongst the different crop management strategies based on station data for the 2013/14 season for cooperative crop farmers in Eastern Cape, South Africa



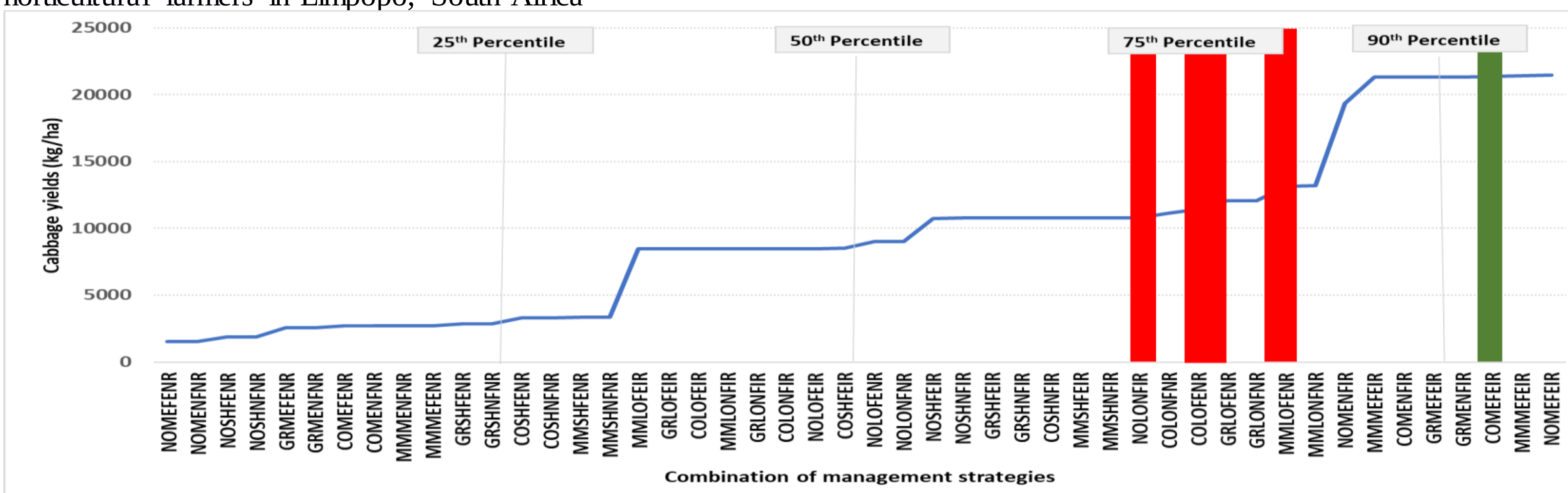
Annexure 5.124: Cabbage yield amongst the different crop management strategies based on station data for the 2014/15 season for cooperative crop farmers in Eastern Cape, South Africa



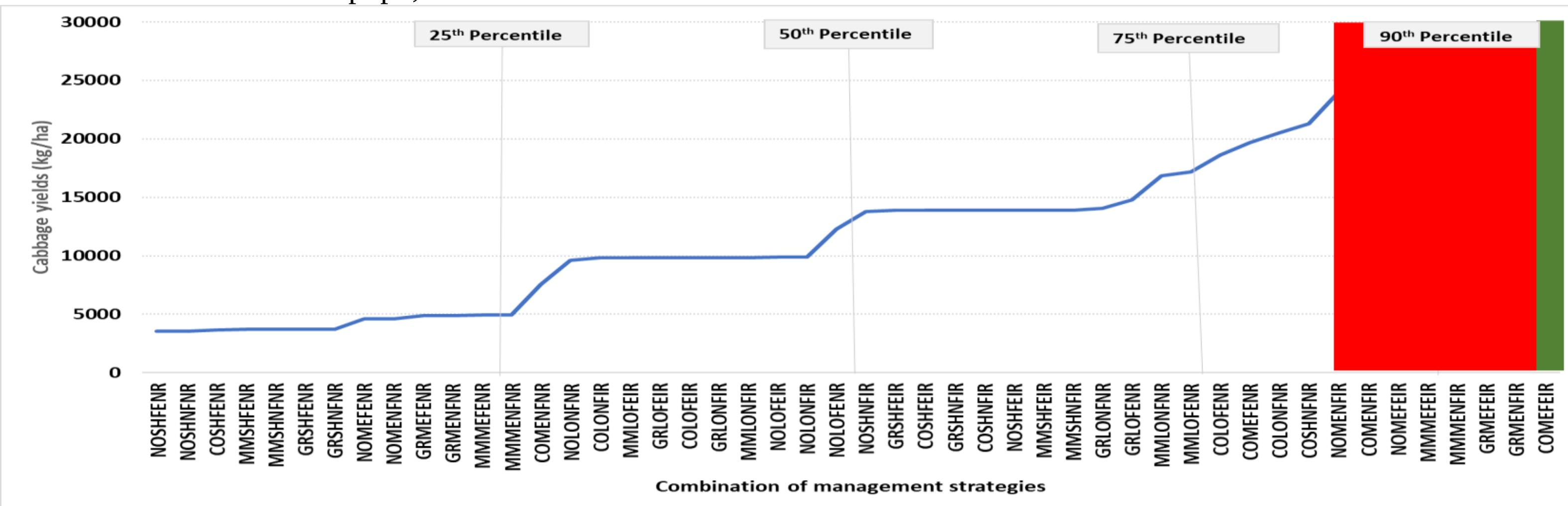
Annexure 5.125: Cabbage yield variation amongst the different crop management strategies based on station data for the 2015/16 season for cooperative crop farmers in Eastern Cape, South Africa



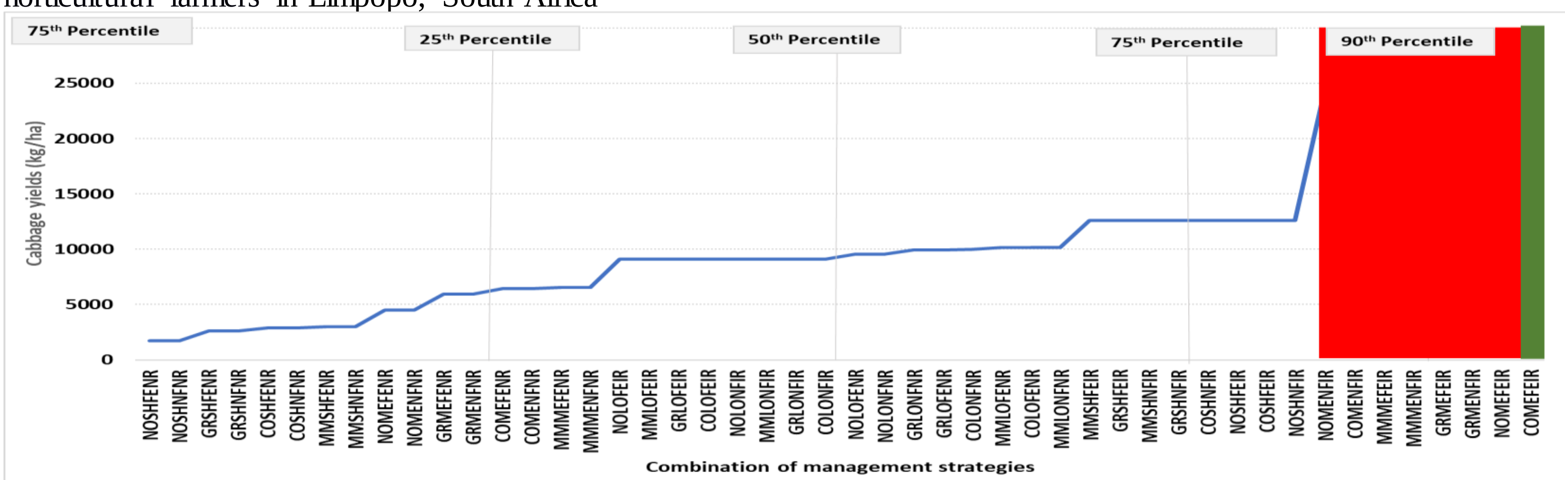
Annexure 5.126: Cabbage yield variation amongst the different crop management strategies based on station data for the 2011/12 season for horticultural farmers in Limpopo, South Africa



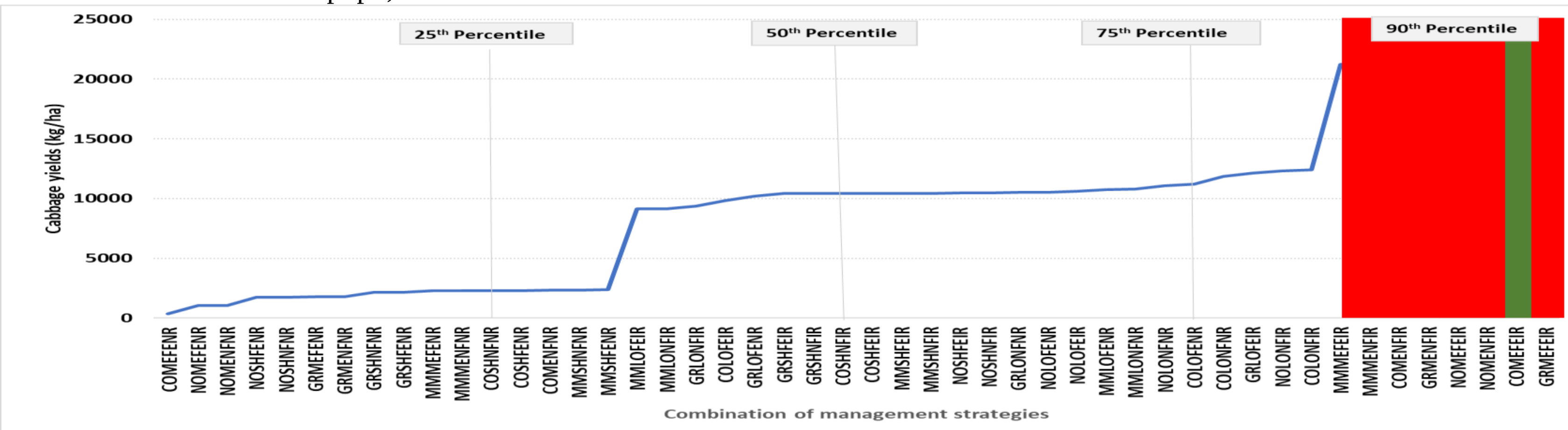
Annexure 5.127: Cabbage yield variation amongst the different crop management strategies based on station data for the 2012/13 season for horticultural farmers in Limpopo, South Africa.



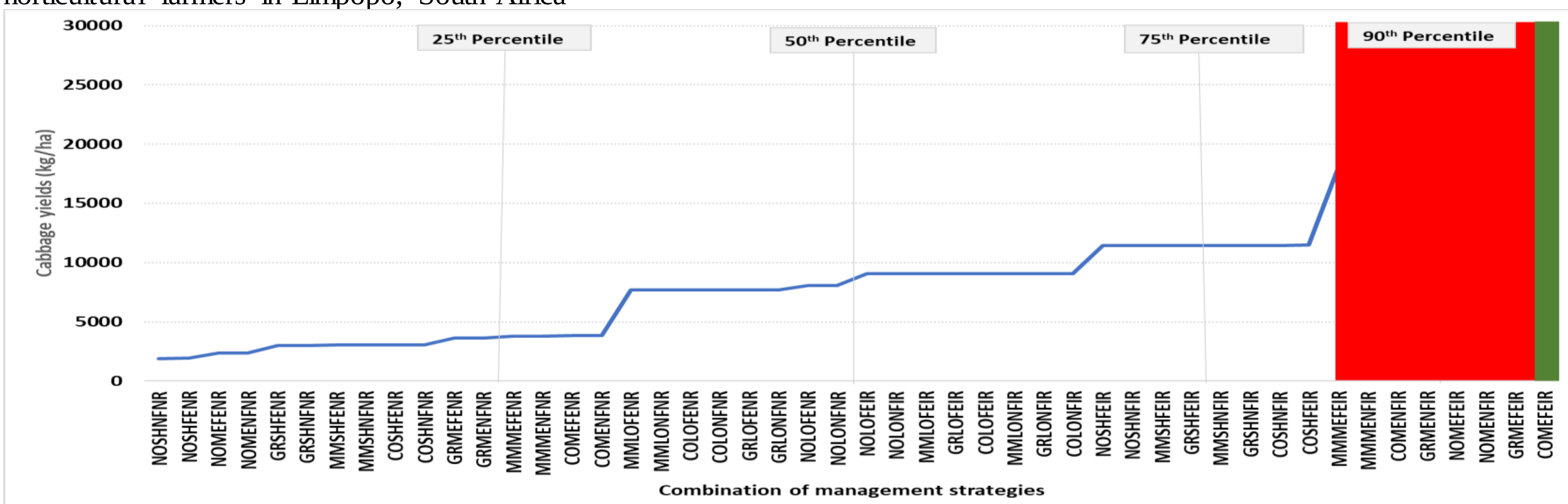
Annexure 5.128: Cabbage yield variation amongst the different crop management strategies based on station data for the 2013/14 season for horticultural farmers in Limpopo, South Africa



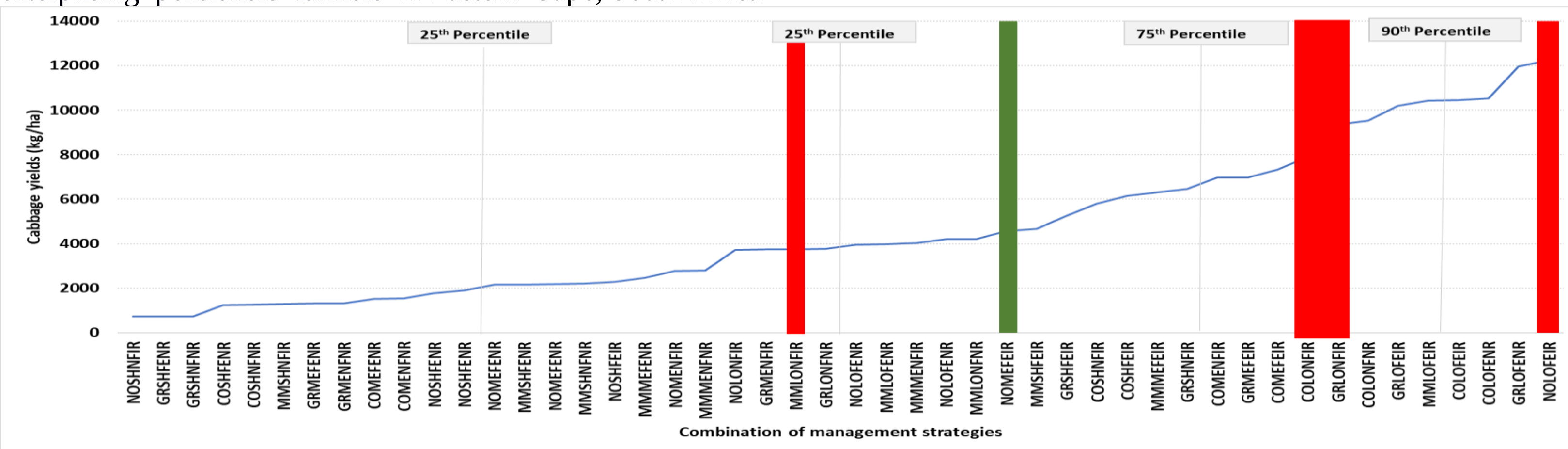
Annexure 5.129: Cabbage yield variation amongst the different crop management strategies based on station data for the 2014/15 season for horticultural farmers in Limpopo, South Africa



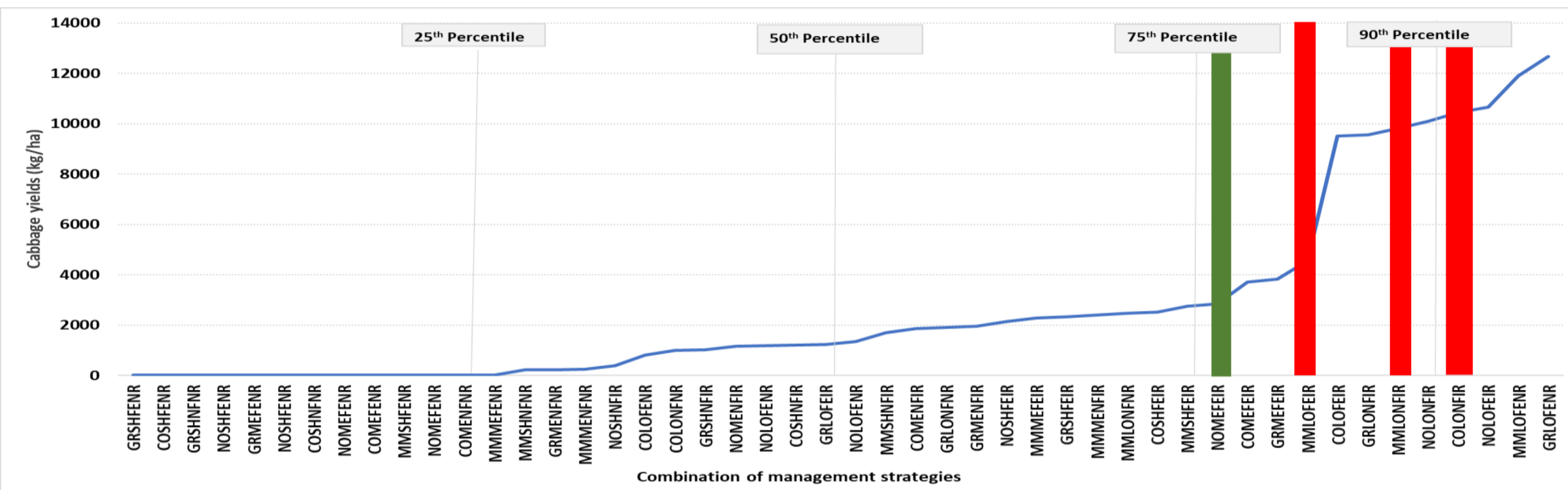
Annexure 5.130: Cabbage yield variation amongst the different crop management strategies based on station data for the 2015/16 season for horticultural farmers in Limpopo, South Africa



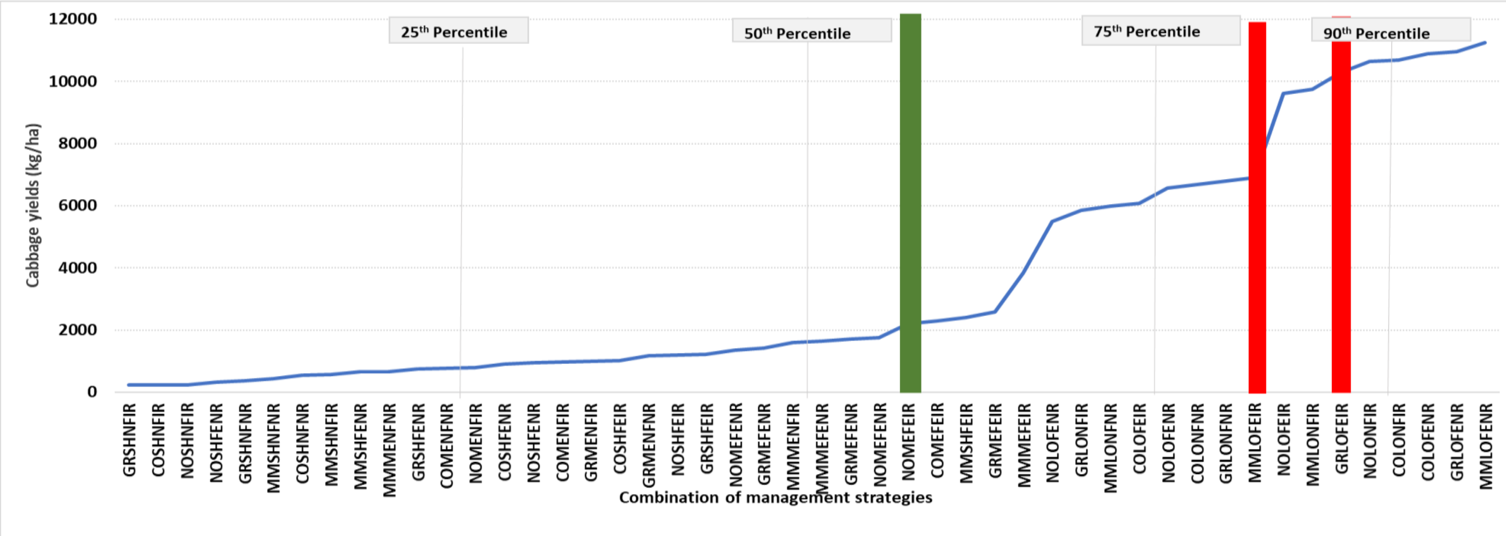
Annexure 5.131: Tomato yield variation amongst the different crop management strategies based on station data for the 2011/12 season for enterprising pensioners farmers in Eastern Cape, South Africa



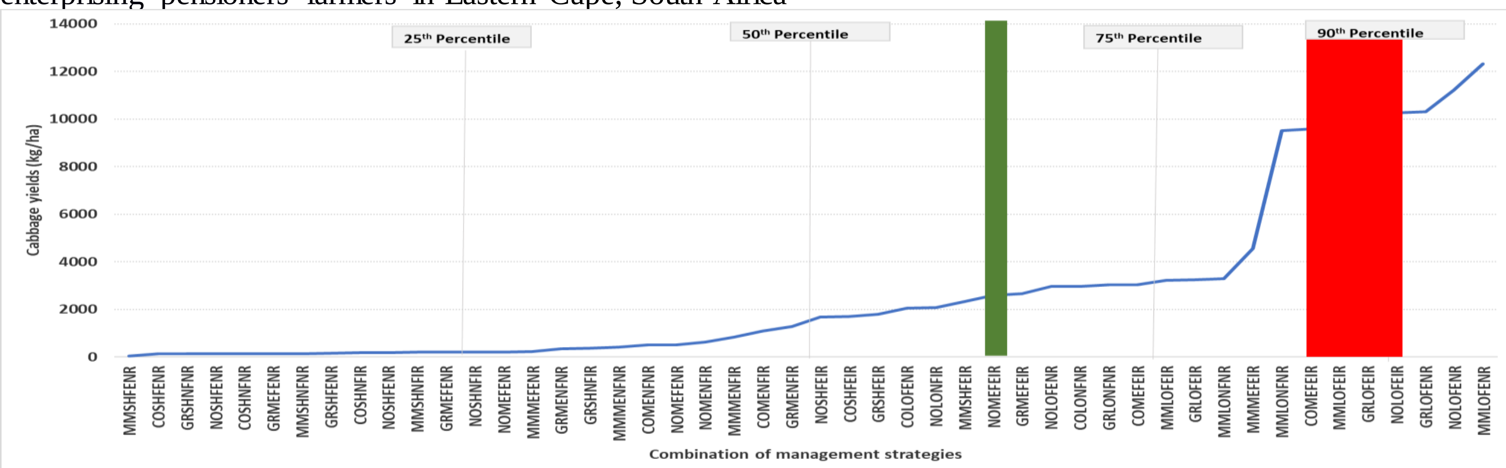
Annexure 5.132: Tomato yield variation amongst the different crop management strategies based on station data for the 2012/13 season for enterprising pensioners farmers in Eastern Cape, South Africa



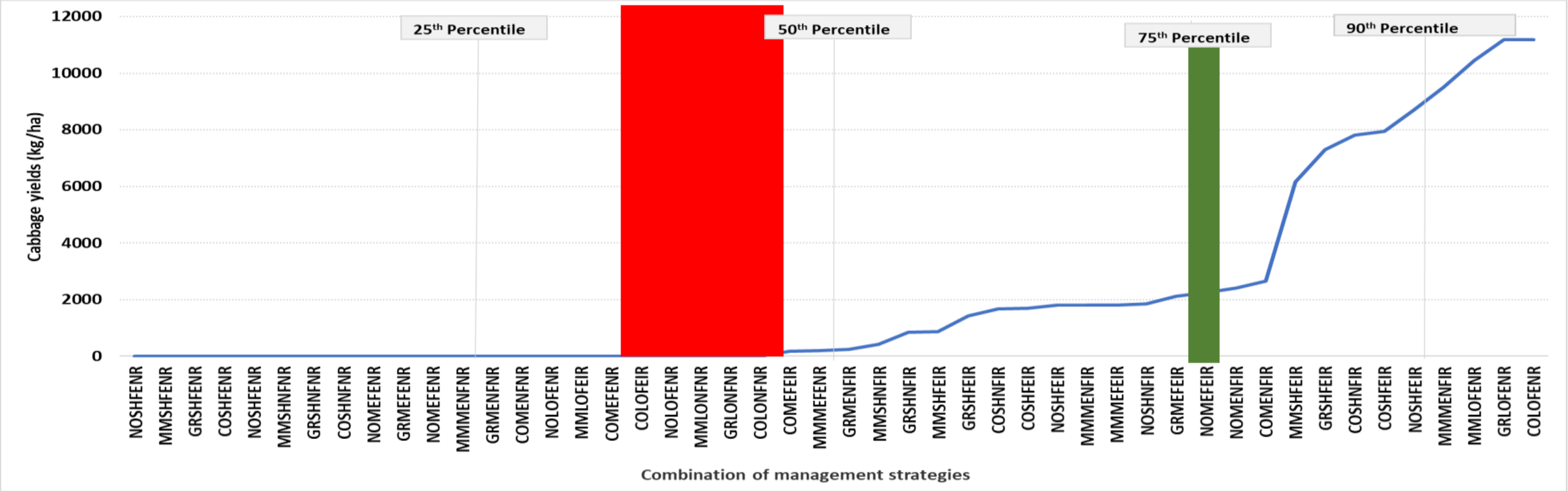
Annexure 5.133: Tomato yield variation amongst the different crop management strategies based on station data for the 2013/14 season for enterprising pensioners farmers in Eastern Cape, South Africa



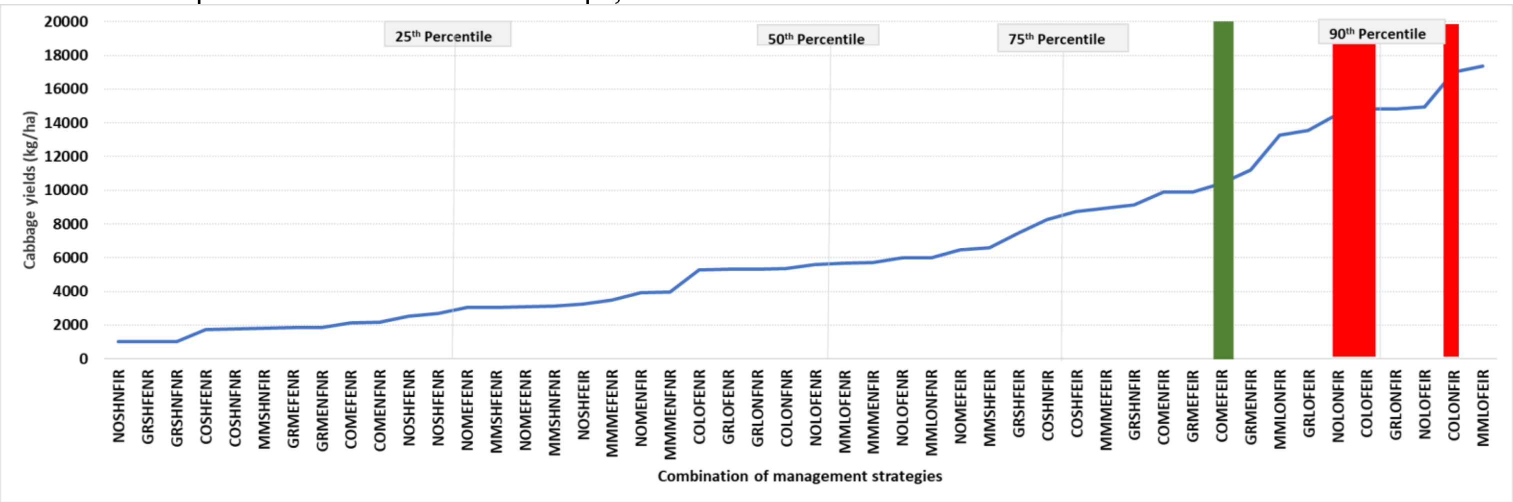
Annexure 5.134: Tomato yield variation amongst the different crop management strategies based on station data for the 2014/15 season for enterprising pensioners farmers in Eastern Cape, South Africa



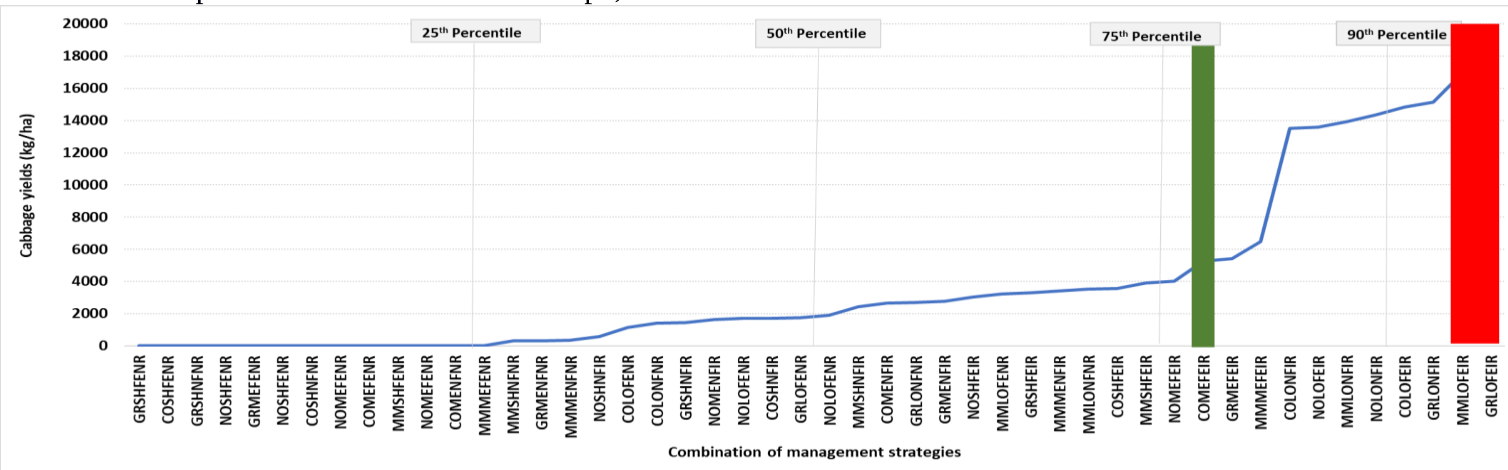
Annexure 5.135: Tomato yield variation amongst the different crop management strategies based on station data for the 2015/16 season for enterprising pensioners farmers in Eastern Cape, South Africa



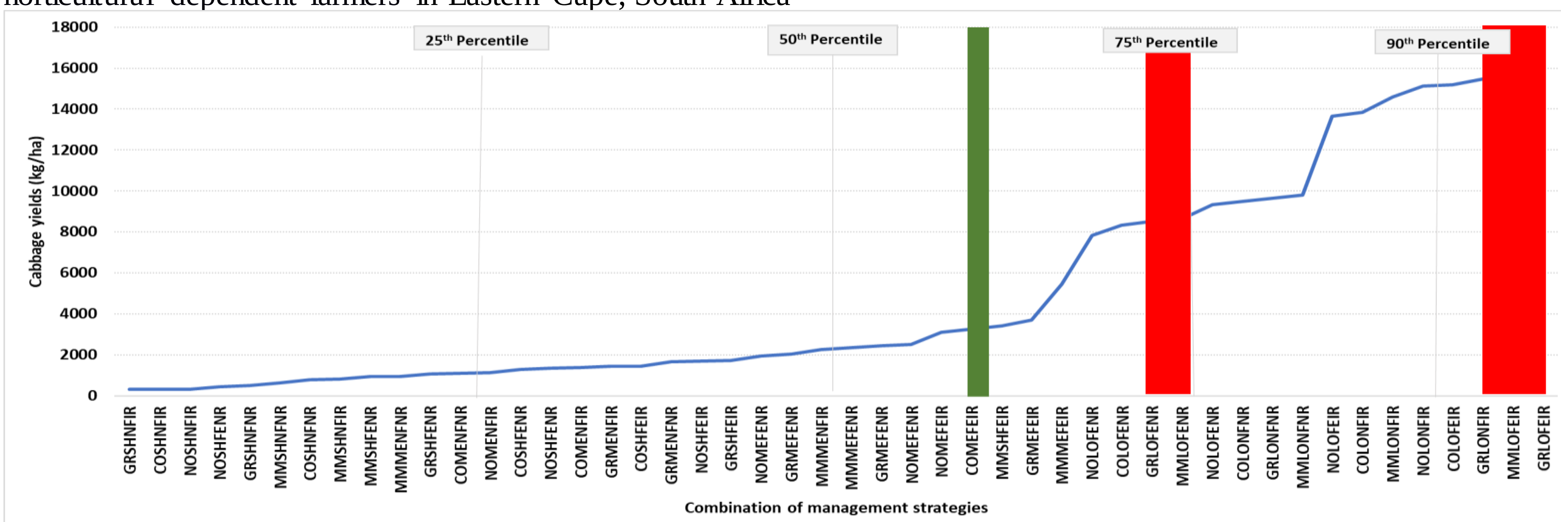
Annexure 5.136: Tomato yield variation amongst the different crop management strategies based on station data for the 2011/12 season for horticultural dependent farmers in Eastern Cape, South Africa



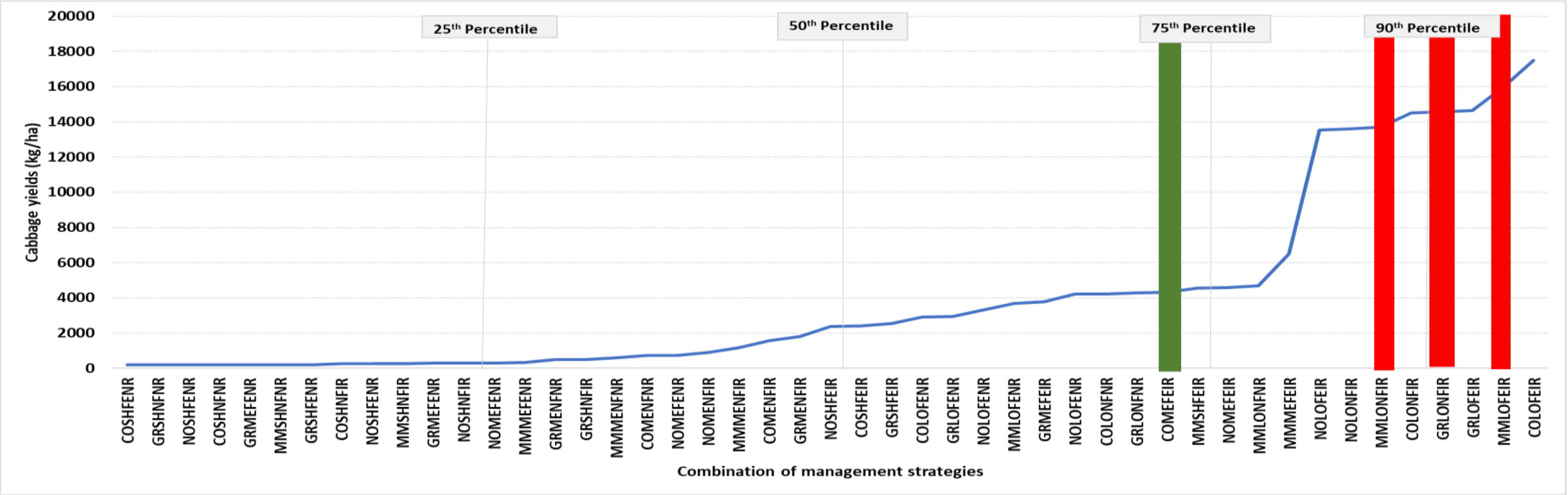
Annexure 5.137: Tomato yield variation amongst the different crop management strategies based on station data for the 2012/13 season for horticultural dependent farmers in Eastern Cape, South Africa



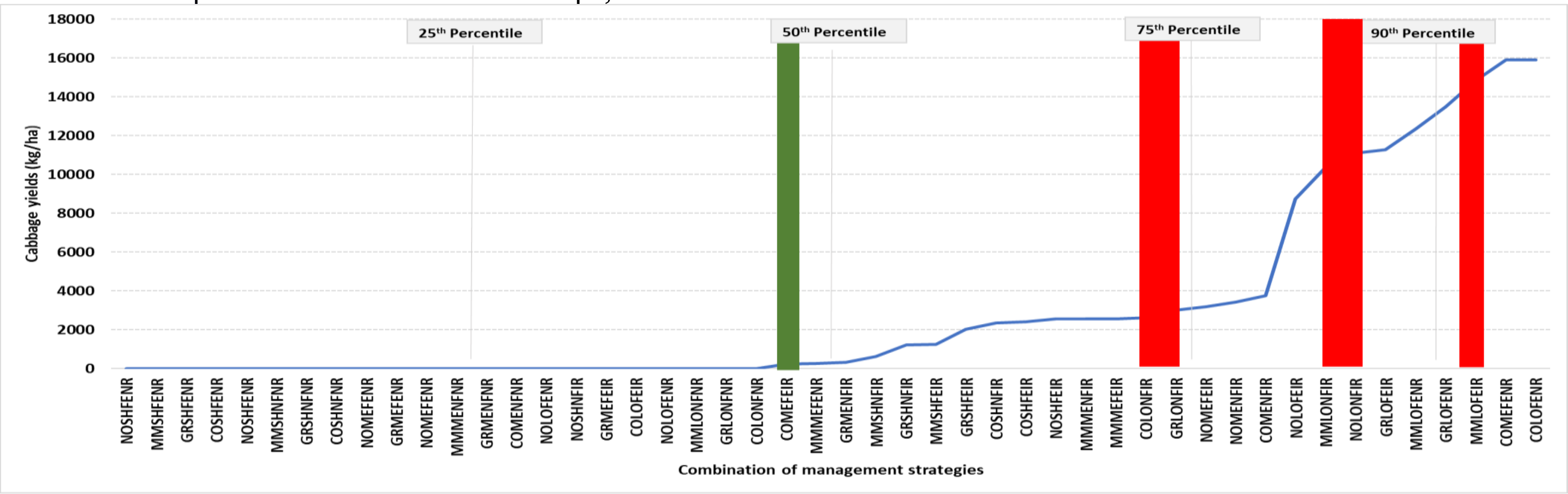
Annexure 5.138: Tomato yield variation amongst the different crop management strategies based on station data for the 2013/14 season for horticultural dependent farmers in Eastern Cape, South Africa



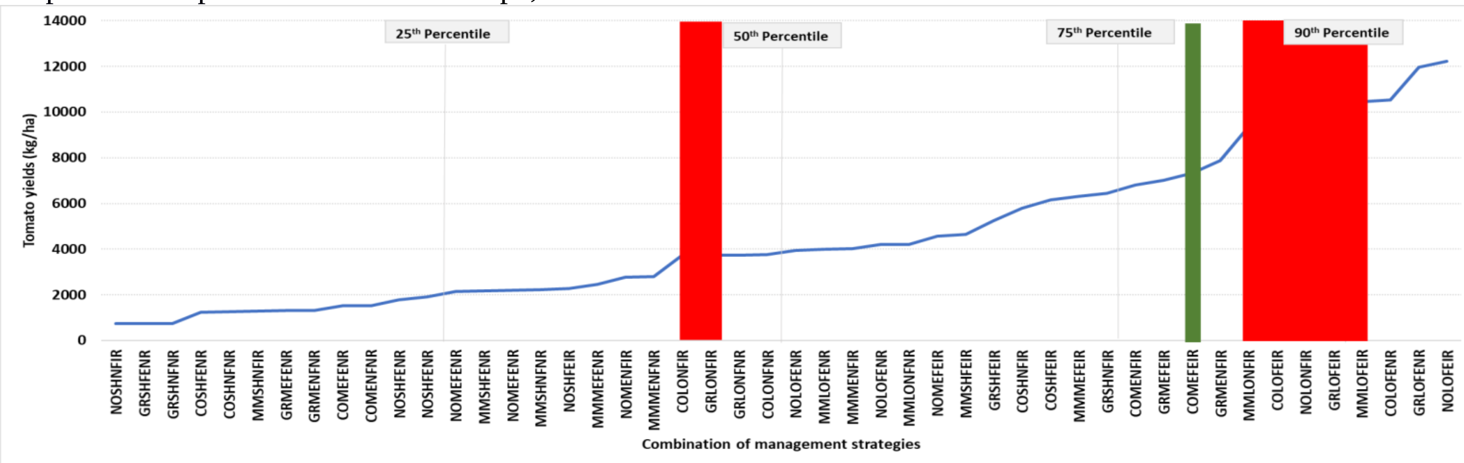
Annexure 5.139: Tomato yield variation amongst the different crop management strategies based on station data for the 2014/15 season for horticultural dependent farmers in Eastern Cape, South Africa



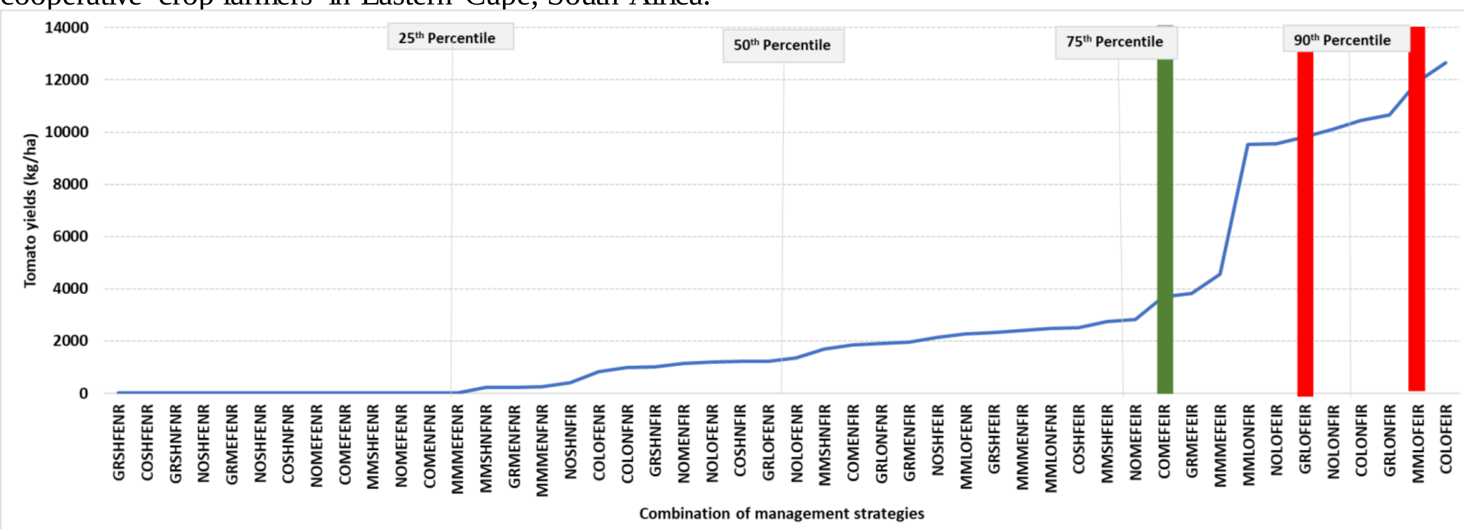
Annexure 5.140: Tomato yield variation amongst the different crop management strategies based on station data for the 2015/16 season for horticultural dependent farmers in Eastern Cape, South Africa.



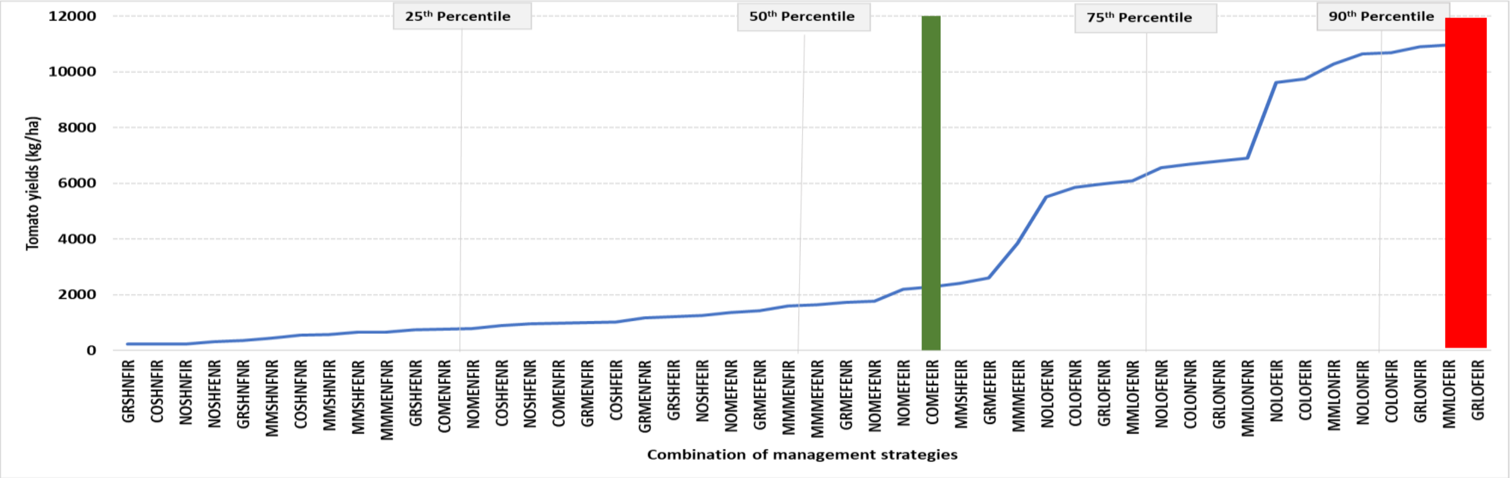
Annexure 5.141: Tomato yield variation amongst the different crop management strategies based on station data for the 2011/12 season for cooperative crop farmers in Eastern Cape, South Africa.



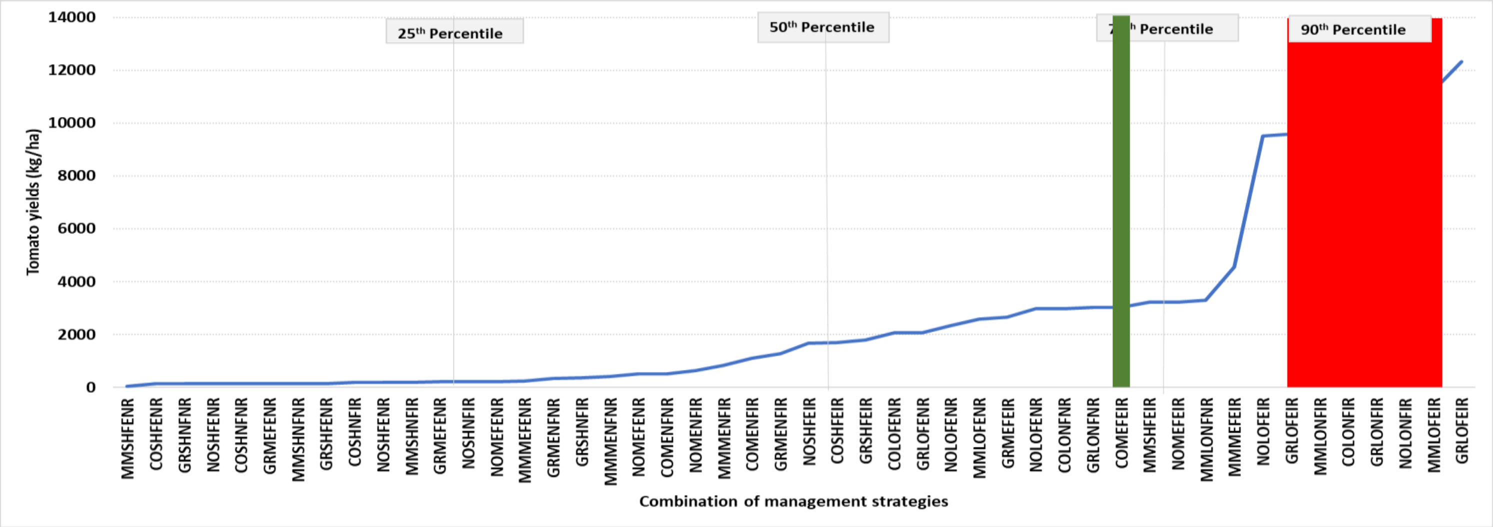
Annexure 5.142: Tomato yield variation amongst the different crop management strategies based on station data for the 2012/13 season for cooperative crop farmers in Eastern Cape, South Africa.



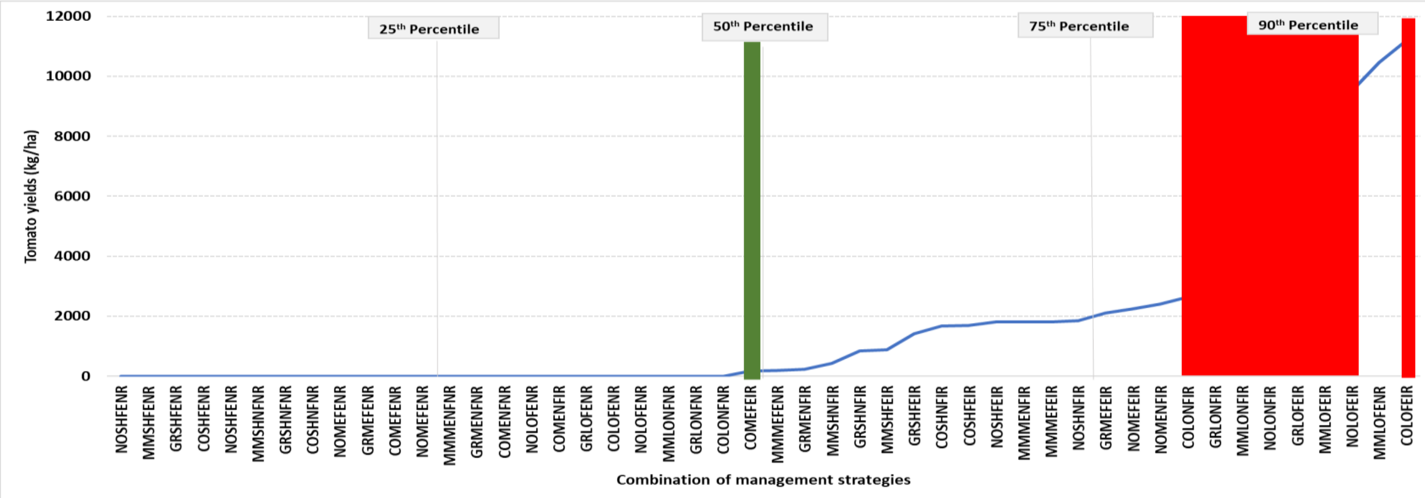
Annexure 5.143: Tomato yield variation amongst the different crop management strategies based on station data for the 2013/14 season for cooperative crop farmers in Eastern Cape, South Africa.



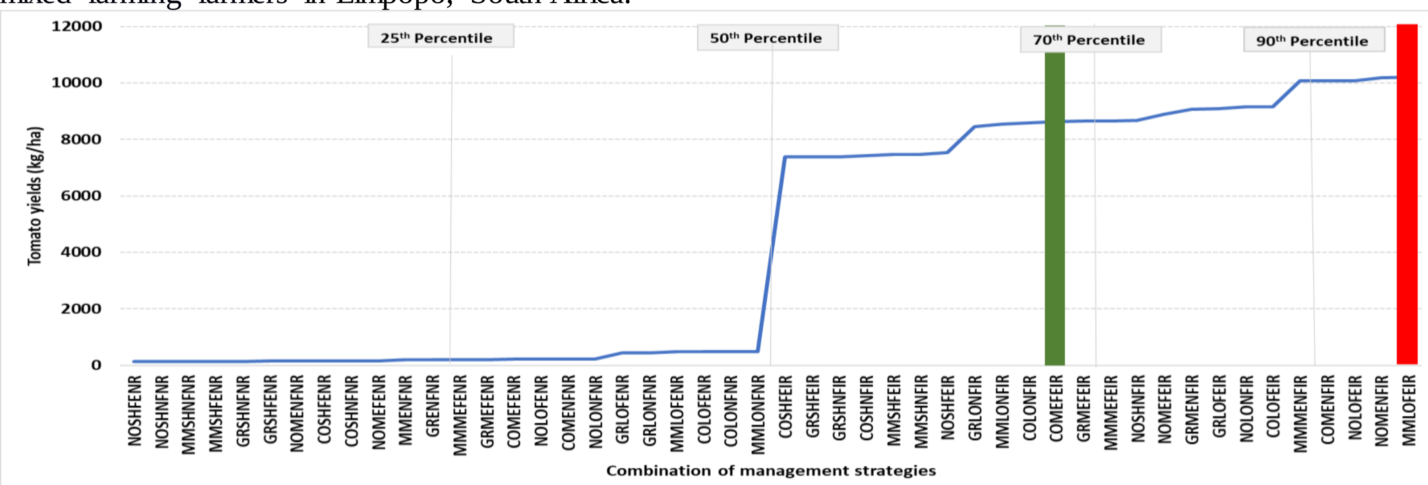
Annexure 5.144: Tomato yield variation amongst the different crop management strategies based on station data for the 2014/15 season for cooperative crop farmers in Eastern Cape, South Africa.



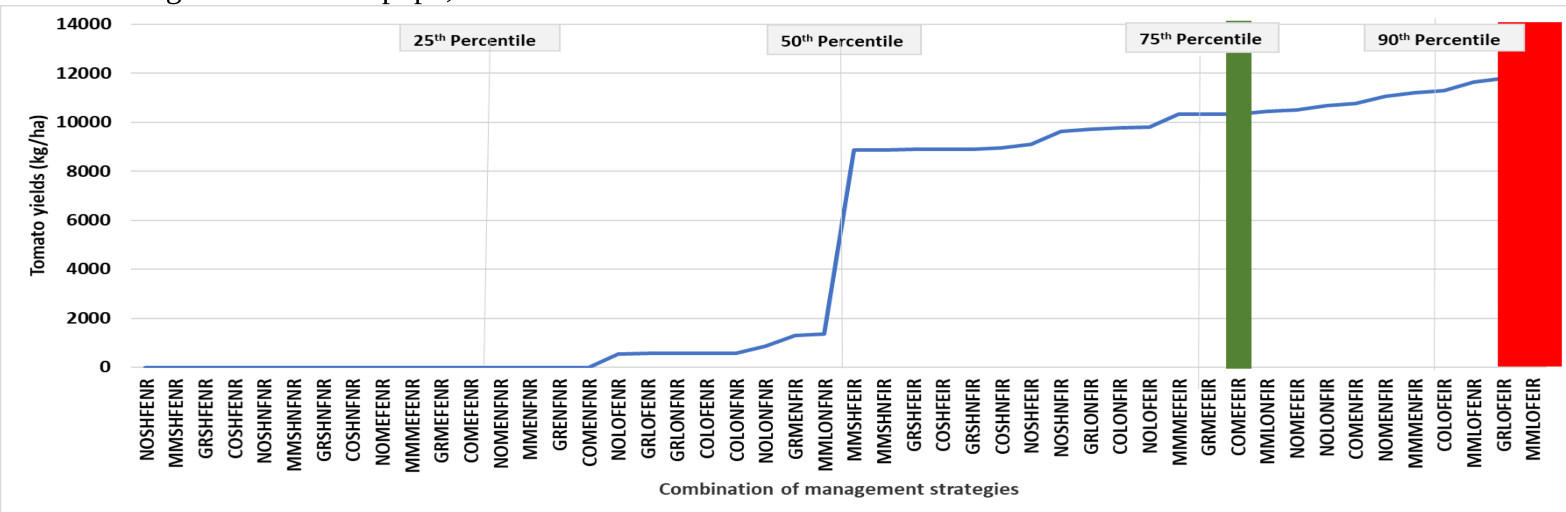
Annexure 5.145: Tomato yield variation amongst the different crop management strategies based on station data for the 2015/16 season for cooperative crop farmers in Eastern Cape, South Africa.



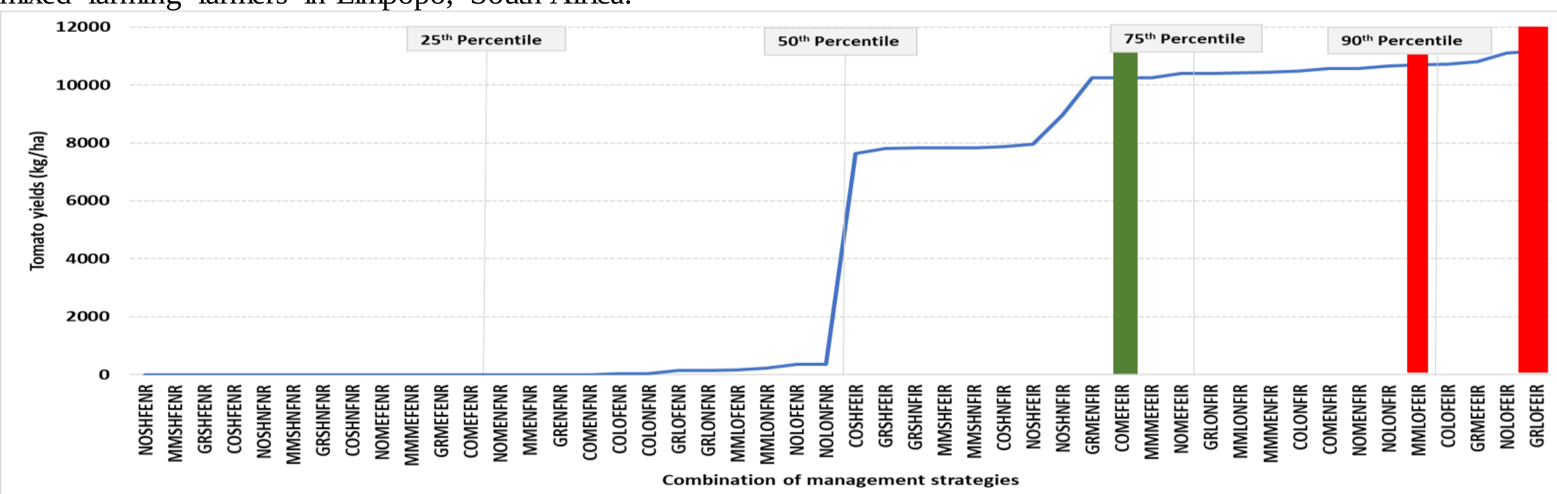
Annexure 5.146: Tomato yield variation amongst the different crop management strategies based on station data for the 2011/12 season for mixed farming farmers in Limpopo, South Africa.



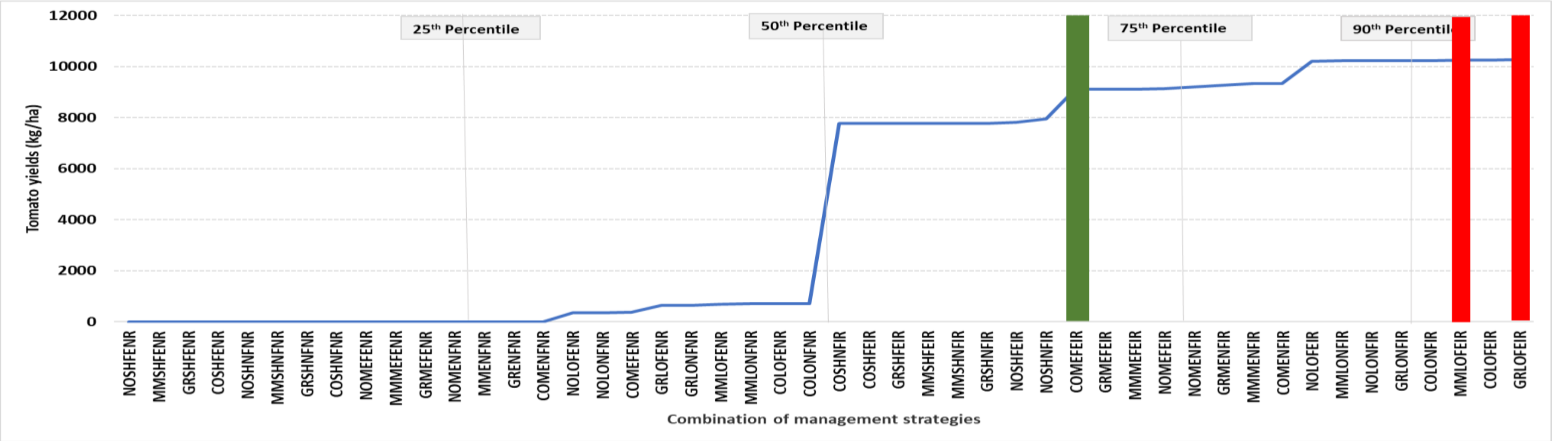
Annexure 5.147: Tomato yield variation amongst the different crop management strategies based on station data for the 2012/13 season for mixed farming farmers in Limpopo, South Africa.



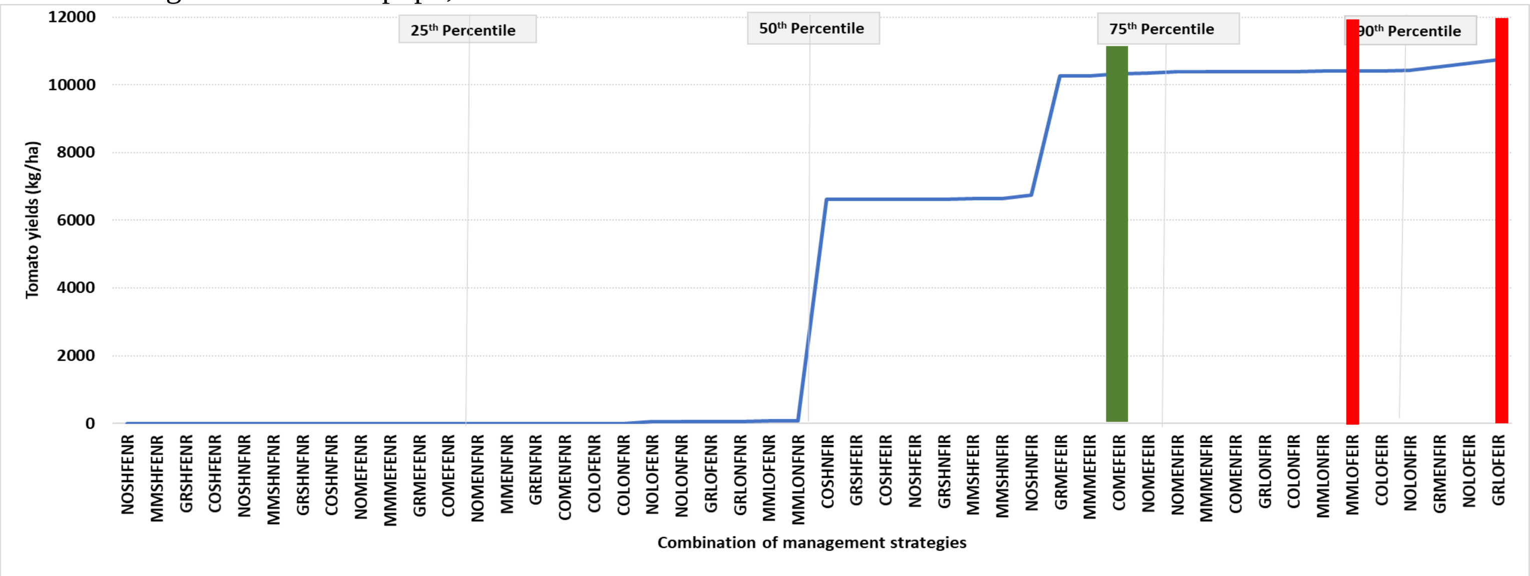
Annexure 5.148: Tomato yield variation amongst the different crop management strategies based on station data for the 2013/14 season for mixed farming farmers in Limpopo, South Africa.



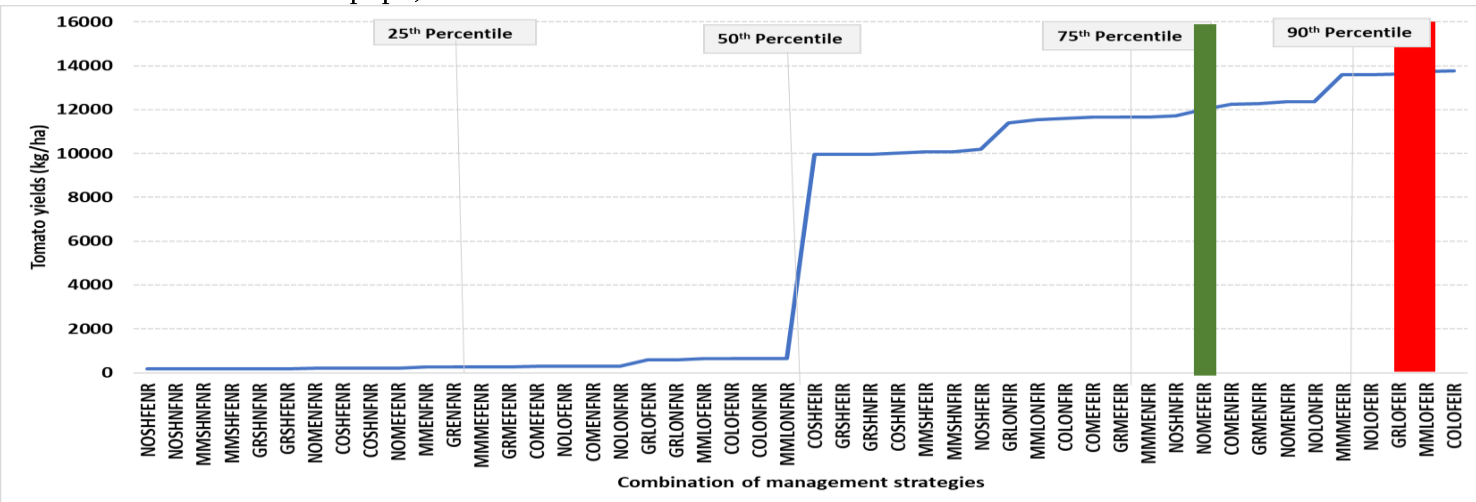
Annexure 5.149: Tomato yield variation amongst the different crop management strategies based on station data for the 2014/15 season for mixed farming farmers in Limpopo, South Africa.



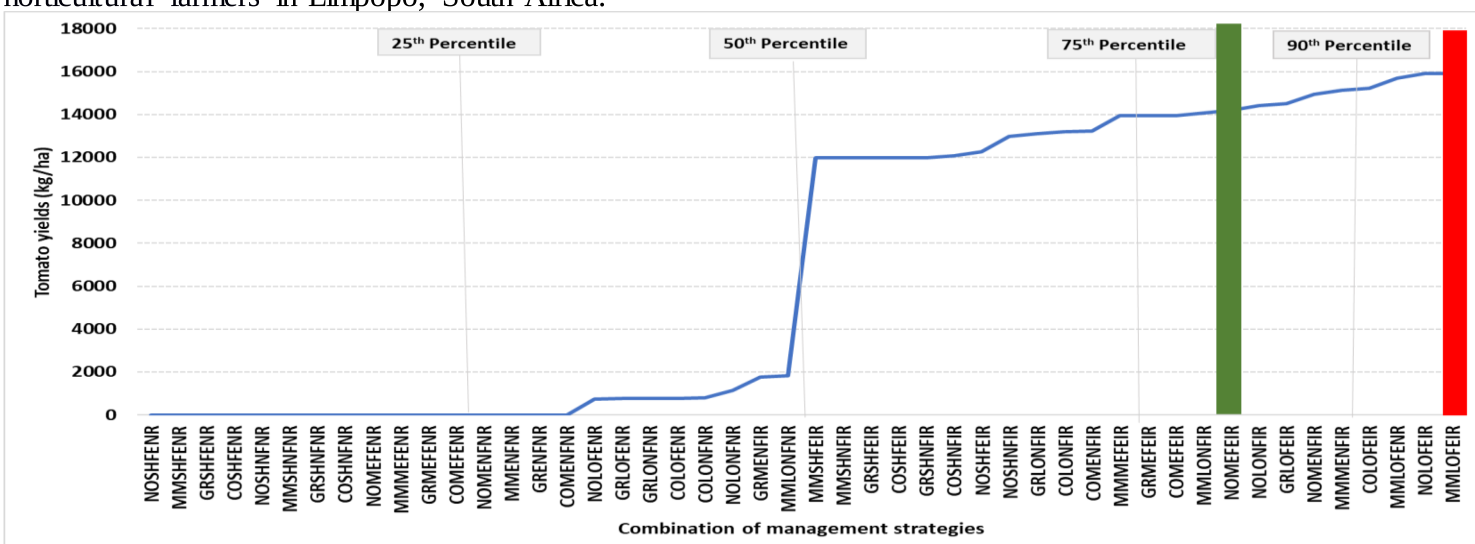
Annexure 5.150: Tomato yield variation amongst the different crop management strategies based on station data for the 2015/16 season for mixed farming farmers in Limpopo, South Africa.



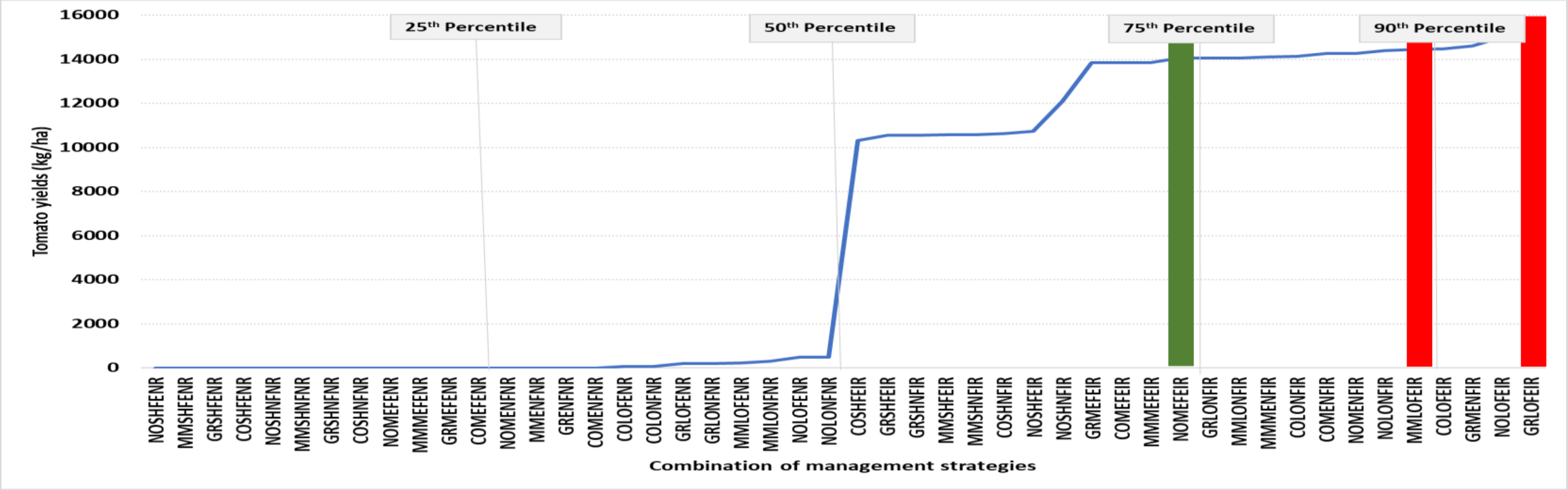
Annexure 5.151: Tomato yield variation amongst the different crop management strategies based on station data for the 2011/12 season for horticultural farmers in Limpopo, South Africa.



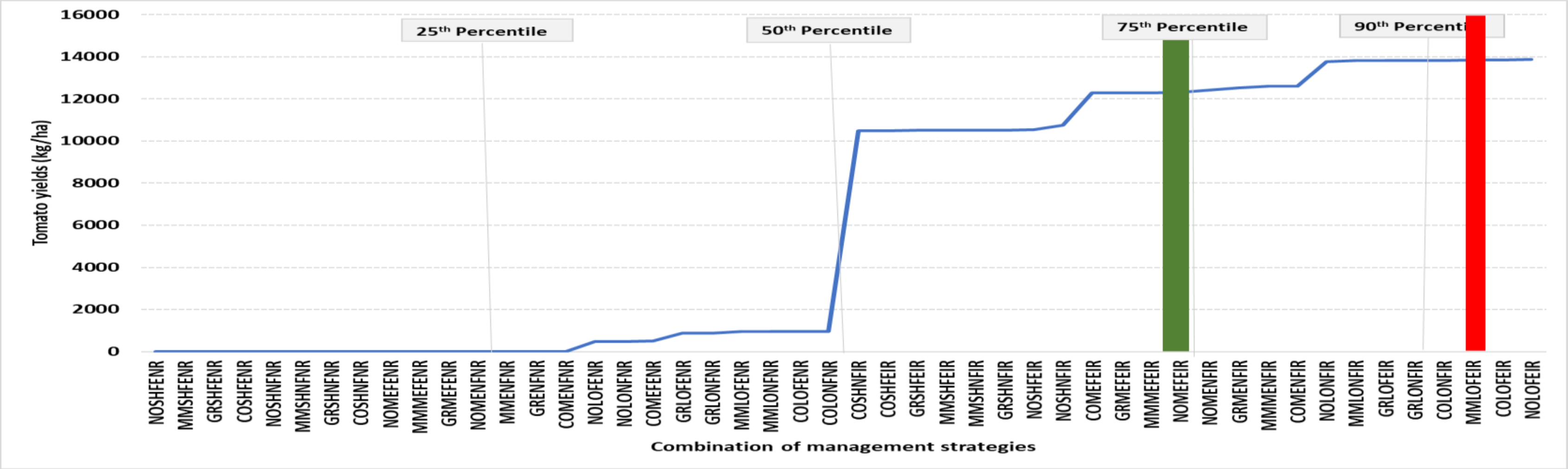
Annexure 5.152: Tomato yield variation amongst the different crop management strategies based on station data for the 2012/13 season for horticultural farmers in Limpopo, South Africa.



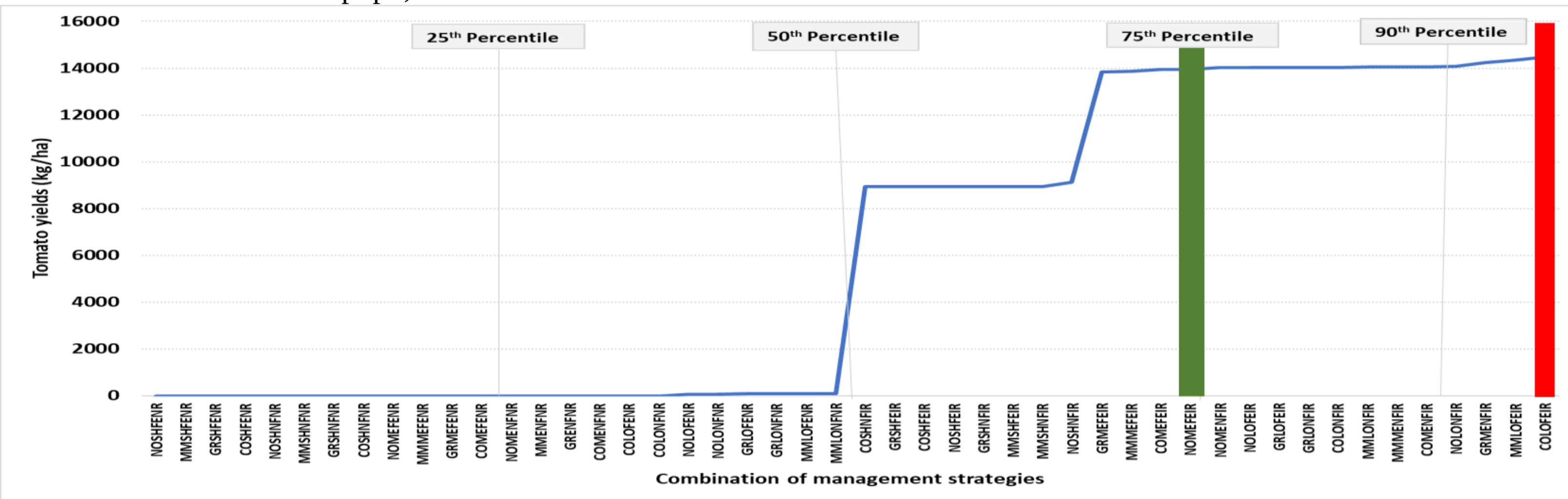
Annexure 5.153: Tomato yield variation amongst the different crop management strategies based on station data for the 2013/14 season for horticultural farmers in Limpopo, South Africa.



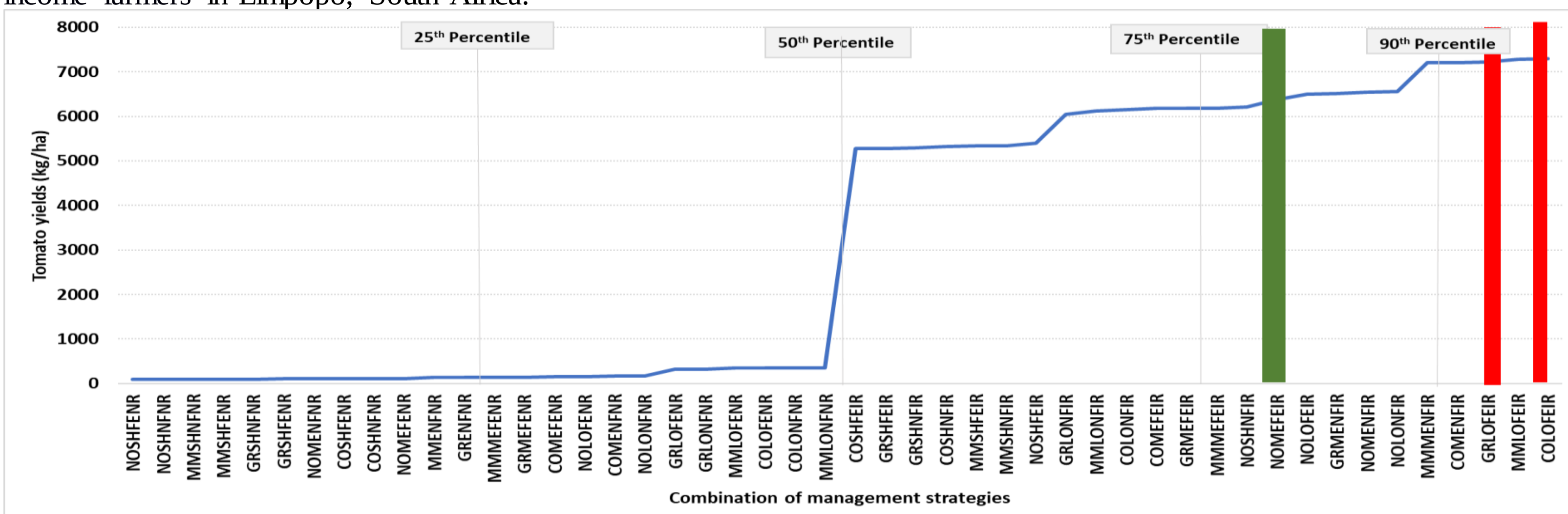
Annexure 5.154: Tomato yield variation amongst the different crop management strategies based on station data for the 2014/15 season for horticultural farmers in Limpopo, South Africa.



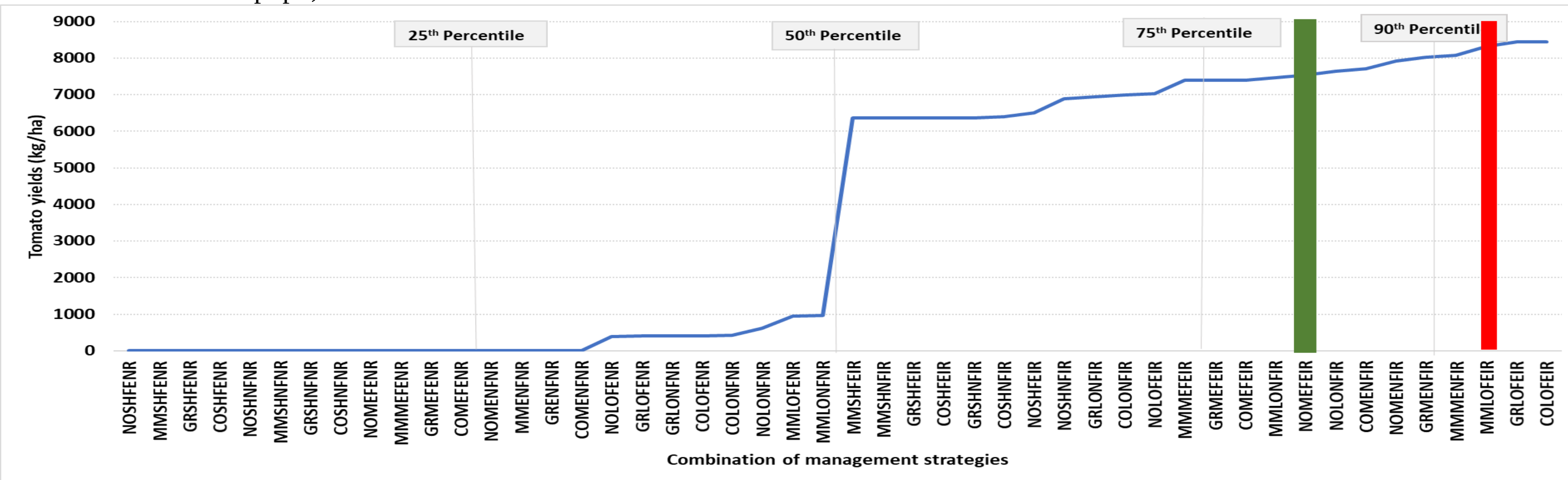
Annexure 5.155: Tomato yield variation amongst the different crop management strategies based on station data for the 2015/16 season for horticultural farmers in Limpopo, South Africa.



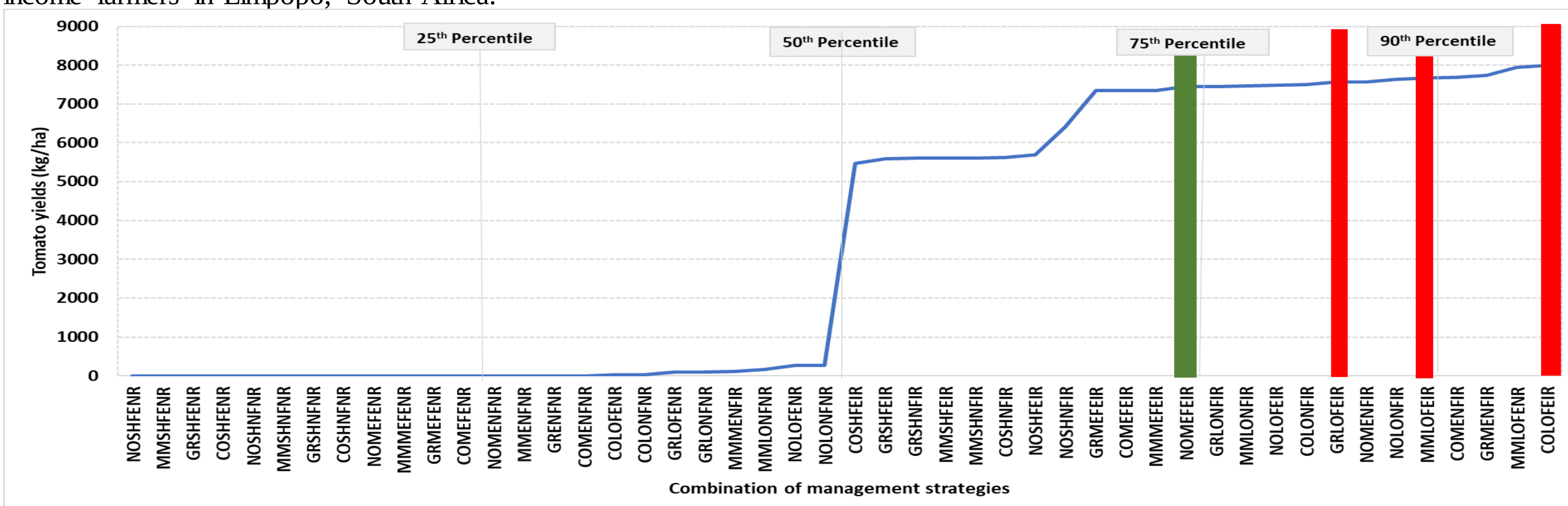
Annexure 5.156: Tomato yield variation amongst the different crop management strategies based on station data for the 2011/12 season for off income farmers in Limpopo, South Africa.



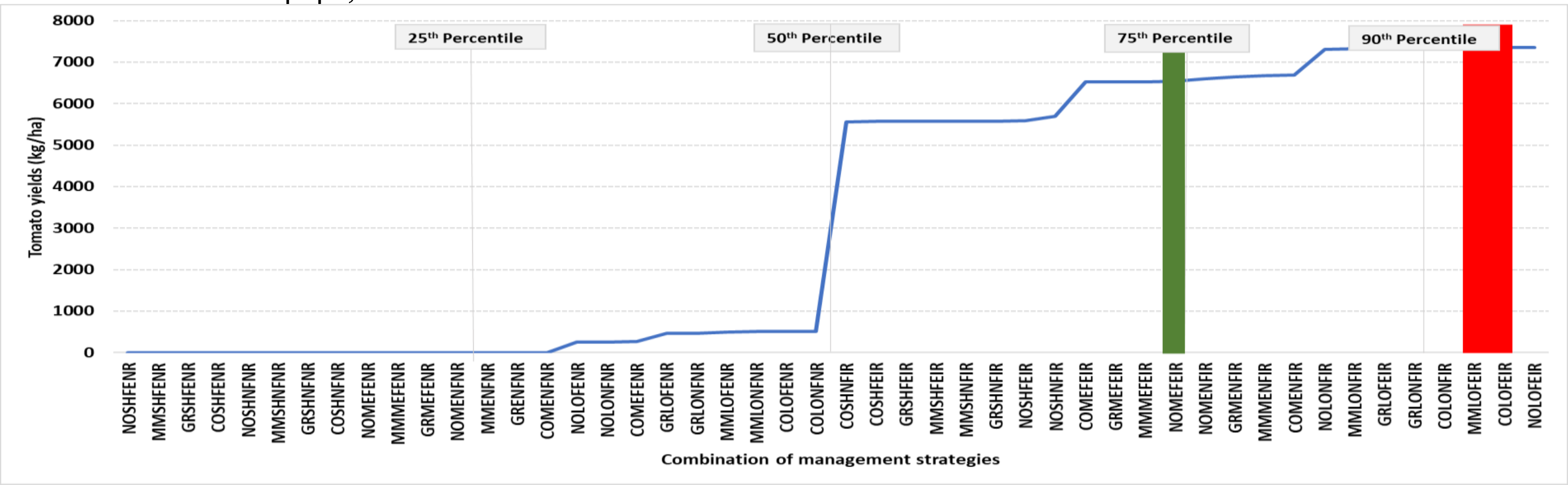
Annexure 5.157: Tomato yield variation amongst the different crop management strategies based on station data for the 2012/13 season for off income farmers in Limpopo, South Africa.



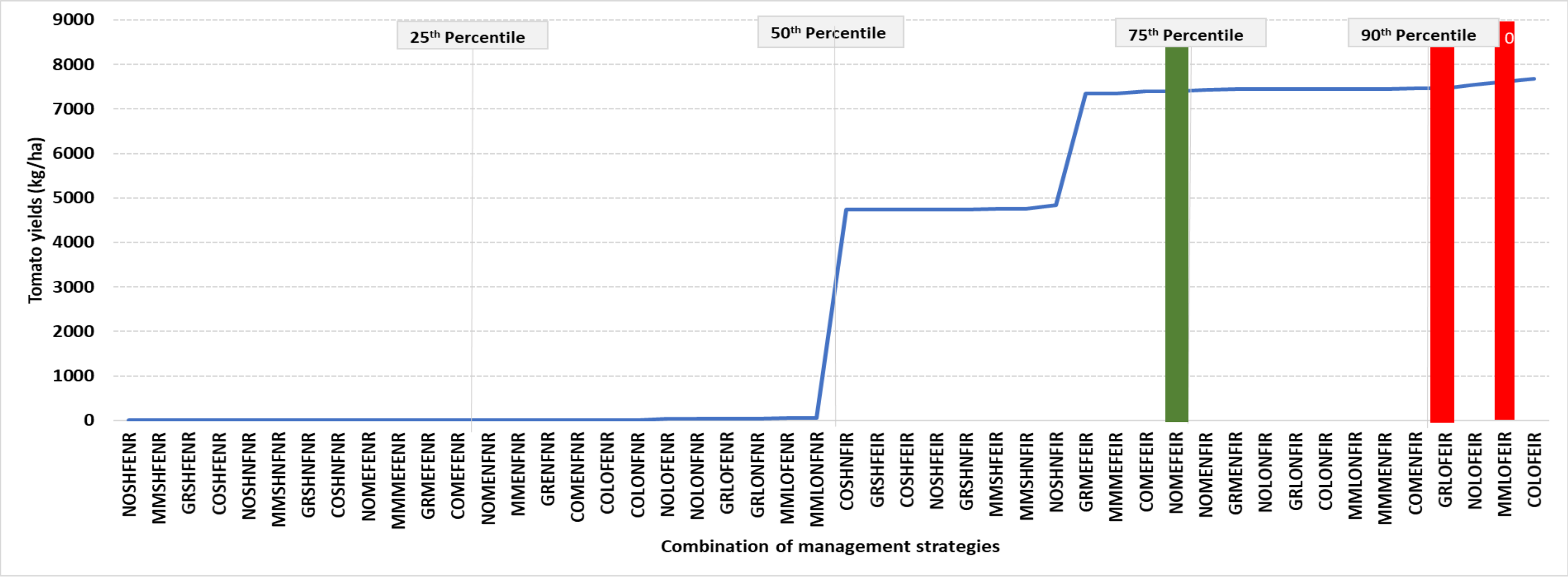
Annexure 5.157: Tomato yield variation amongst the different crop management strategies based on station data for the 2013/14 season for off income farmers in Limpopo, South Africa.



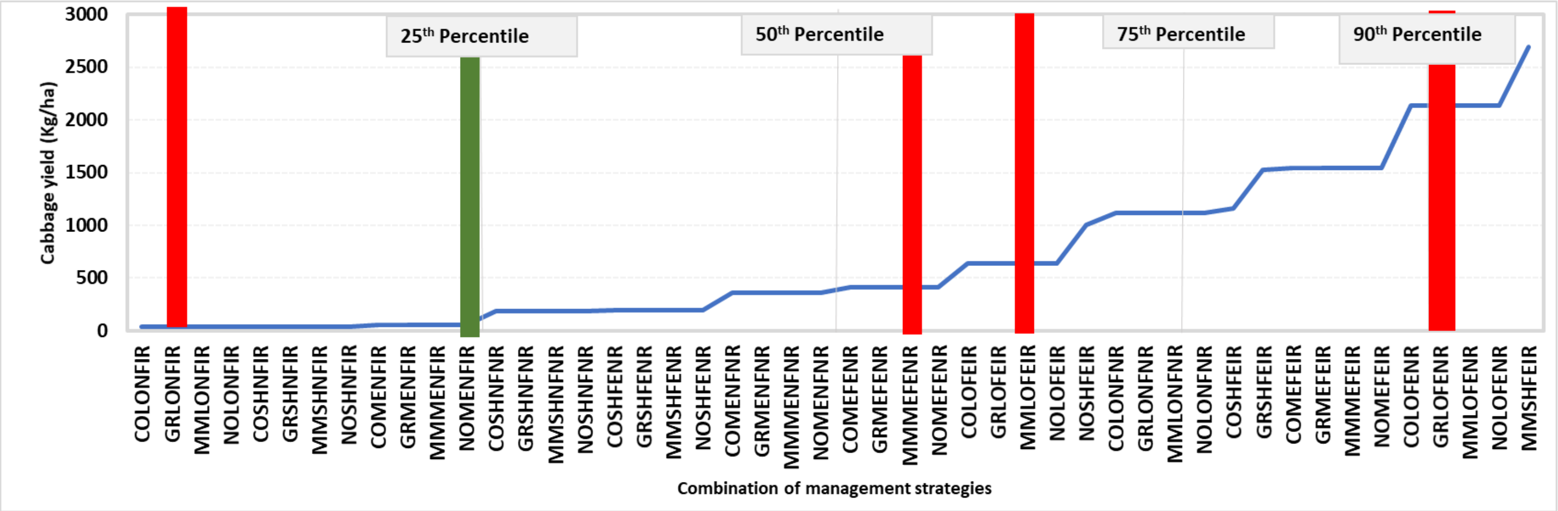
Annexure 5.158: Tomato yield variation amongst the different crop management strategies based on station data for the 2014/15 season for off income farmers in Limpopo, South Africa.



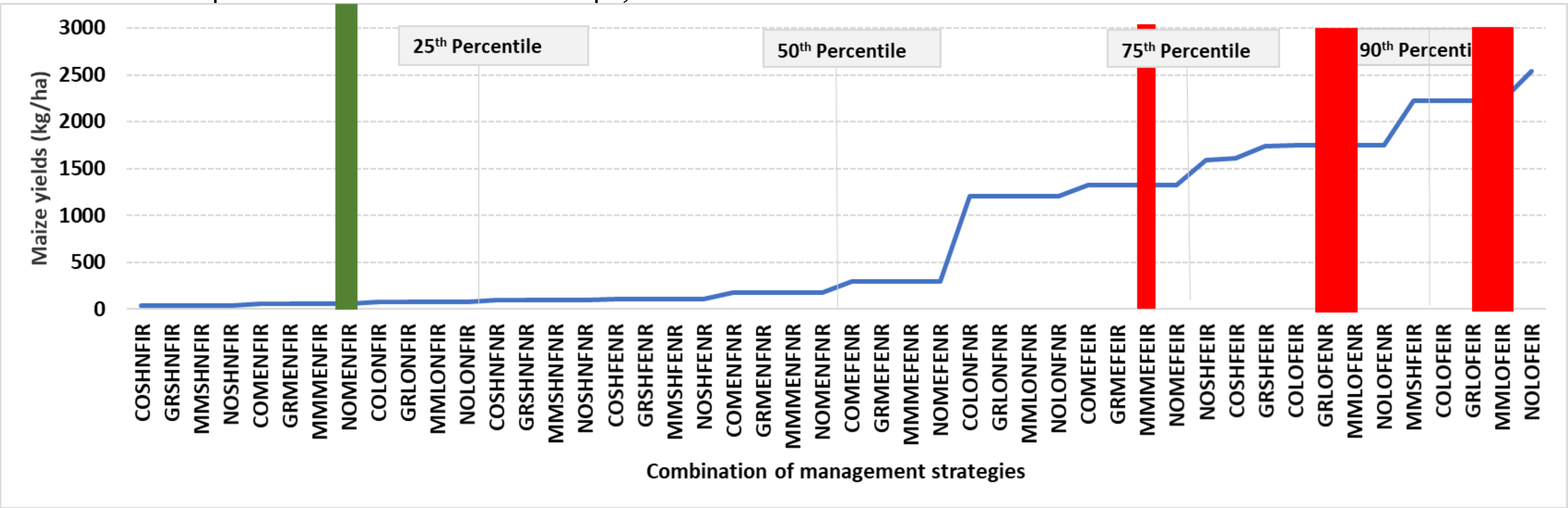
Annexure 5.159: Tomato yield variation amongst the different crop management strategies based on station data for the 2015/16 season for off income farmers in Limpopo, South Africa.



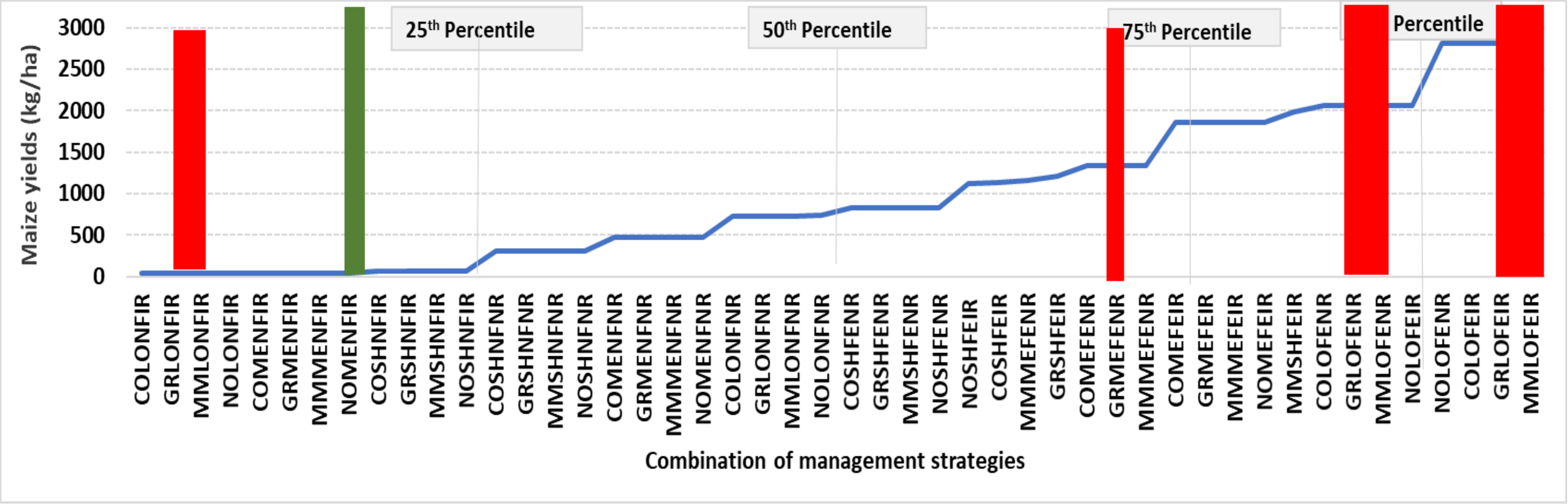
Annexure 5.160: Maize yield variation amongst the different crop management strategies based on station data for the 2011/12 season for social welfare dependent farmers in Eastern Cape, South Africa.



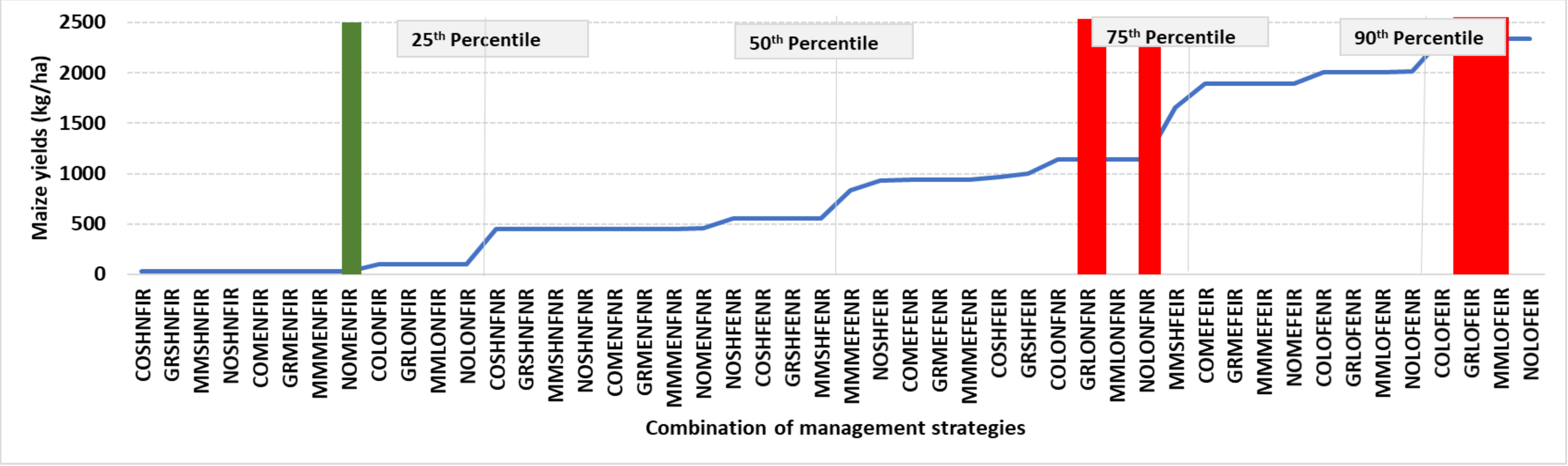
Annexure 5.161: Maize yield variation amongst the different crop management strategies based on station data for the 2012/13 season for social welfare dependent farmers in Eastern Cape, South Africa.



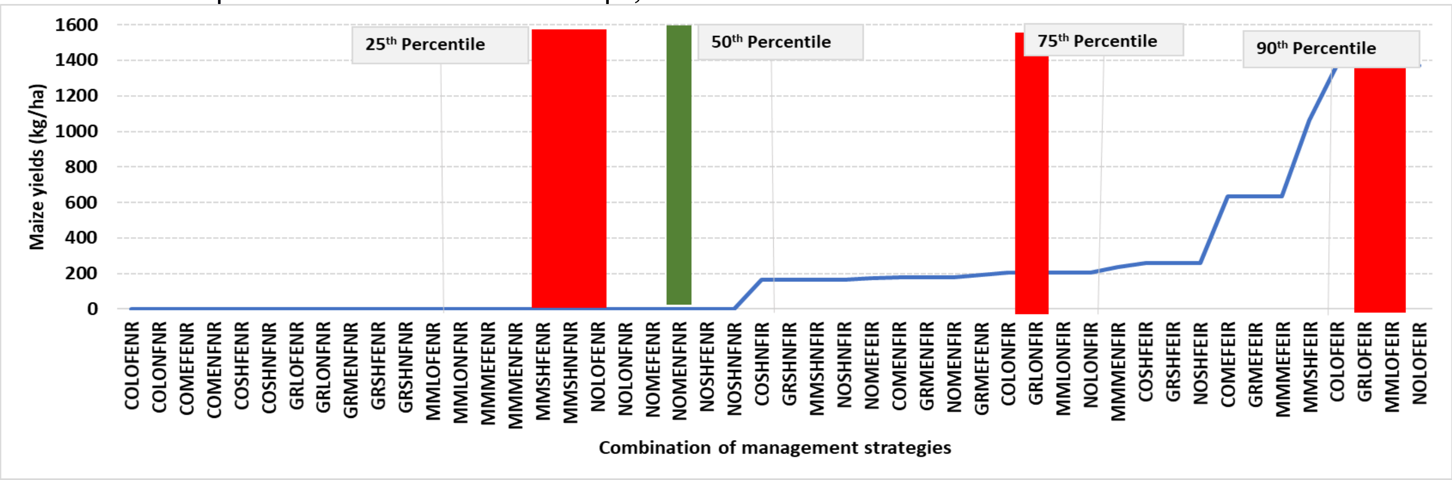
Annexure 5.162: Maize yield variation amongst the different crop management strategies based on station data for the 2013/14 season for social welfare dependent farmers in Eastern Cape, South Africa.



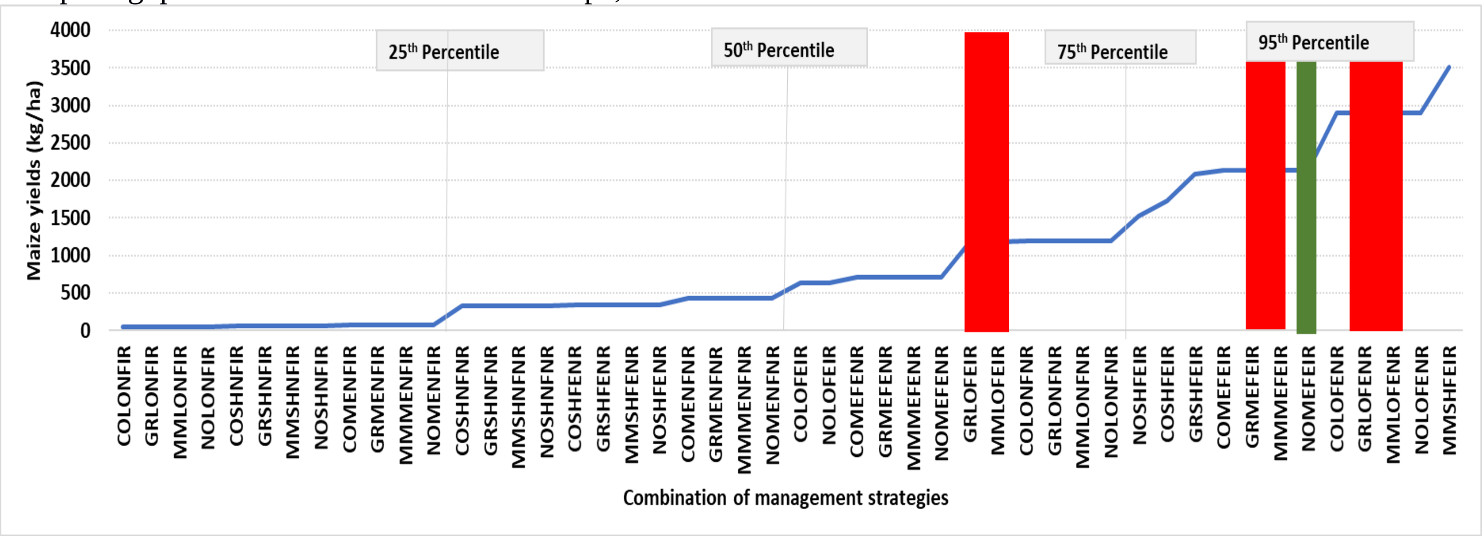
Annexure 5.163: Maize yield variation amongst the different crop management strategies based on station data for the 2014/15 season for social welfare dependent farmers in Eastern Cape, South Africa.



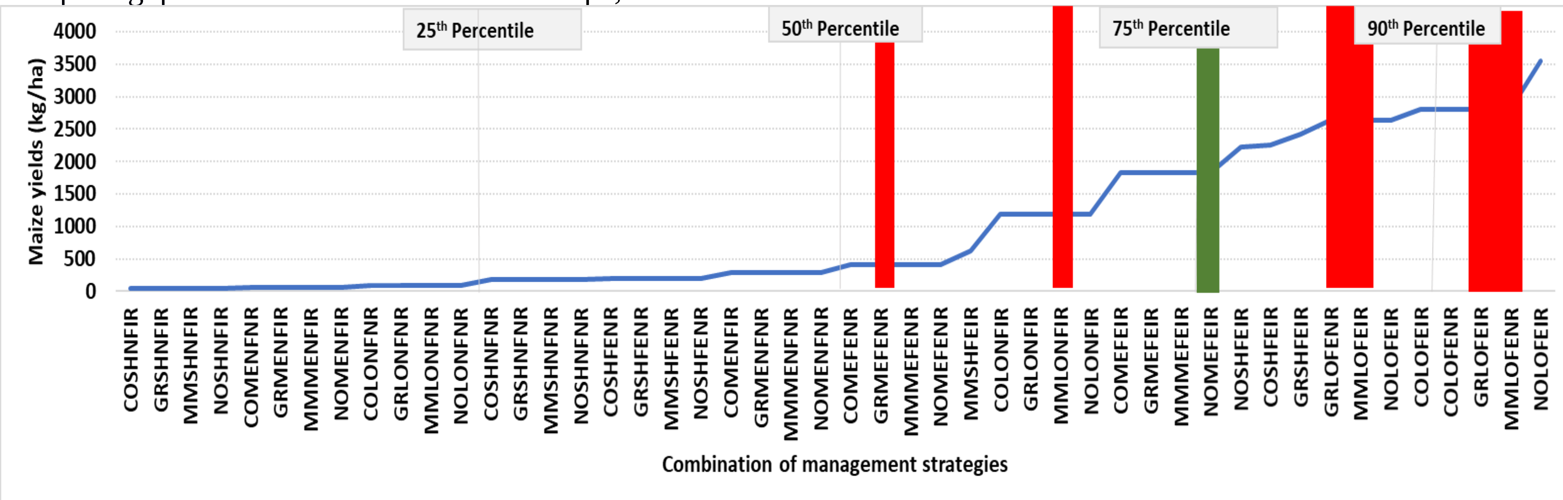
Annexure 5.164: Maize yield variation amongst the different crop management strategies based on station data for the 2015/16 season for social welfare dependent farmers in Eastern Cape, South Africa.



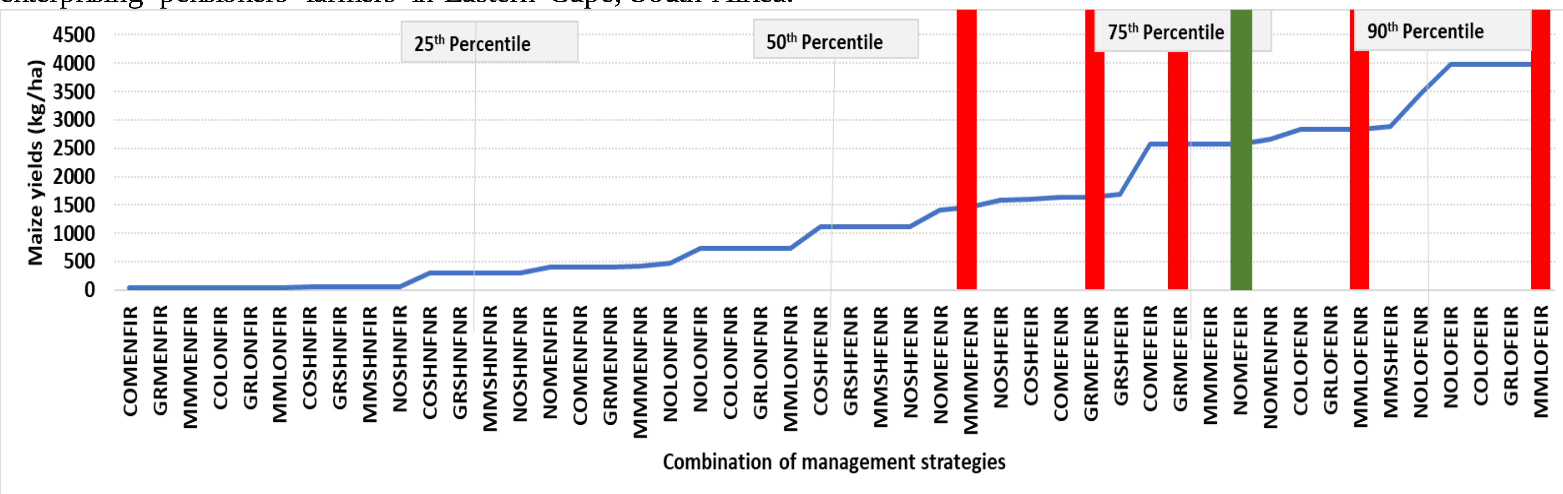
Annexure 5.165: Maize yield variation amongst the different crop management strategies based on station data for the 2011/12 season for enterprising pensioners farmers in Eastern Cape, South Africa.



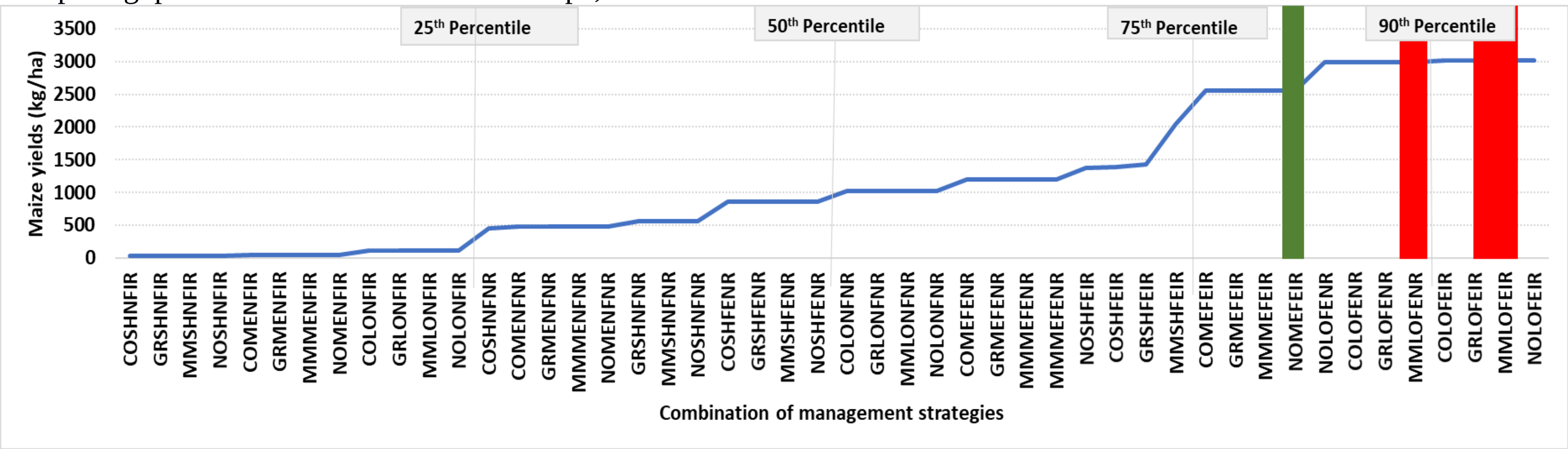
Annexure 5.166: Maize yield variation amongst the different crop management strategies based on station data for the 2012/13 season for enterprising pensioners farmers in Eastern Cape, South Africa.



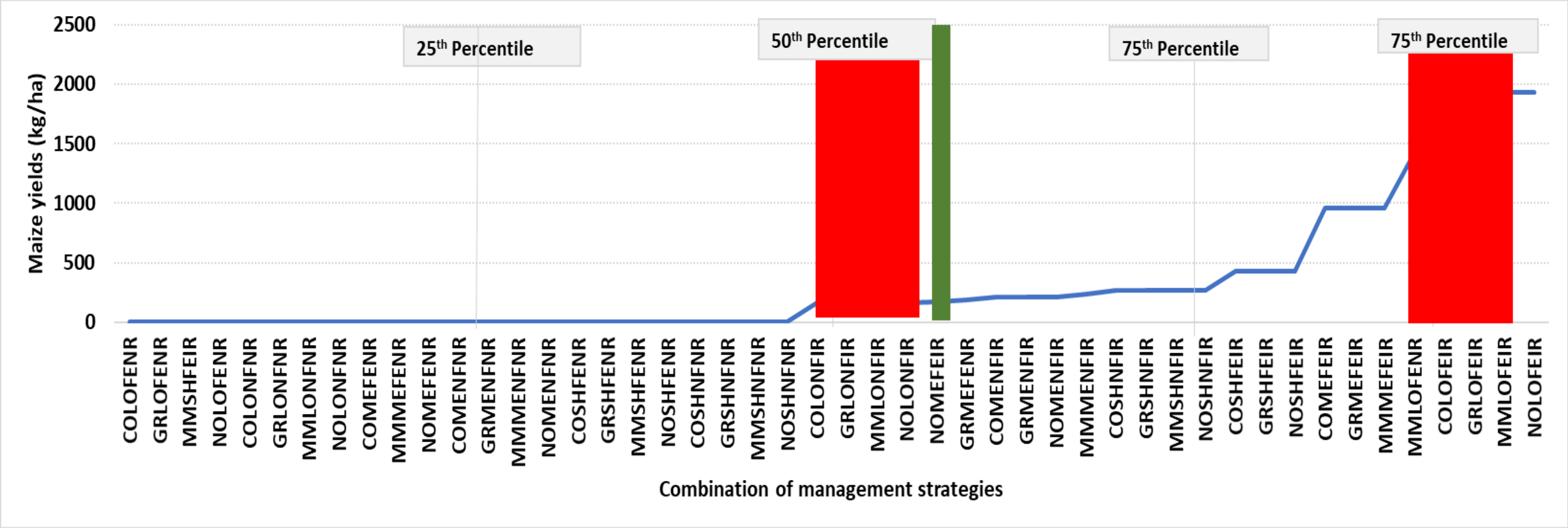
Annexure 5.167: Maize yield variation amongst the different crop management strategies based on station data for the 2013/14 season for enterprising pensioners farmers in Eastern Cape, South Africa.



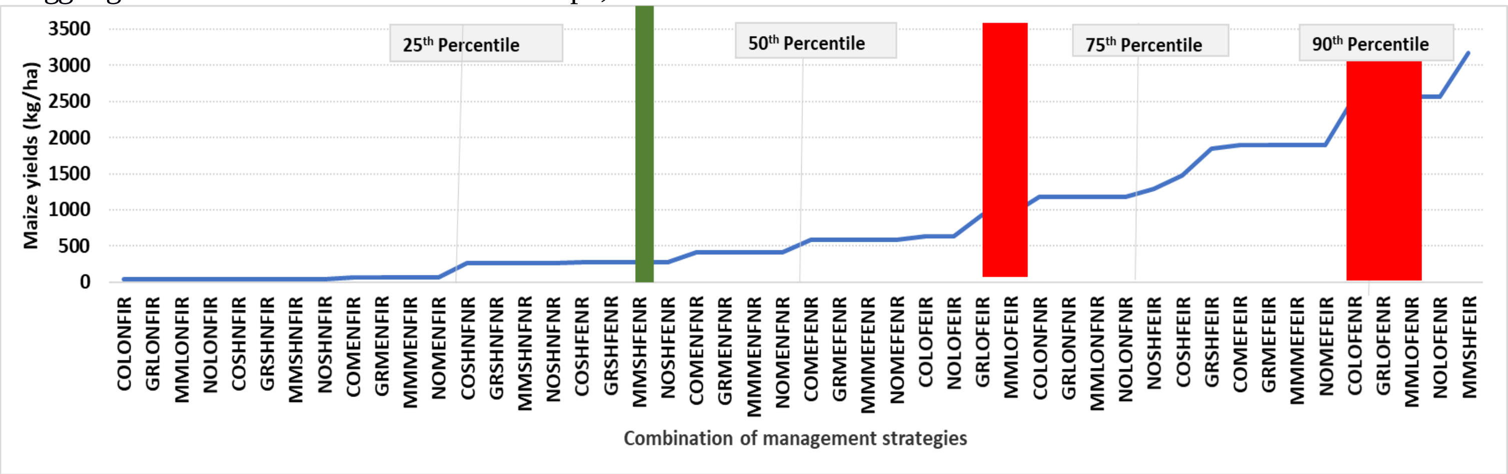
Annexure 5.168: Maize yield variation amongst the different crop management strategies based on station data for the 2014/15 season for enterprising pensioners farmers in Eastern Cape, South Africa.



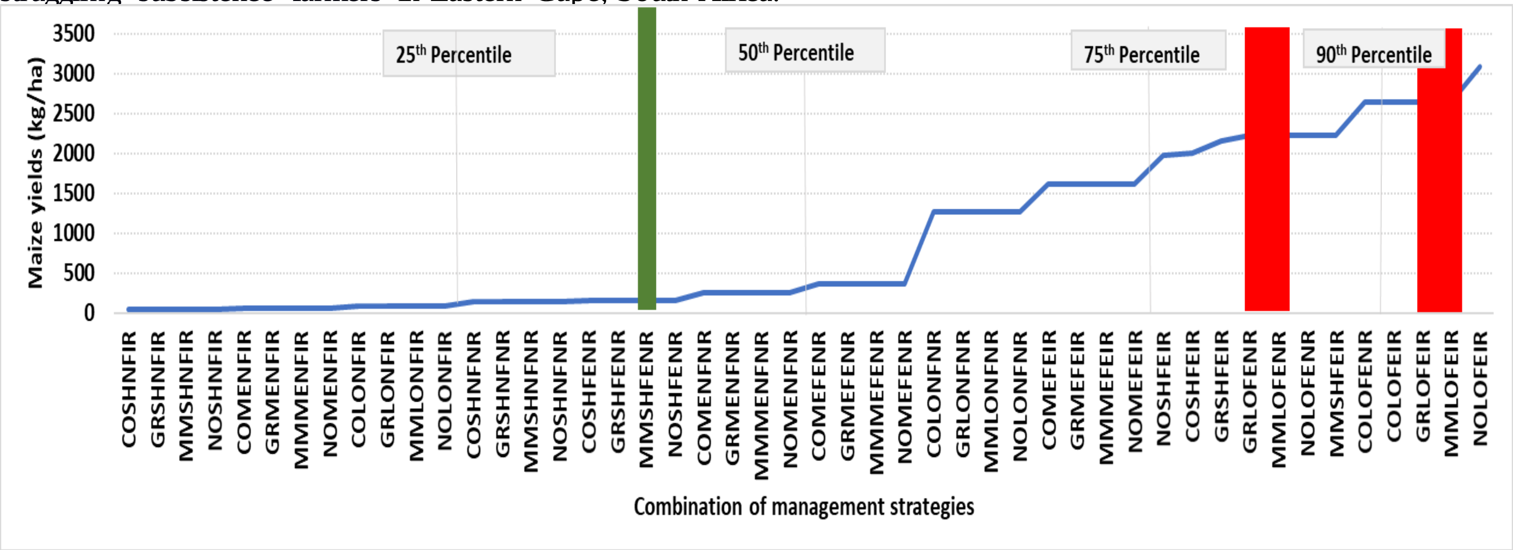
Annexure 5.169: Maize yield variation amongst the different crop management strategies based on station data for the 2015/16 season for enterprising pensioners farmers in Eastern Cape, South Africa.



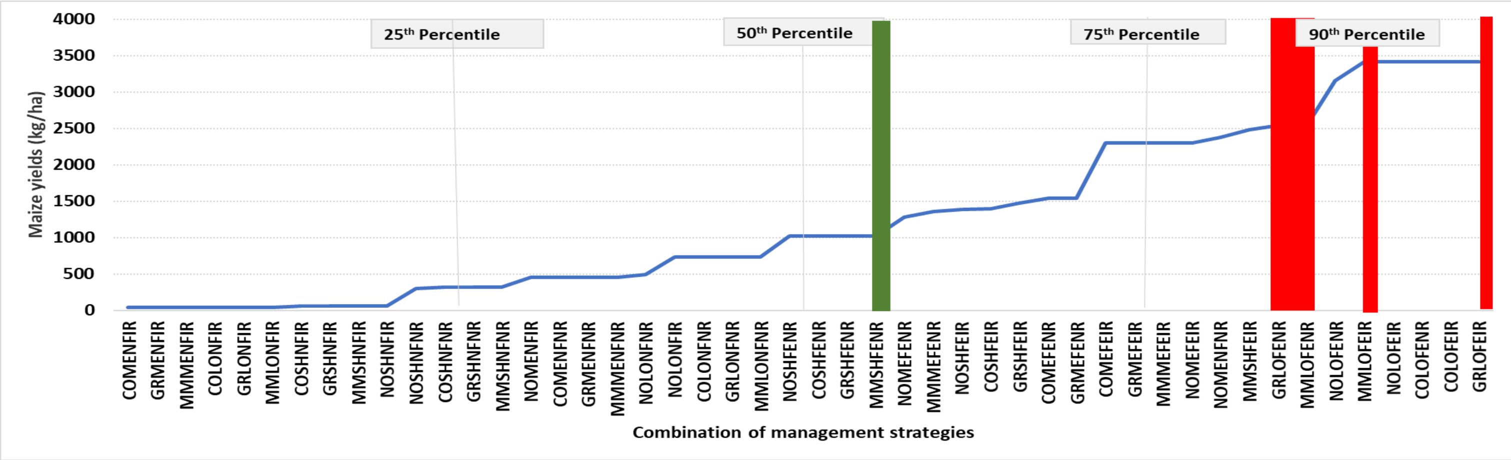
Annexure 5.170: Maize yield variation amongst the different crop management strategies based on station data for the 2011/12 season for struggling subsistence farmers in Eastern Cape, South Africa.



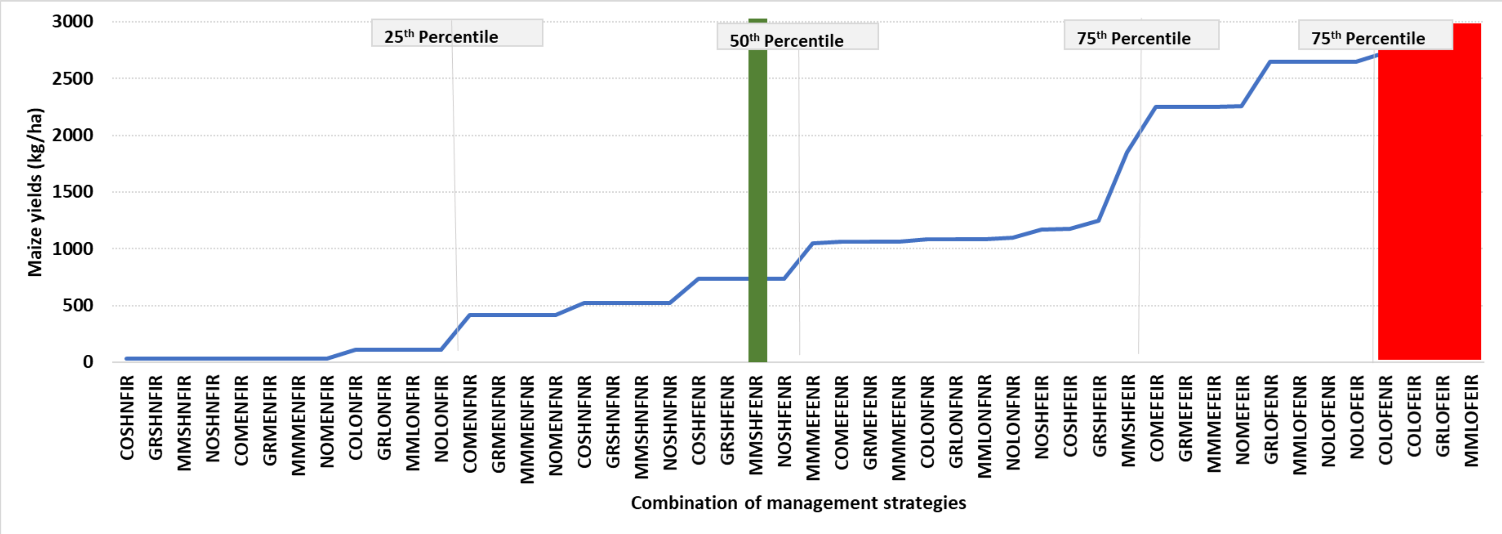
Annexure 5.171: Maize yield variation amongst the different crop management strategies based on station data for the 2012/13 season for struggling subsistence farmers in Eastern Cape, South Africa.



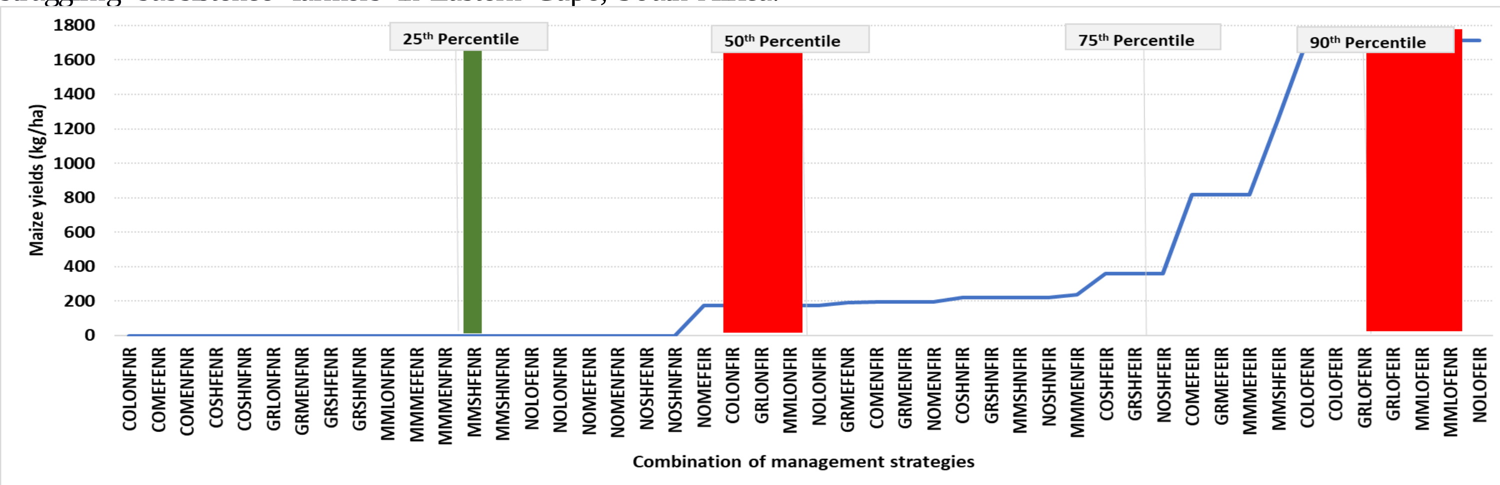
Annexure 5.172: Maize yield variation amongst the different crop management strategies based on station data for the 2013/14 season for struggling subsistence farmers in Eastern Cape, South Africa.



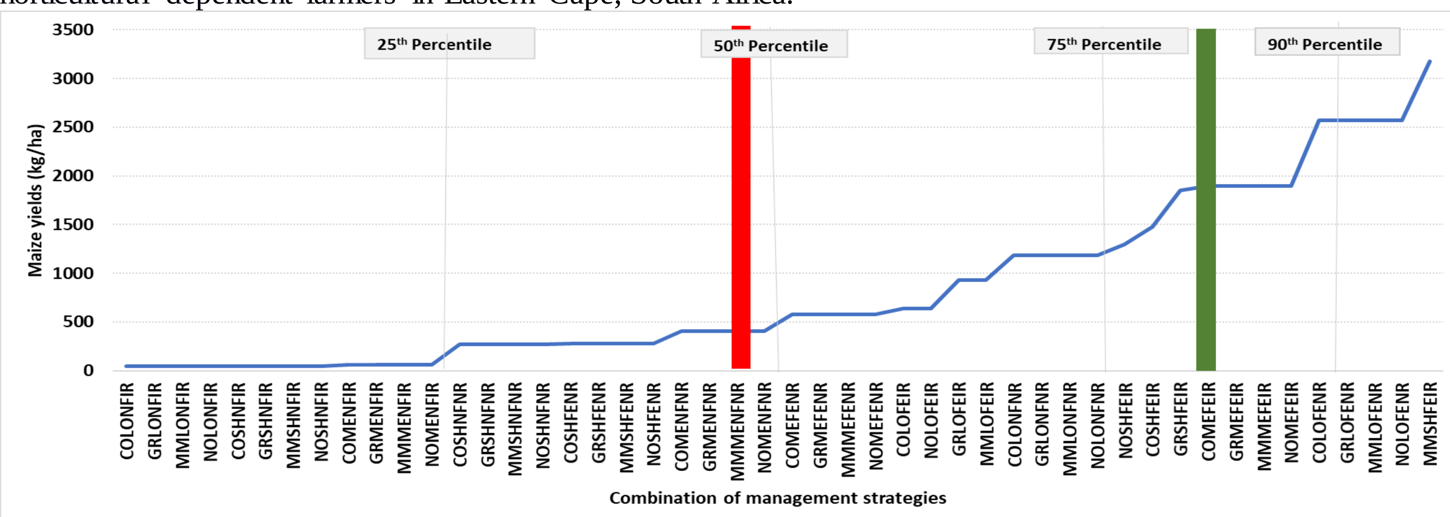
Annexure 5.173: Maize yield variation amongst the different crop management strategies based on station data for the 2014/15 season for struggling subsistence farmers in Eastern Cape, South Africa.



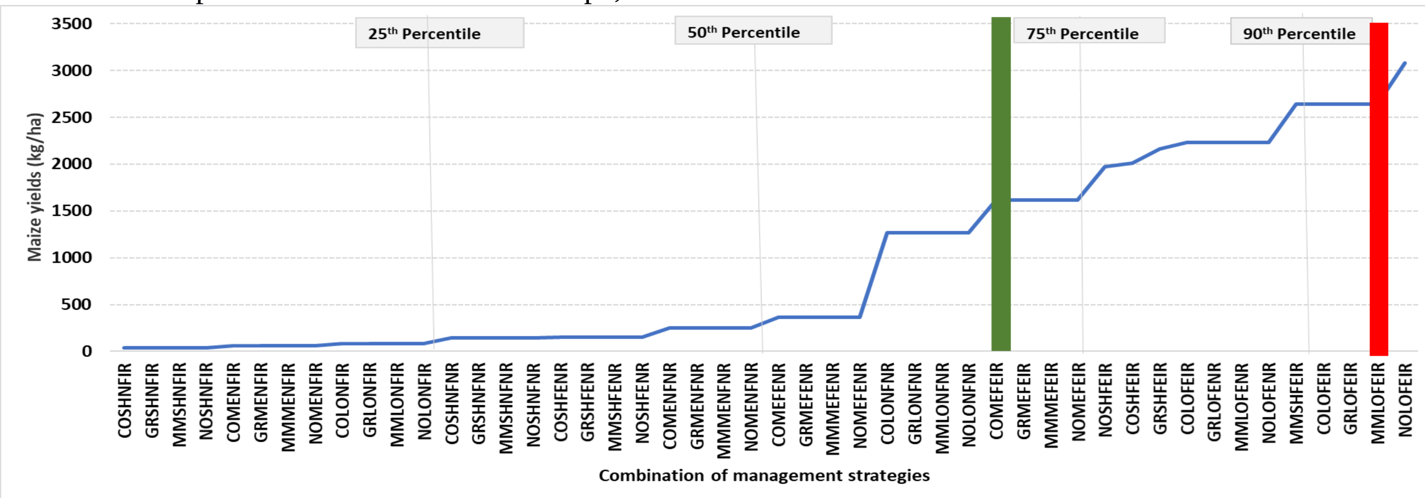
Annexure 5.174: Maize yield variation amongst the different crop management strategies based on station data for the 2015/16 season for struggling subsistence farmers in Eastern Cape, South Africa.



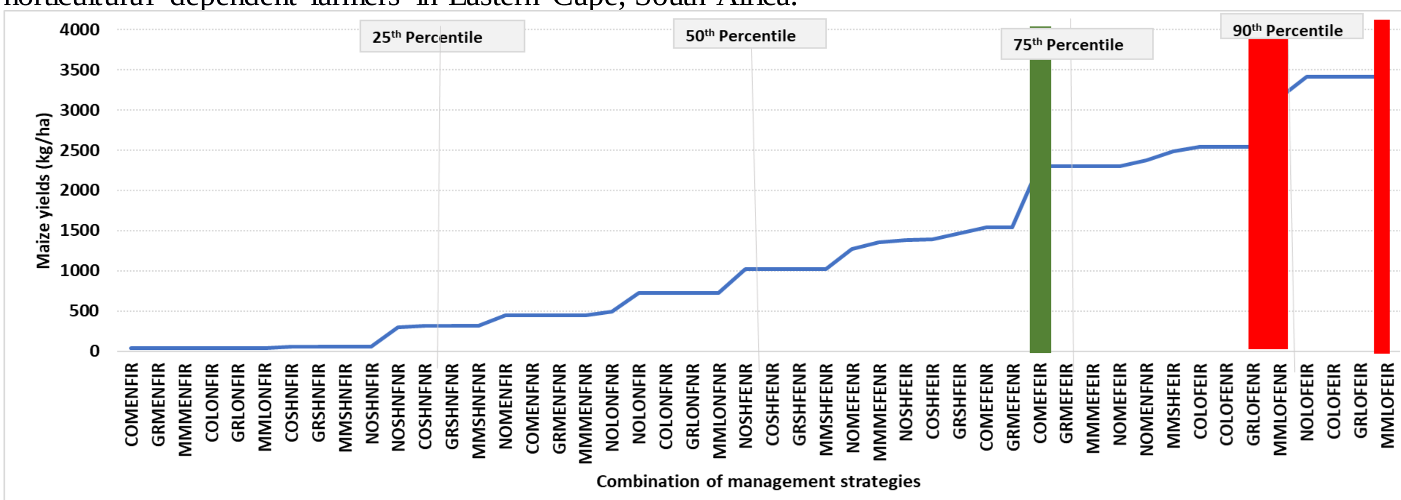
Annexure 5.175: Maize yield variation amongst the different crop management strategies based on station data for the 2011/12 season for horticultural dependent farmers in Eastern Cape, South Africa.



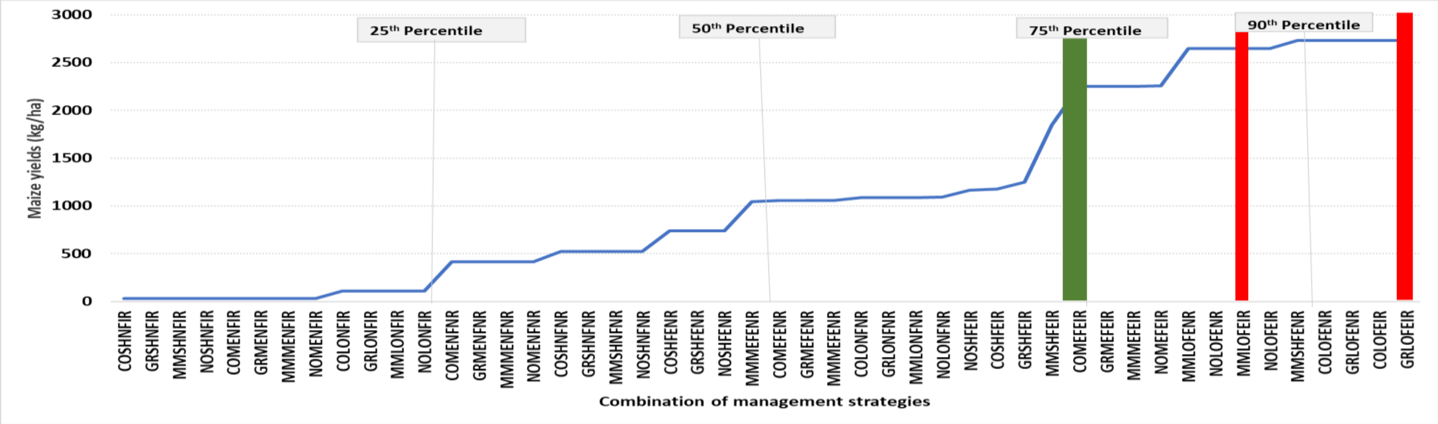
Annexure 5.176: Maize yield variation amongst the different crop management strategies based on station data for the 2012/13 season for horticultural dependent farmers in Eastern Cape, South Africa.



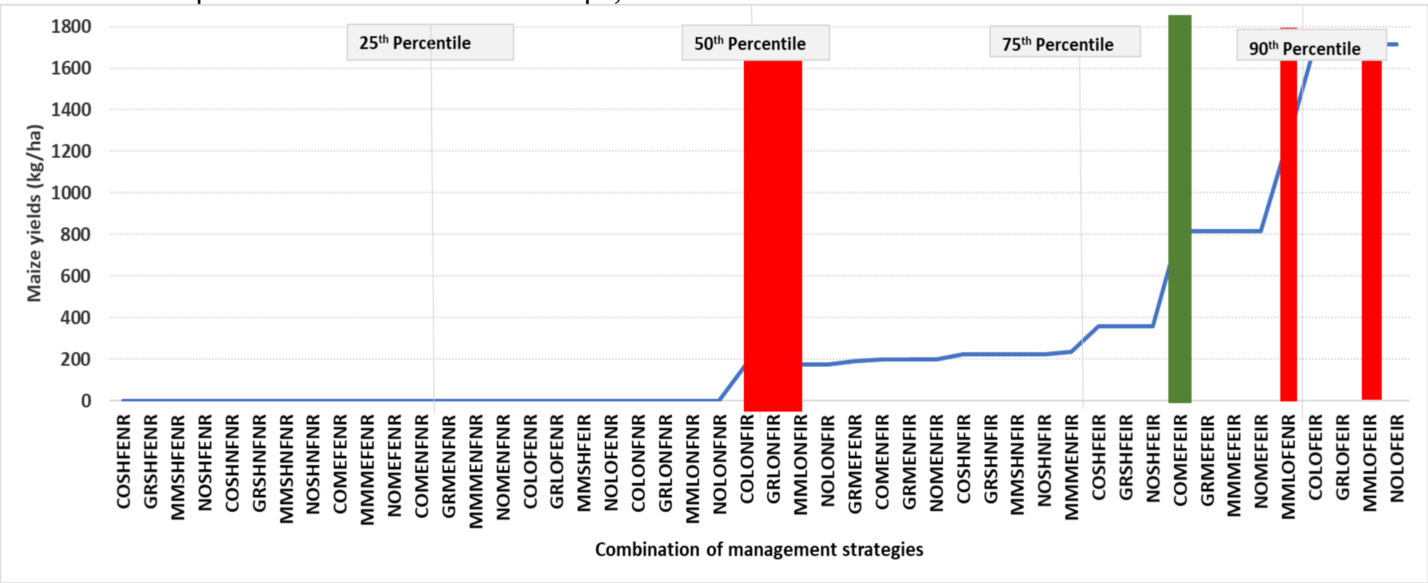
Annexure 5.177: Maize yield variation amongst the different crop management strategies based on station data for the 2013/14 season for horticultural dependent farmers in Eastern Cape, South Africa.



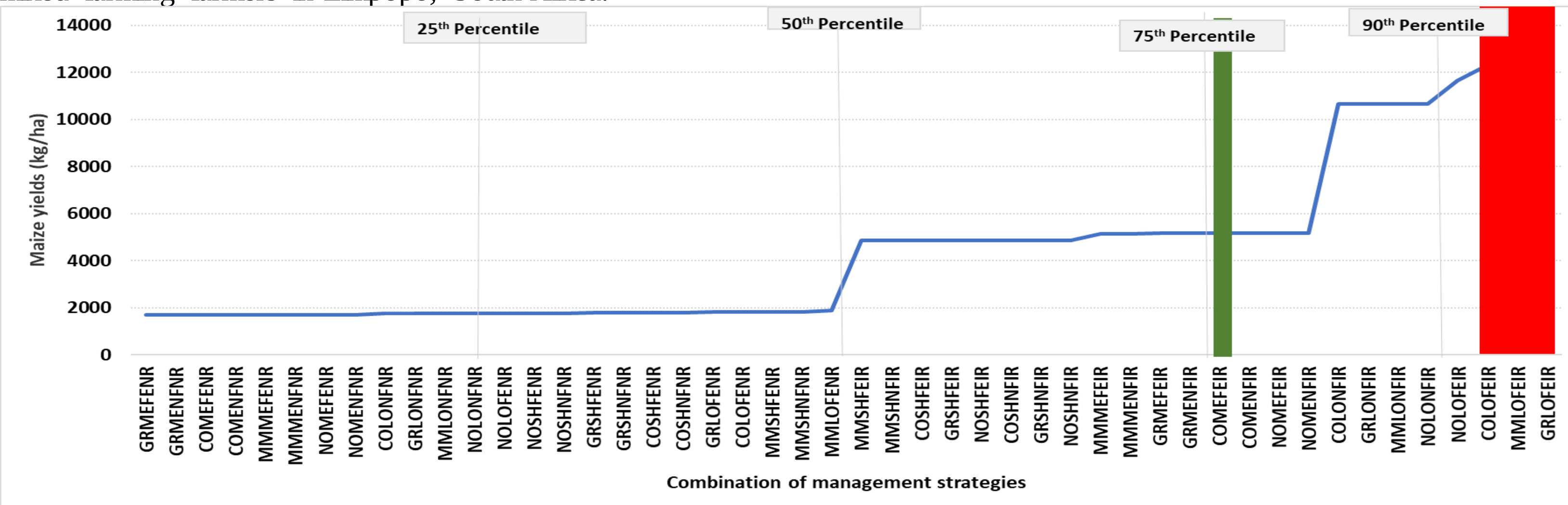
Annexure 5.178: Maize yield variation amongst the different crop management strategies based on station data for the 2014/15 season for horticultural dependent farmers in Eastern Cape, South Africa.



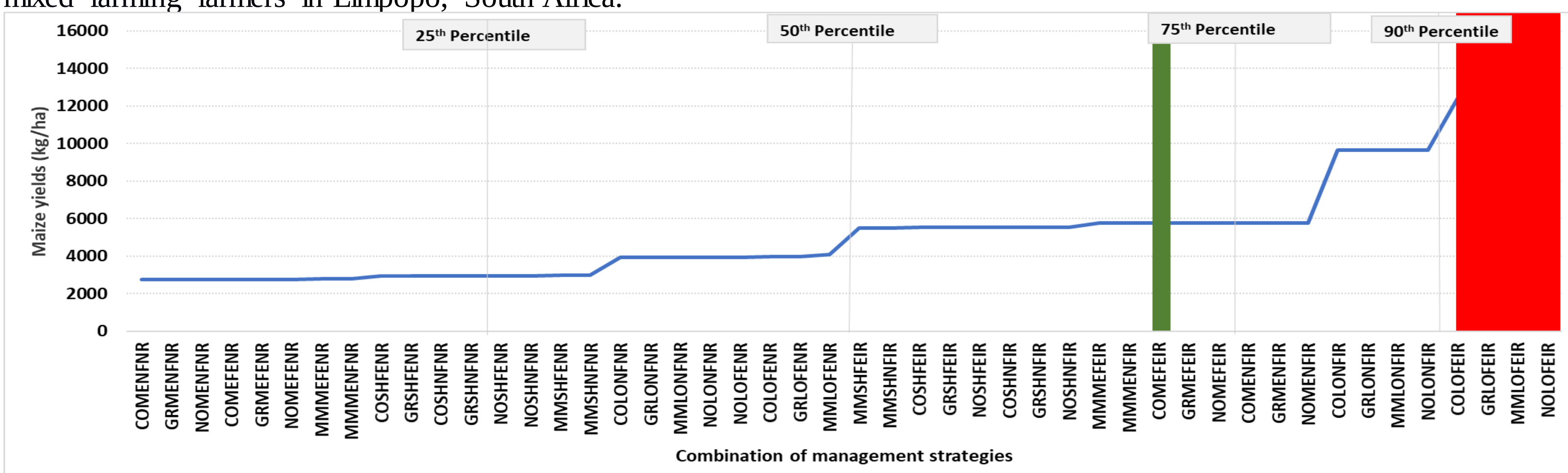
Annexure 5.179: Maize yield variation amongst the different crop management strategies based on station data for the 2015/16 season for horticultural dependent farmers in Eastern Cape, South Africa.



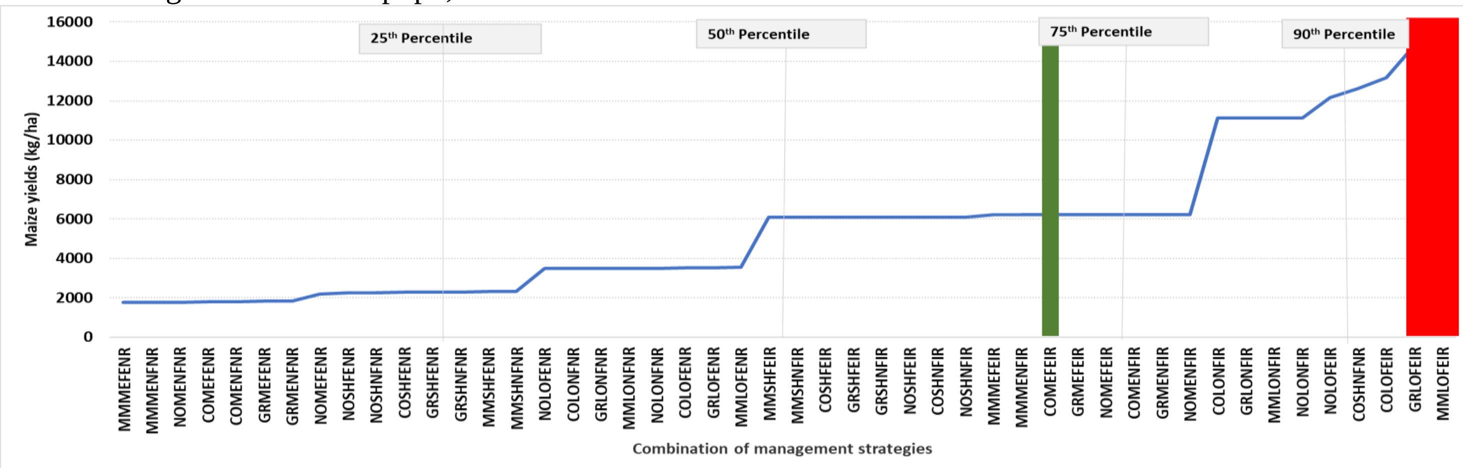
Annexure 5.180: Maize yield variation amongst the different crop management strategies based on station data for the 2011/12 season for mixed farming farmers in Limpopo, South Africa.



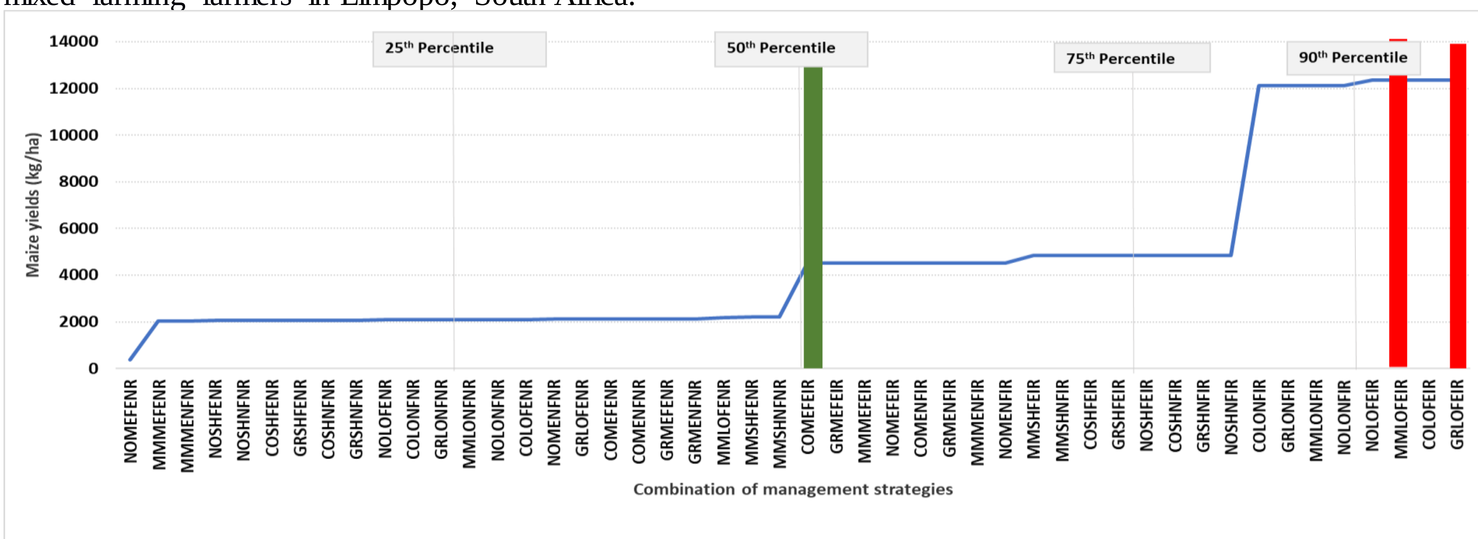
Annexure 5.181: Maize yield variation amongst the different crop management strategies based on station data for the 2012/13 season for mixed farming farmers in Limpopo, South Africa.



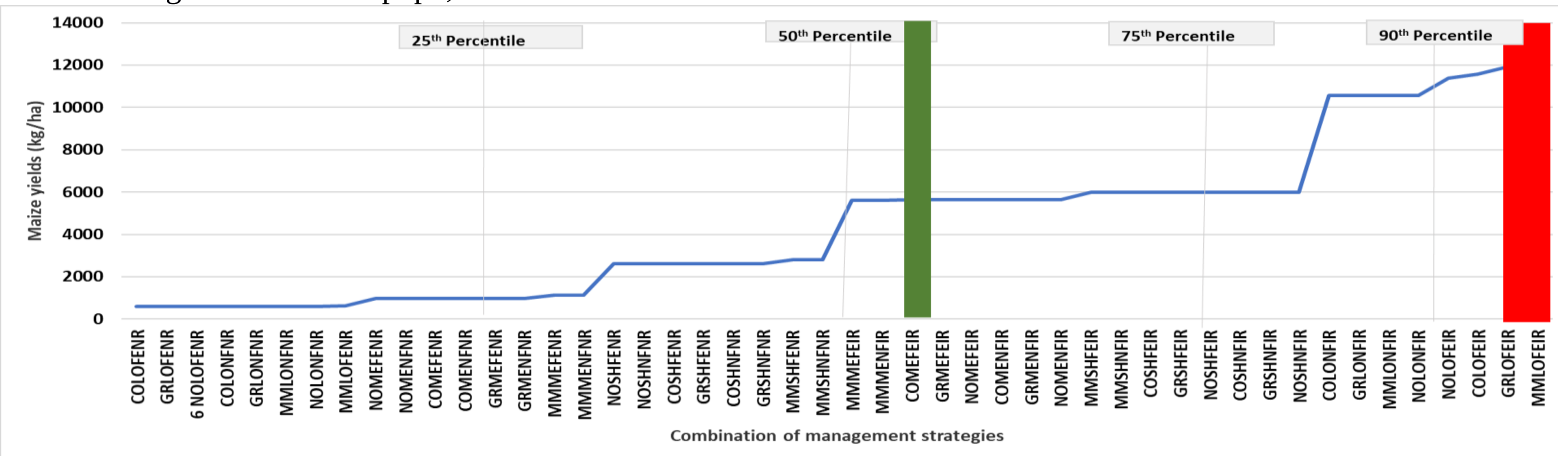
Annexure 5.182: Maize yield variation amongst the different crop management strategies based on station data for the 2013/14 season for mixed farming farmers in Limpopo, South Africa.



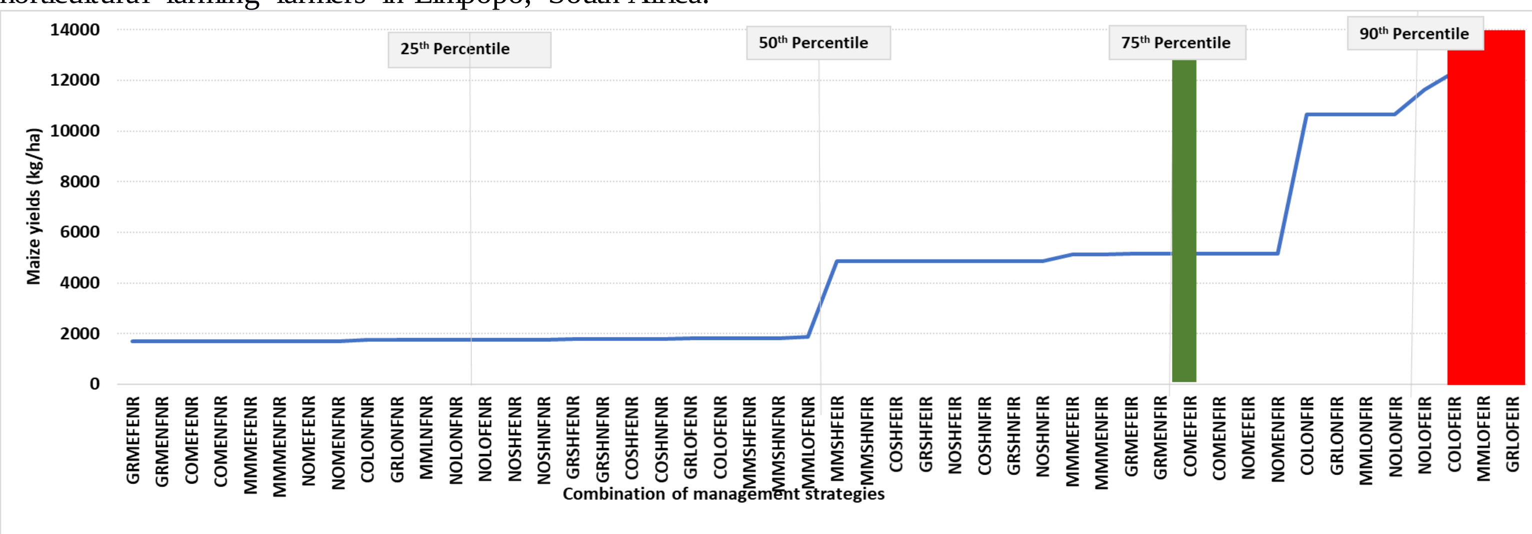
Annexure 5.183: Maize yield variation amongst the different crop management strategies based on station data for the 2014/15 season for mixed farming farmers in Limpopo, South Africa.



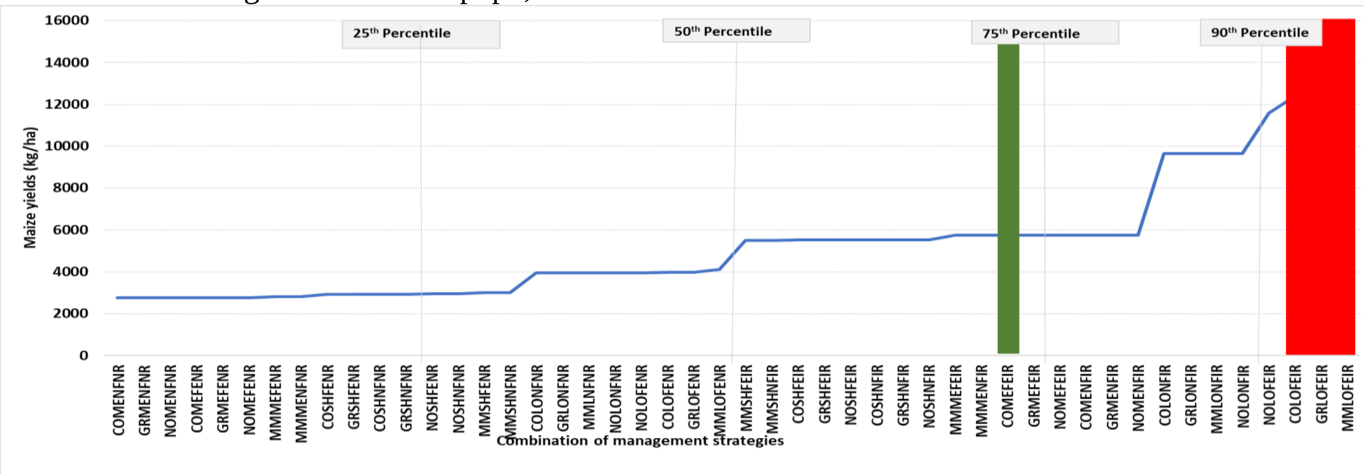
Annexure 5.184: Maize yield variation amongst the different crop management strategies based on station data for the 2015/16 season for mixed farming farmers in Limpopo, South Africa.



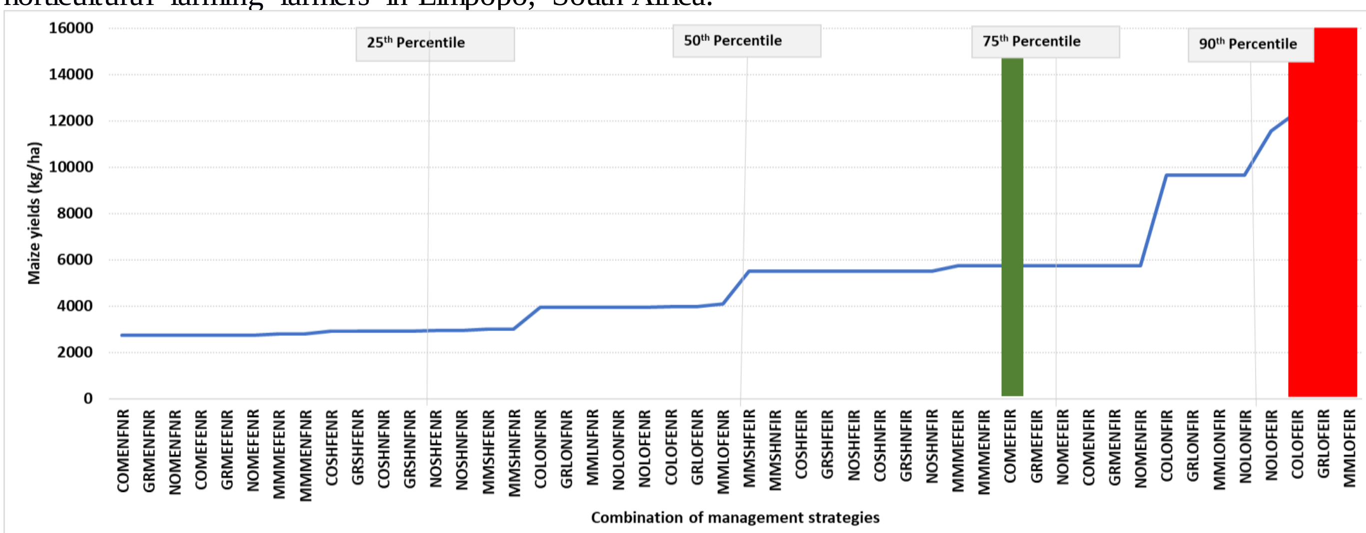
Annexure 5.185: Maize yield variation amongst the different crop management strategies based on station data for the 2011/12 season for horticultural farming farmers in Limpopo, South Africa.



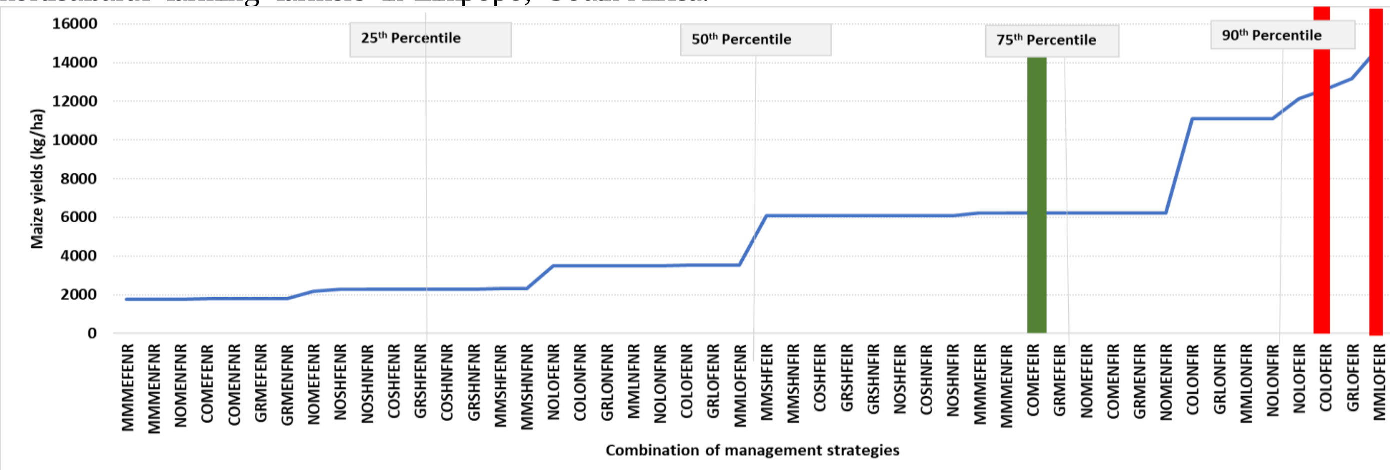
Annexure 5.186: Maize yield variation amongst the different crop management strategies based on station data for the 2012/13 season for horticultural farming farmers in Limpopo, South Africa.



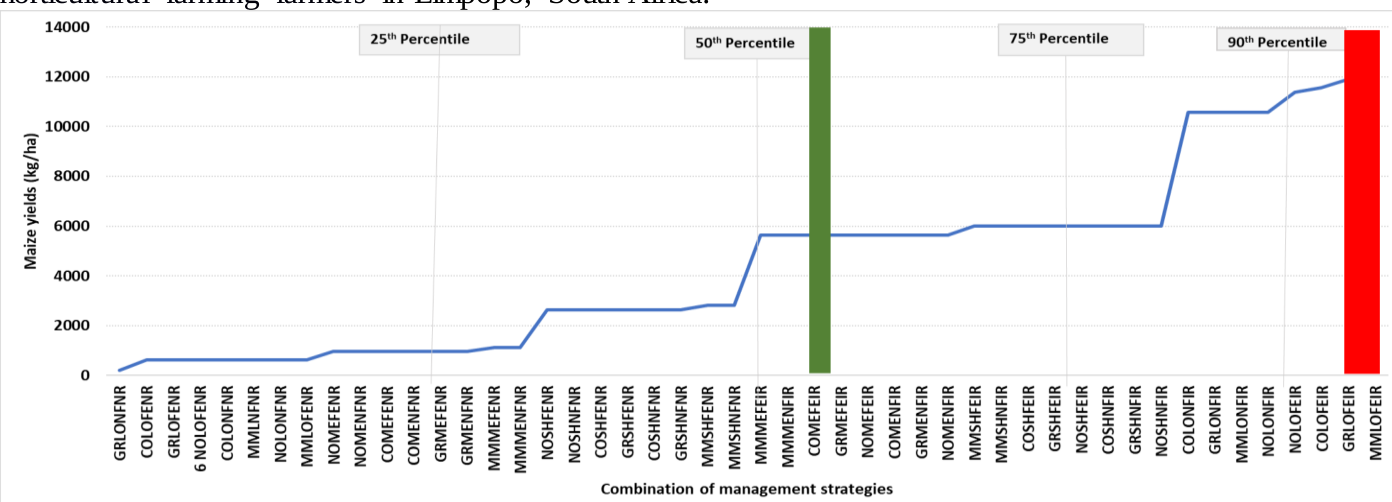
Annexure 5.187: Maize yield variation amongst the different crop management strategies based on station data for the 2013/14 season for horticultural farming farmers in Limpopo, South Africa.



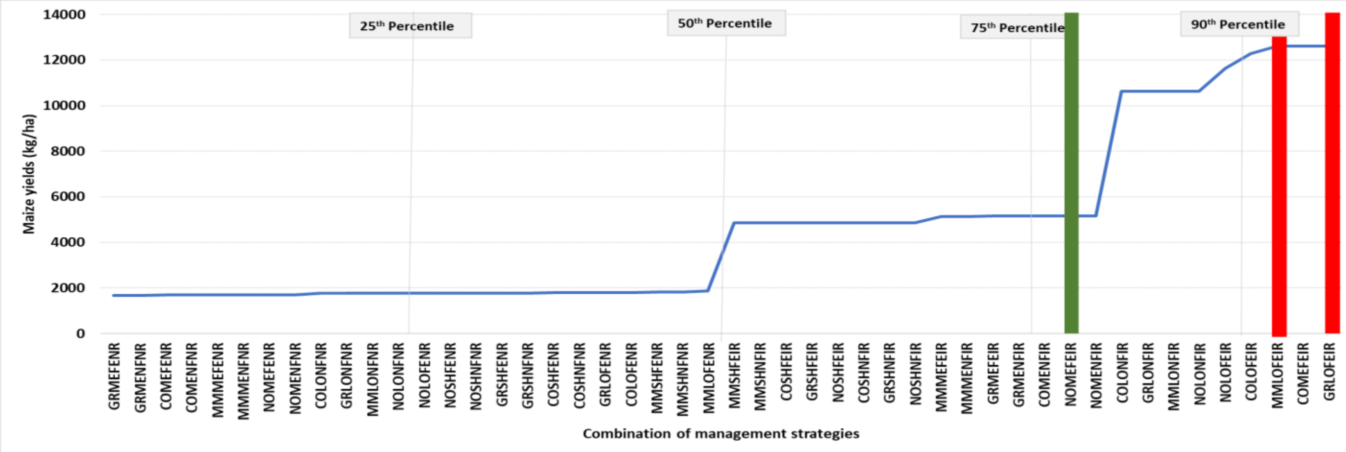
Annexure 5.188: Maize yield variation amongst the different crop management strategies based on station data for the 2014/15 season for horticultural farming farmers in Limpopo, South Africa.



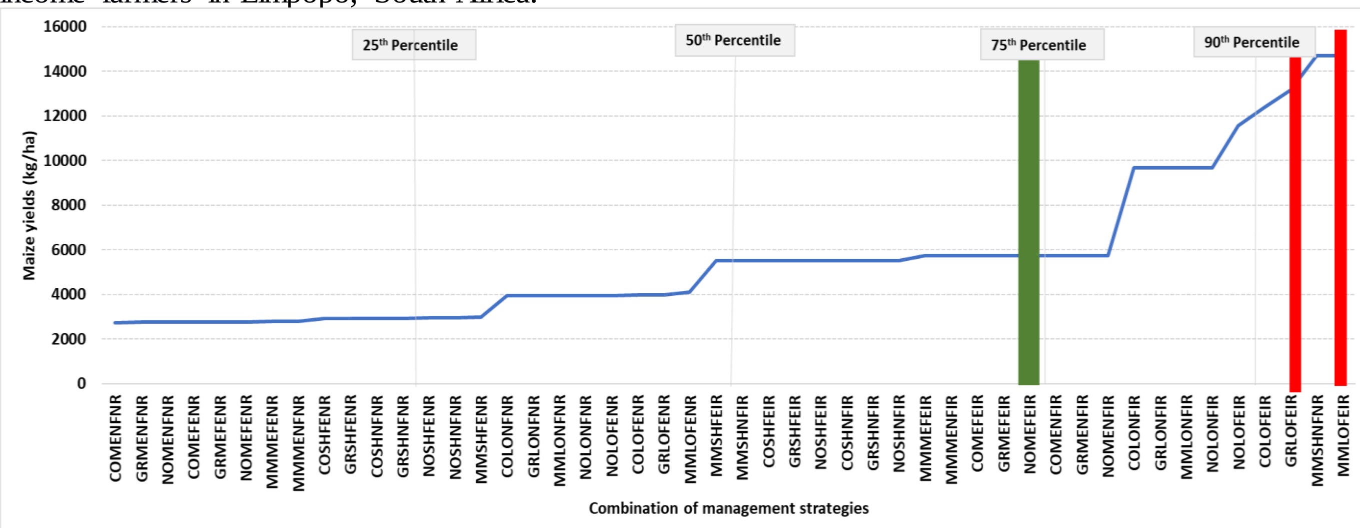
Annexure 5.189: Maize yield variation amongst the different crop management strategies based on station data for the 2015/16 season for horticultural farming farmers in Limpopo, South Africa.



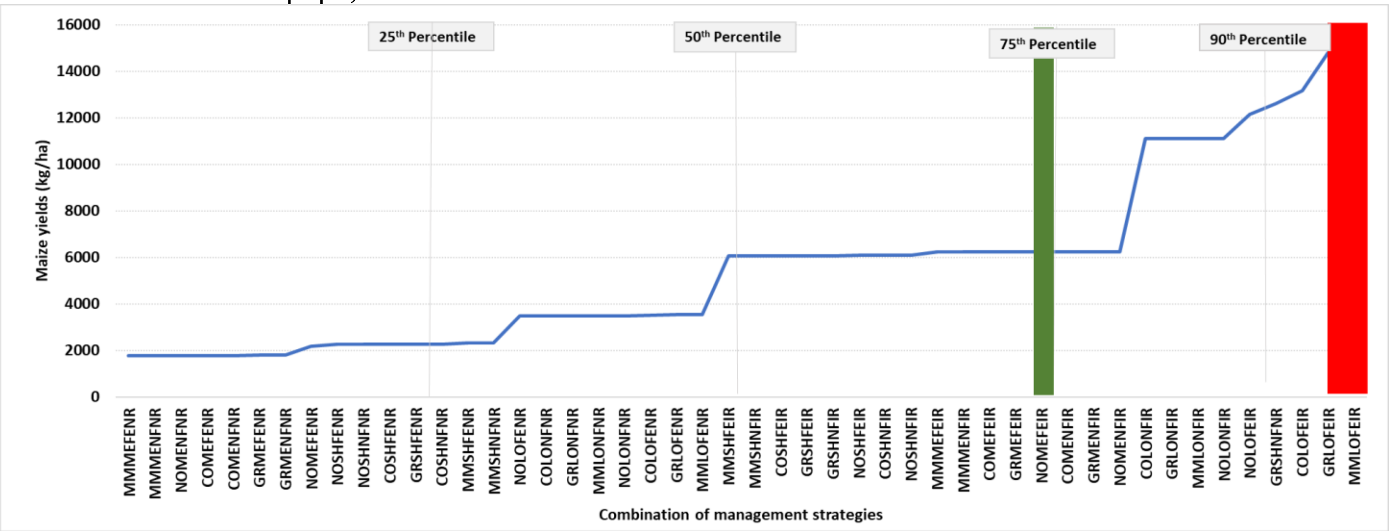
Annexure 5.190: Maize yield variation amongst the different crop management strategies based on station data for the 2011/12 season for off income farmers in Limpopo, South Africa.



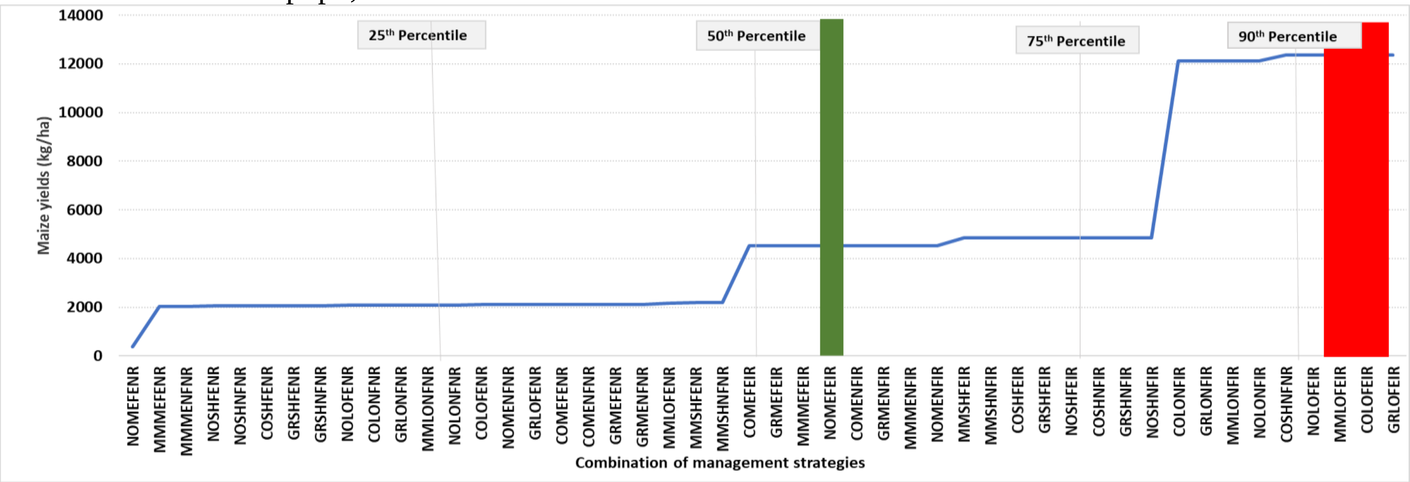
Annexure 5.191: Maize yield variation amongst the different crop management strategies based on station data for the 2012/13 season for off income farmers in Limpopo, South Africa.



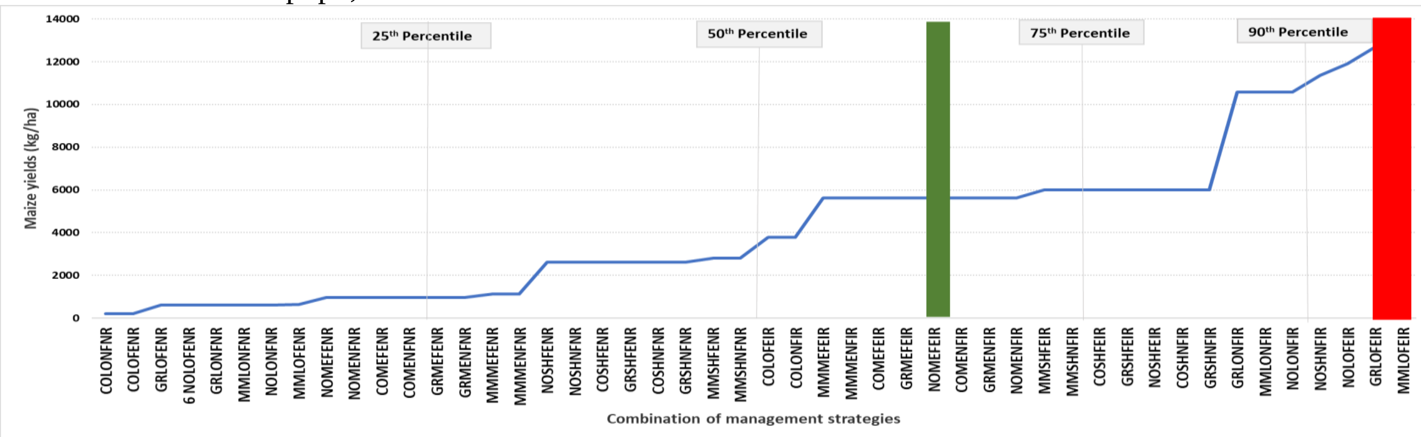
Annexure 5.192: Maize yield variation amongst the different crop management strategies based on station data for the 2013/14 season for off income farmers in Limpopo, South Africa.



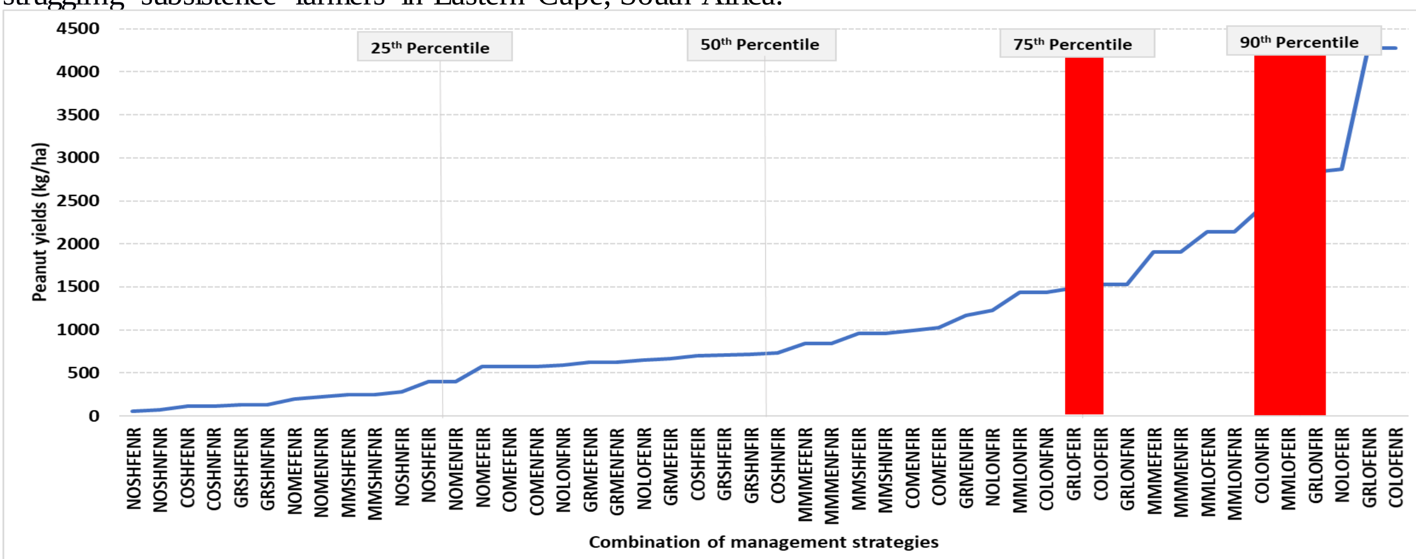
Annexure 5.193: Maize yield variation amongst the different crop management strategies based on station data for the 2014/15 season for off income farmers in Limpopo, South Africa.



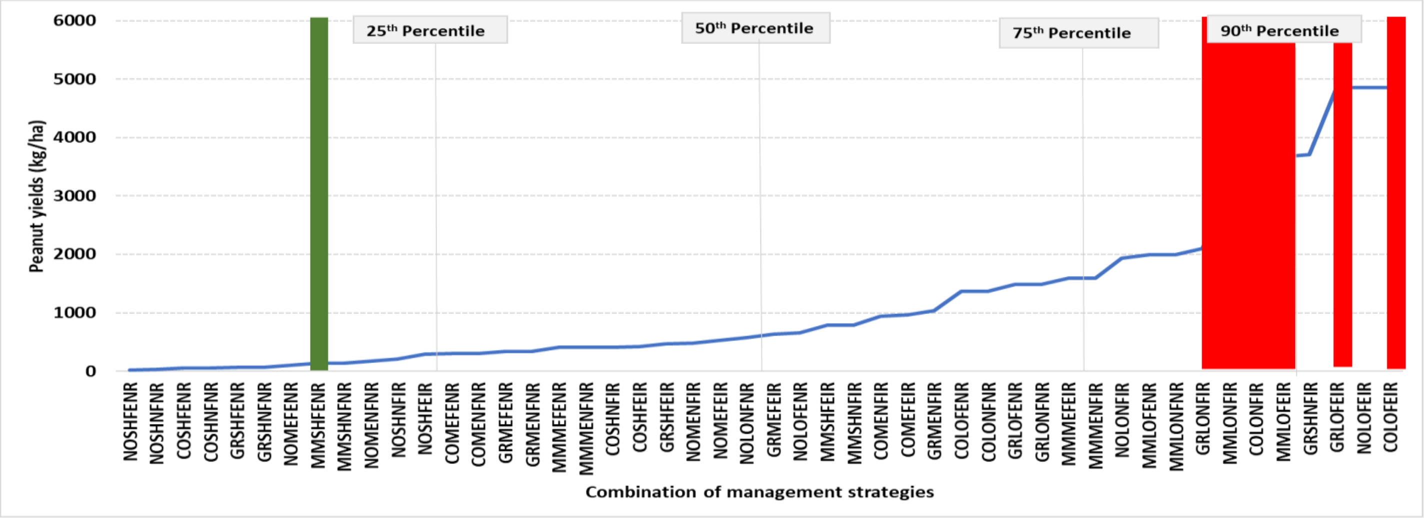
Annexure 5.194: Maize yield variation amongst the different crop management strategies based on station data for the 2015/16 season for off income farmers in Limpopo, South Africa.



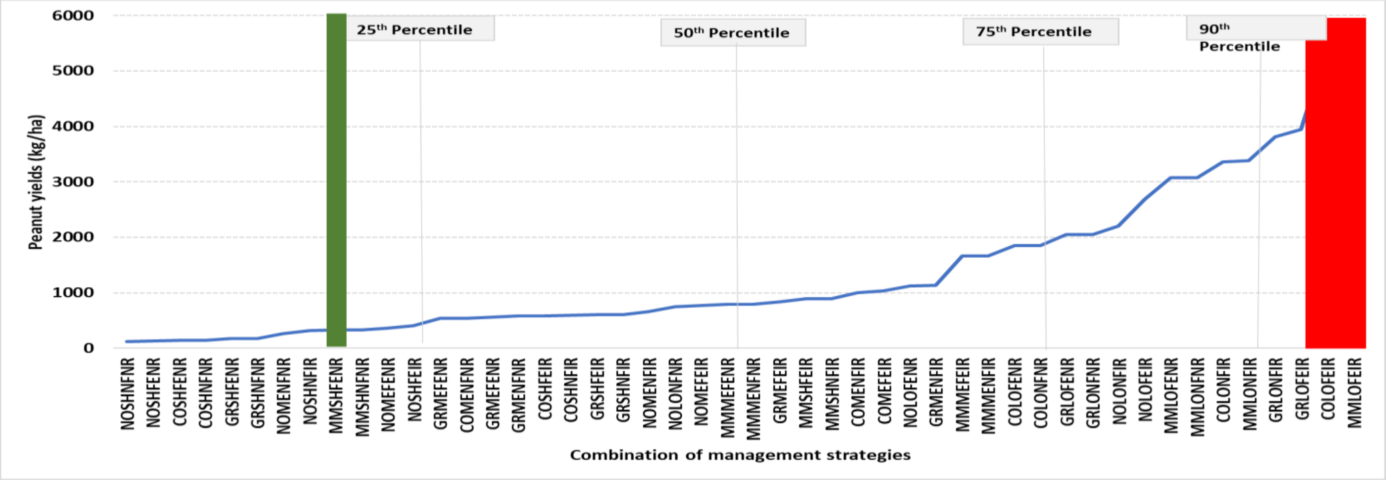
Annexure 5.195: Dry bean yield variation amongst the different crop management strategies based on station data for the 2011/12 season for struggling subsistence farmers in Eastern Cape, South Africa.



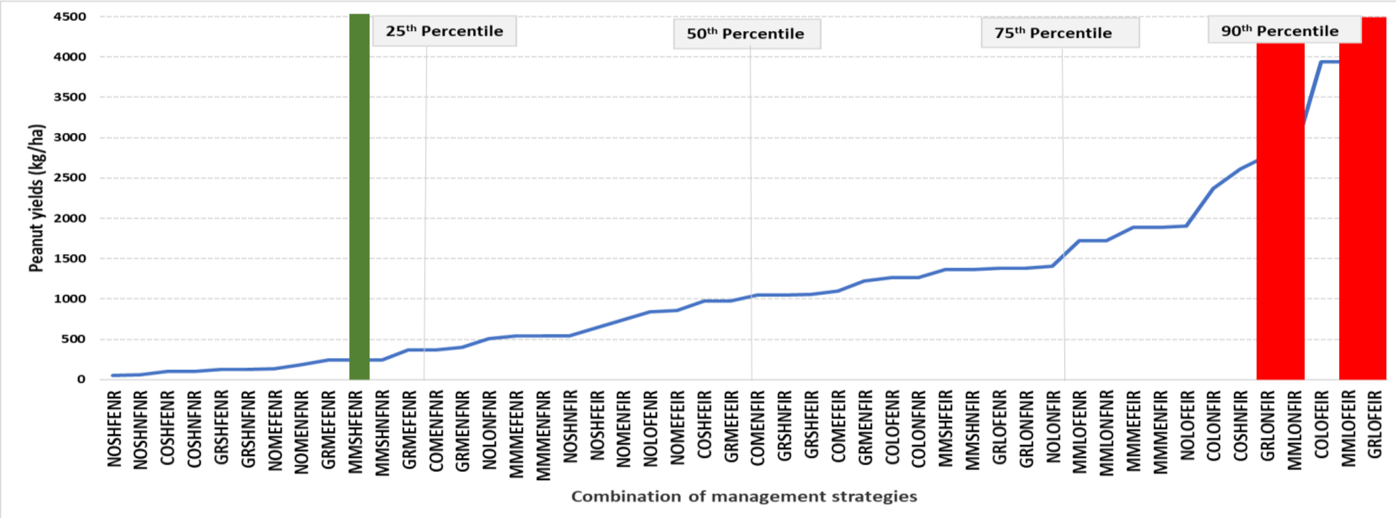
Annexure 5.196: Dry bean yield variation amongst the different crop management strategies based on station data for the 2012/13 season for struggling subsistence farmers in Eastern Cape, South Africa.



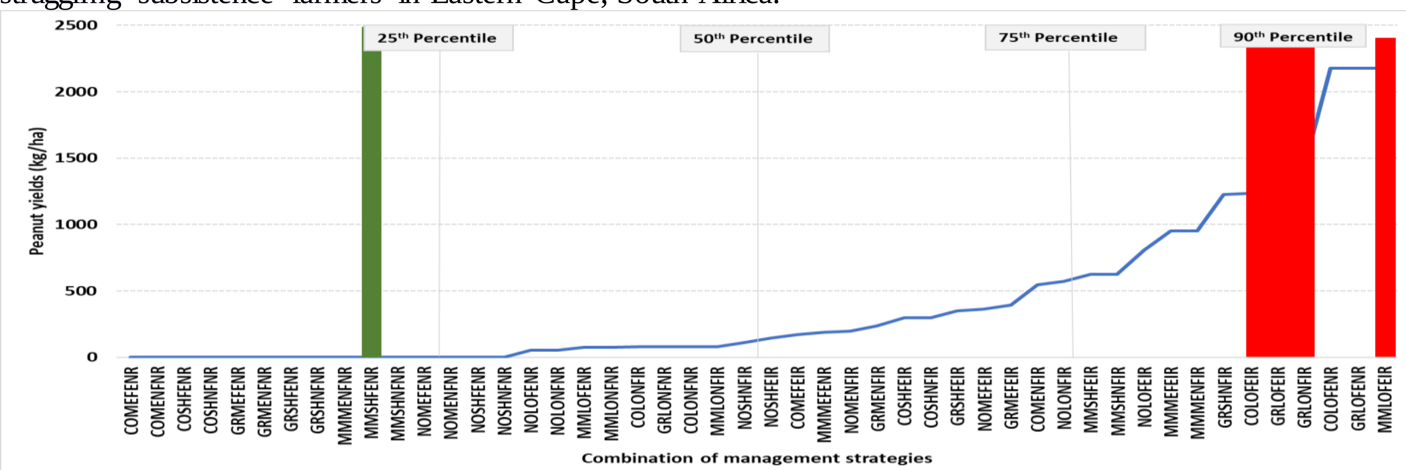
Annexure 5.197: Dry bean yield variation amongst the different crop management strategies based on station data for the 2013/14 season for struggling subsistence farmers in Eastern Cape, South Africa.



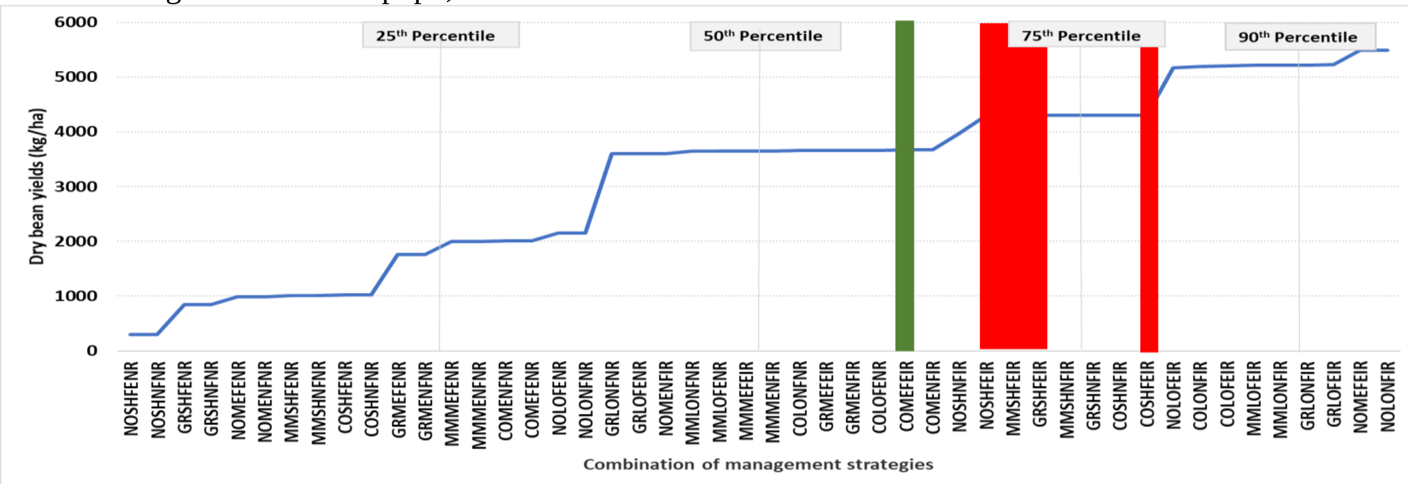
Annexure 5.198: Dry bean yield variation amongst the different crop management strategies based on station data for the 2014/15 season for struggling subsistence farmers in Eastern Cape, South Africa.



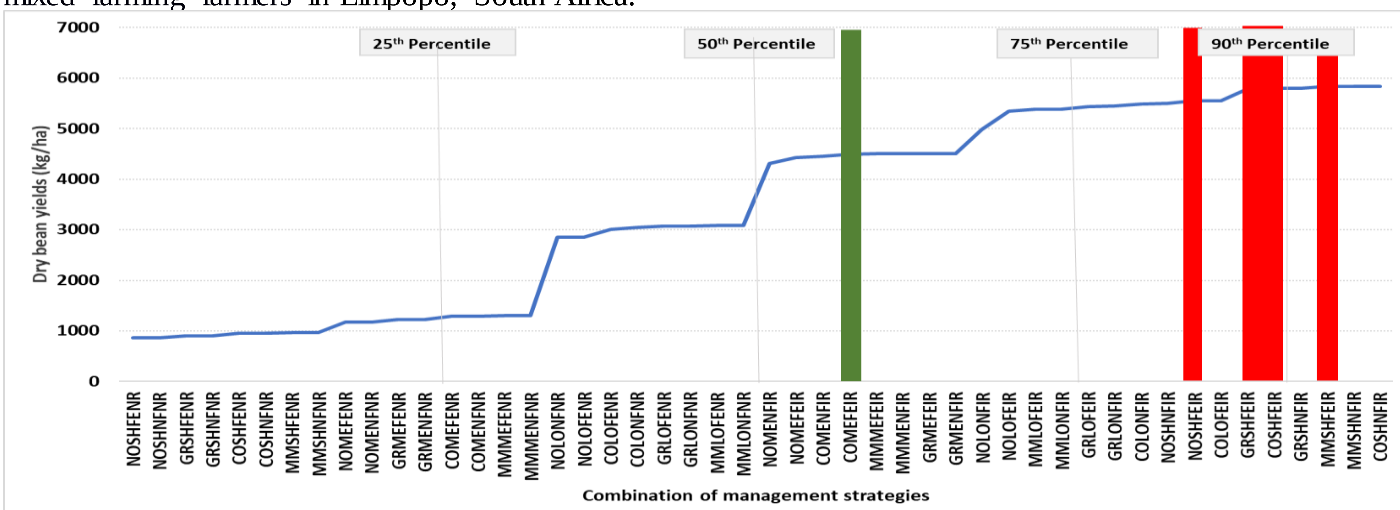
Annexure 5.199: Dry bean yield variation amongst the different crop management strategies based on station data for the 2015/16 season for struggling subsistence farmers in Eastern Cape, South Africa.



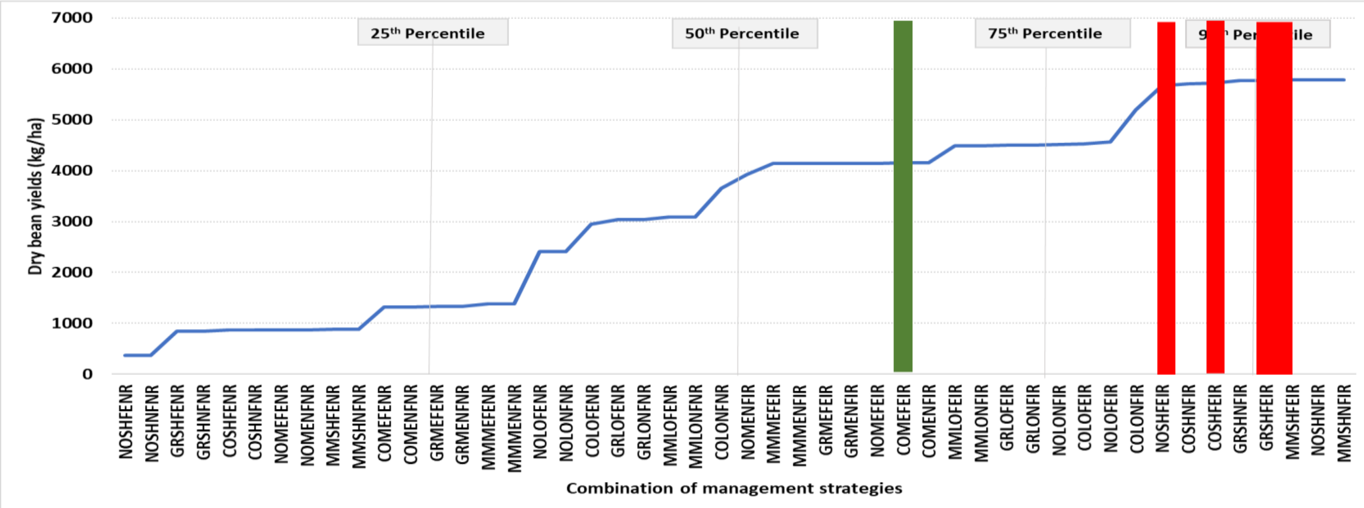
Annexure 5.200: Dry bean yield variation amongst the different crop management strategies based on station data for the 2011/12 season for mixed farming farmers in Limpopo, South Africa.



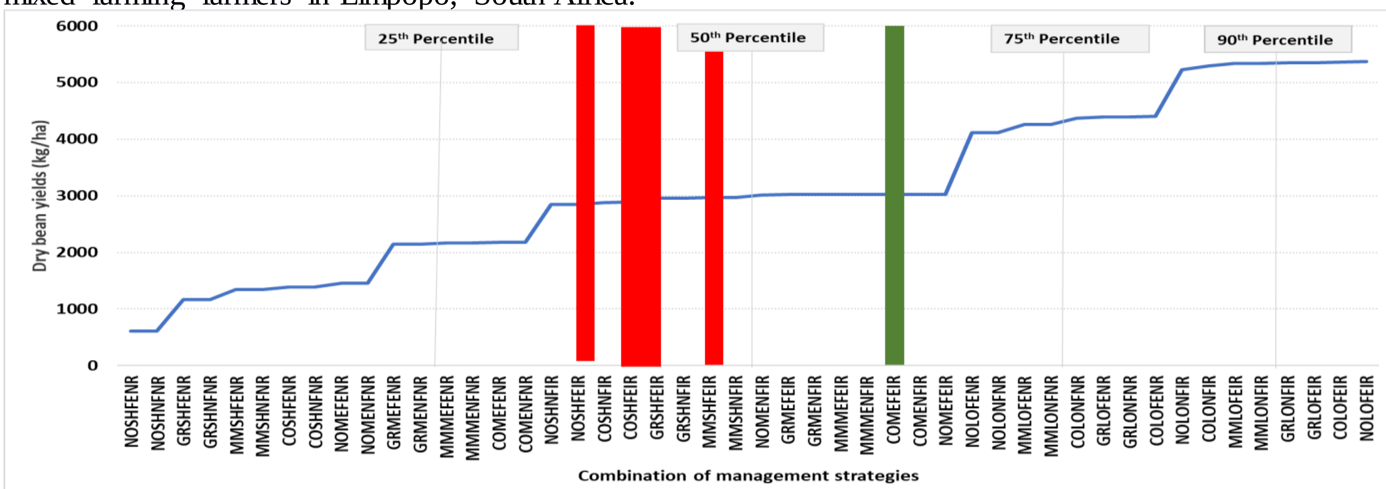
Annexure 5.201: Dry bean yield variation amongst the different crop management strategies based on station data for the 2012/13 season for mixed farming farmers in Limpopo, South Africa.



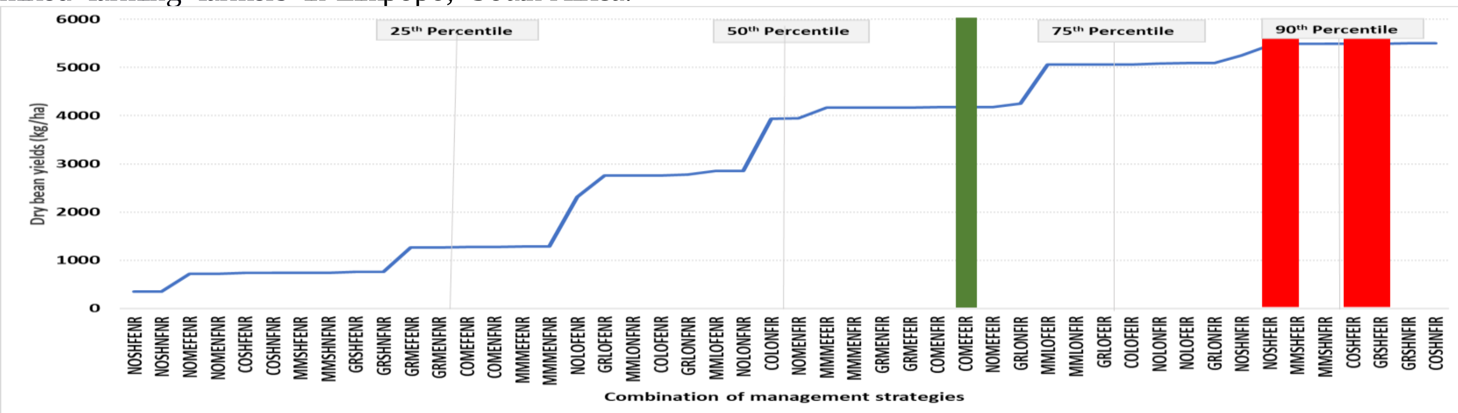
Annexure 5.202: Dry bean yield variation amongst the different crop management strategies based on station data for the 2013/14 season for mixed farming farmers in Limpopo, South Africa.



Annexure 5.203: Dry bean yield variation amongst the different crop management strategies based on station data for the 2014/15 season for mixed farming farmers in Limpopo, South Africa.

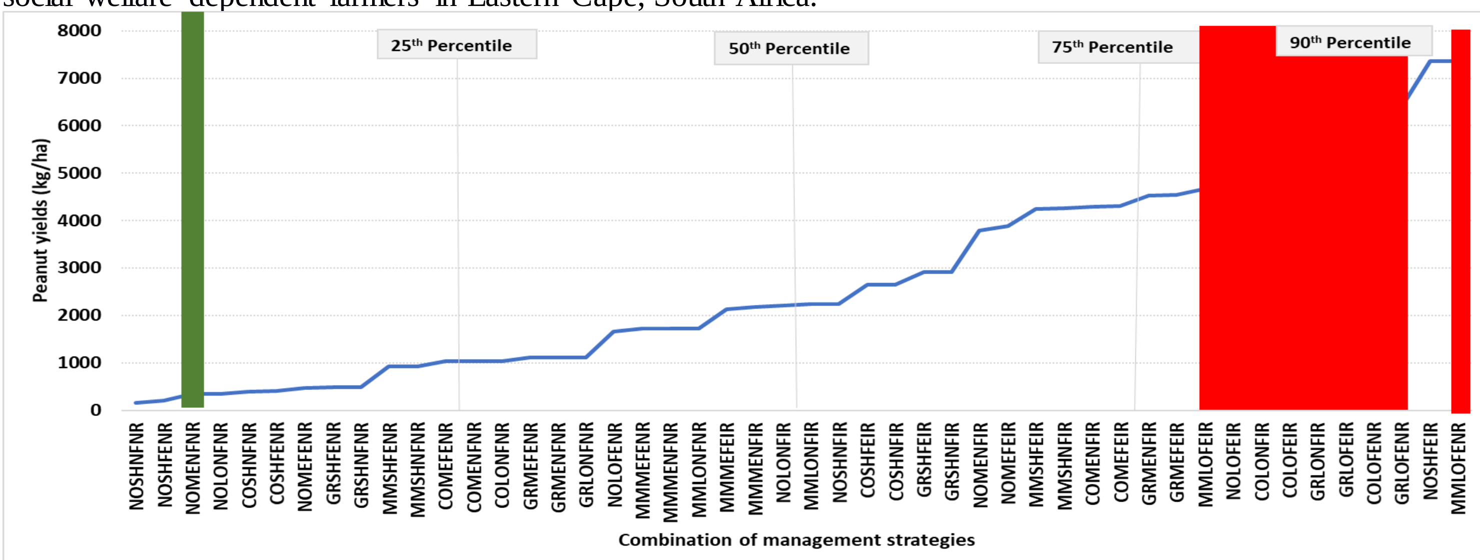


Annexure 5.204: Dry bean yield variation amongst the different crop management strategies based on station data for the 2015/16 season for mixed farming farmers in Limpopo, South Africa.

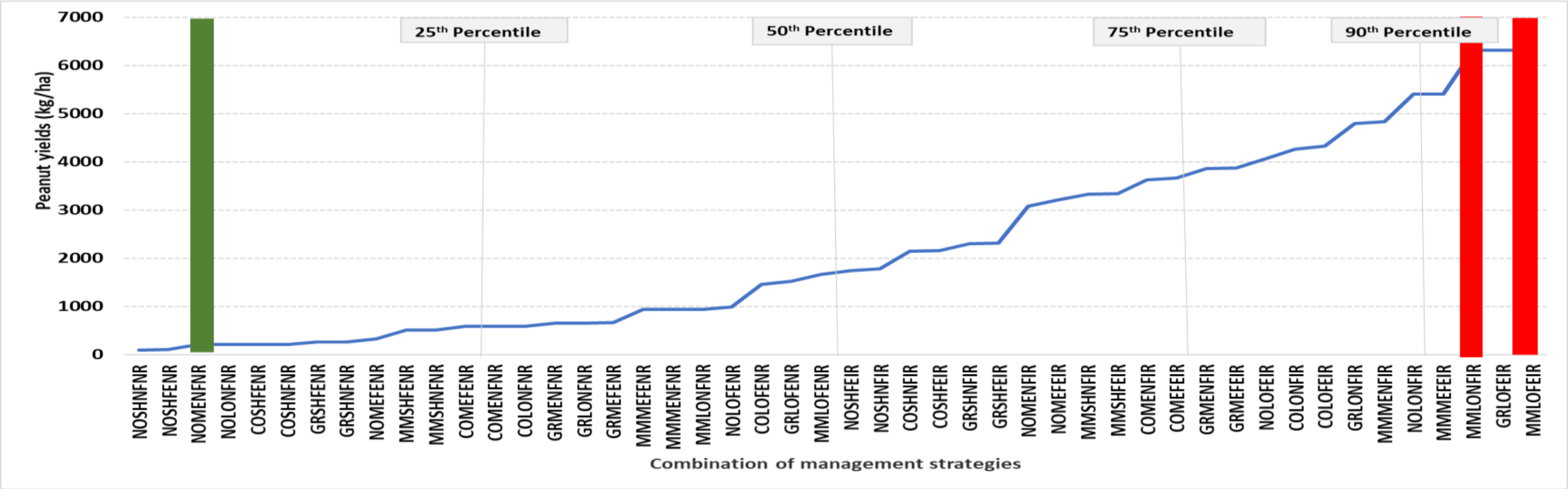


Peanut

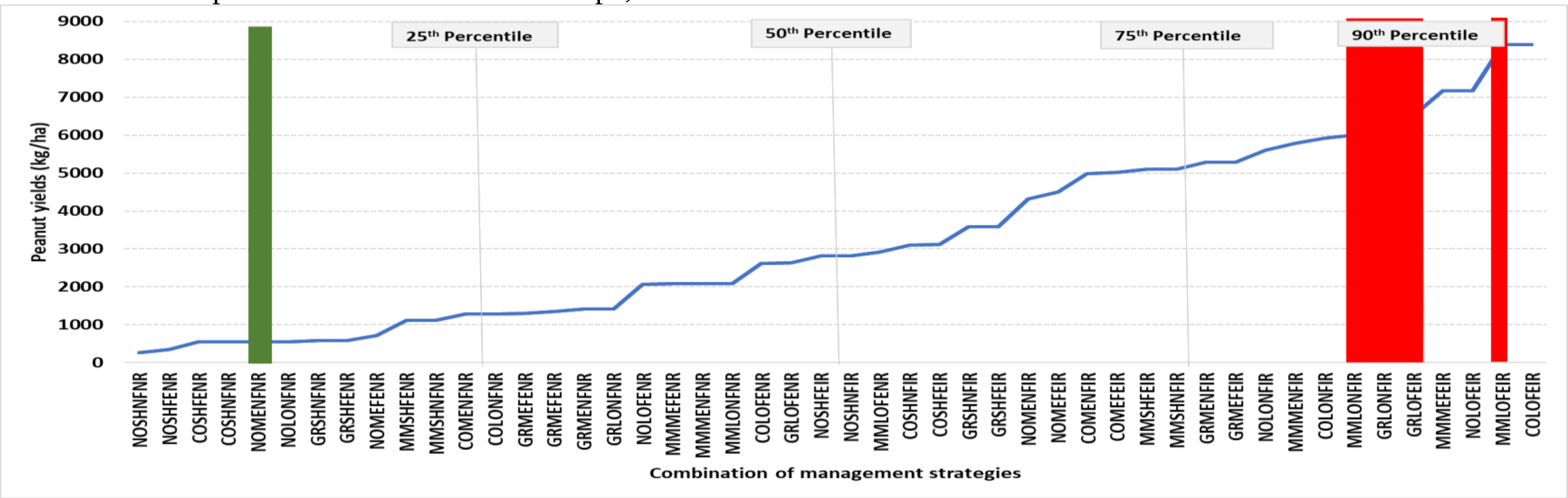
Annexure 5.205: Peanut yield variation amongst the different crop management strategies based on station data for the 2011/12 season for social welfare dependent farmers in Eastern Cape, South Africa.



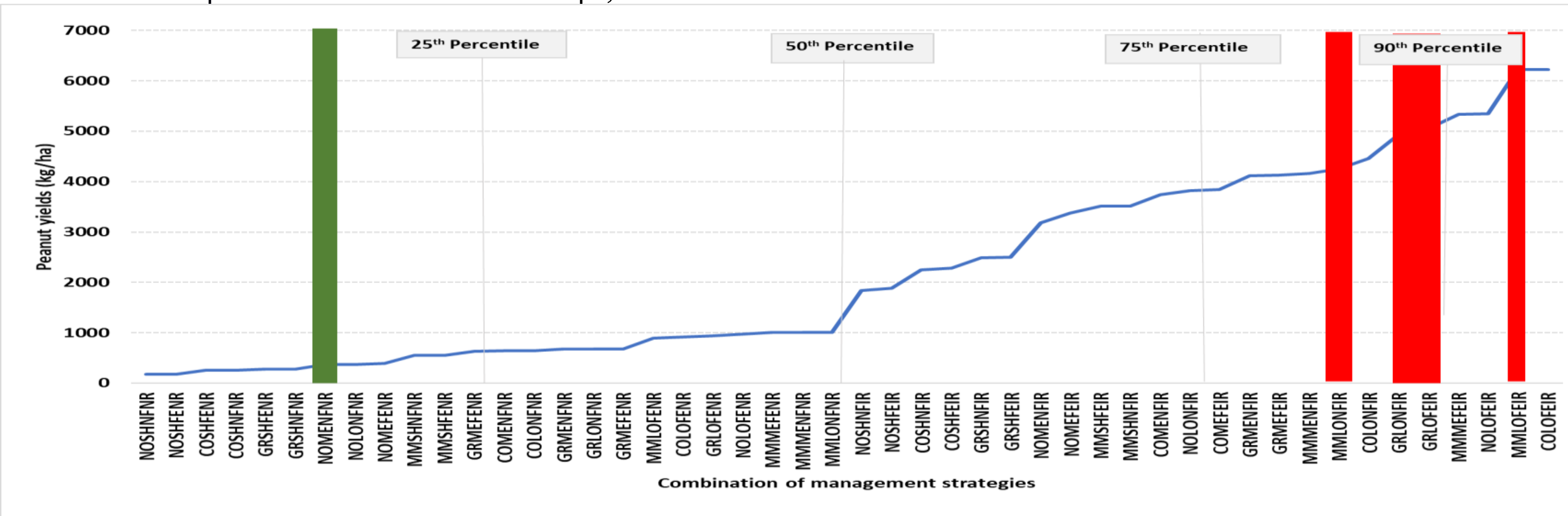
Annexure 5.206: Peanut yield variation amongst the different crop management strategies based on station data for the 2012/13 season for social welfare dependent farmers in Eastern Cape, South Africa.



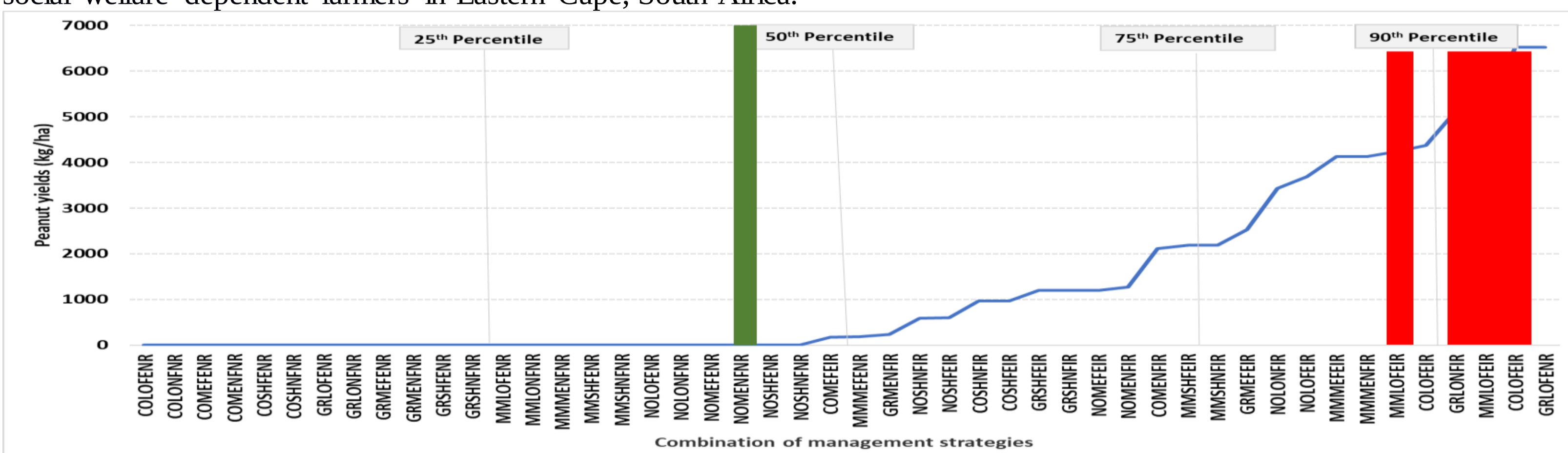
Annexure 5.207: Peanut yield variation amongst the different crop management strategies based on station data for the 2013/14 season for social welfare dependent farmers in Eastern Cape, South Africa.



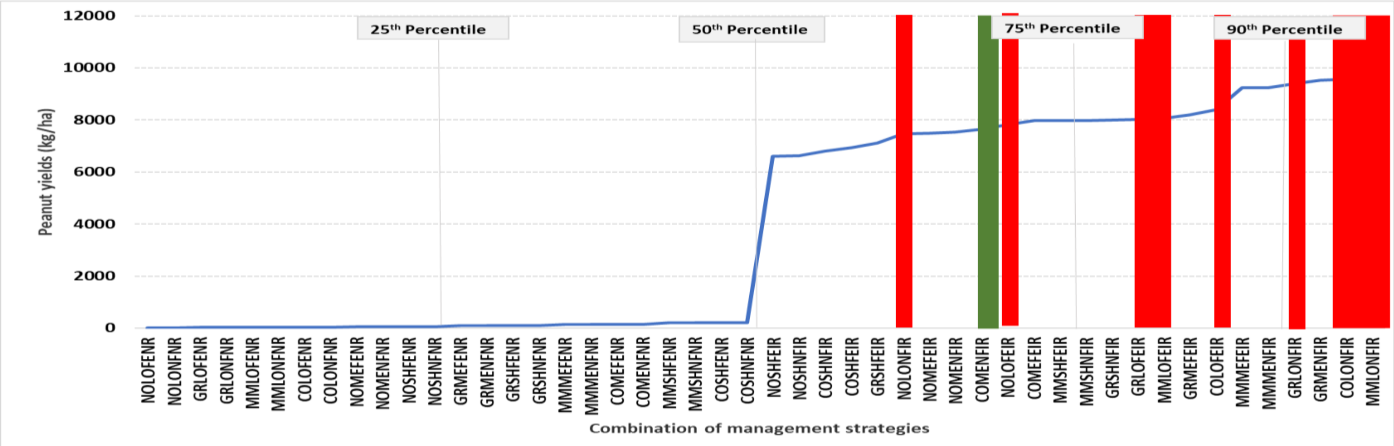
Annexure 5.208: Peanut yield variation amongst the different crop management strategies based on station data for the 2014/15 season for social welfare dependent farmers in Eastern Cape, South Africa.



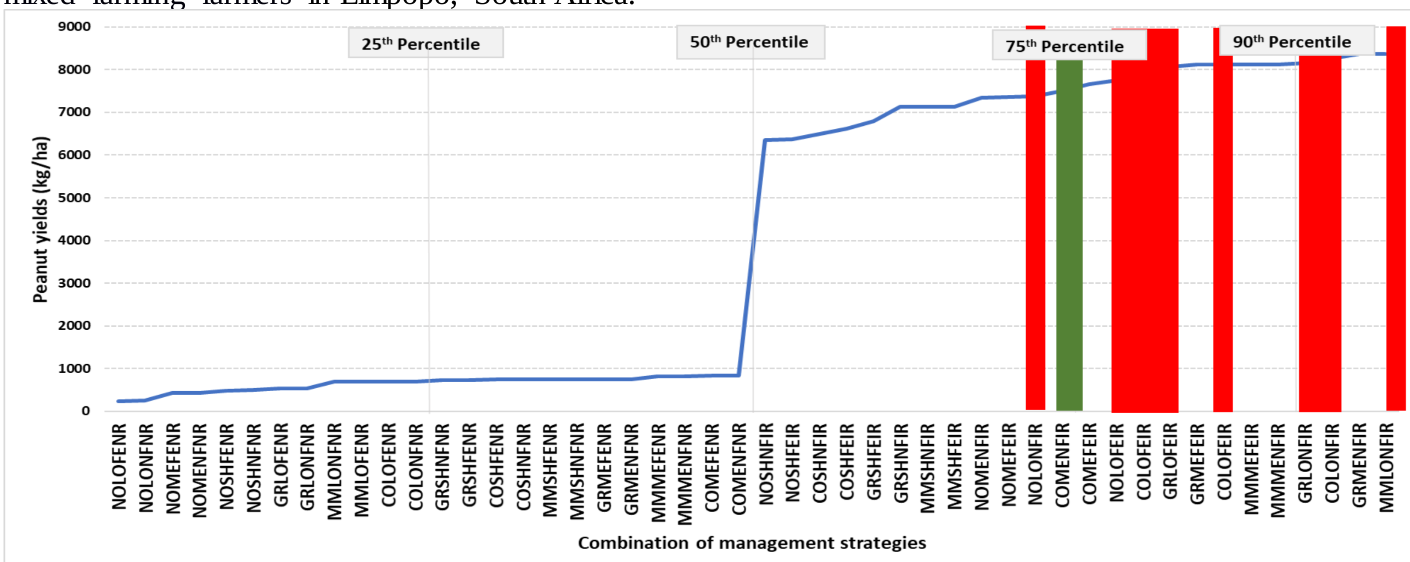
Annexure 5.209: Peanut yield variation amongst the different crop management strategies based on station data for the 2015/16 season for social welfare dependent farmers in Eastern Cape, South Africa.



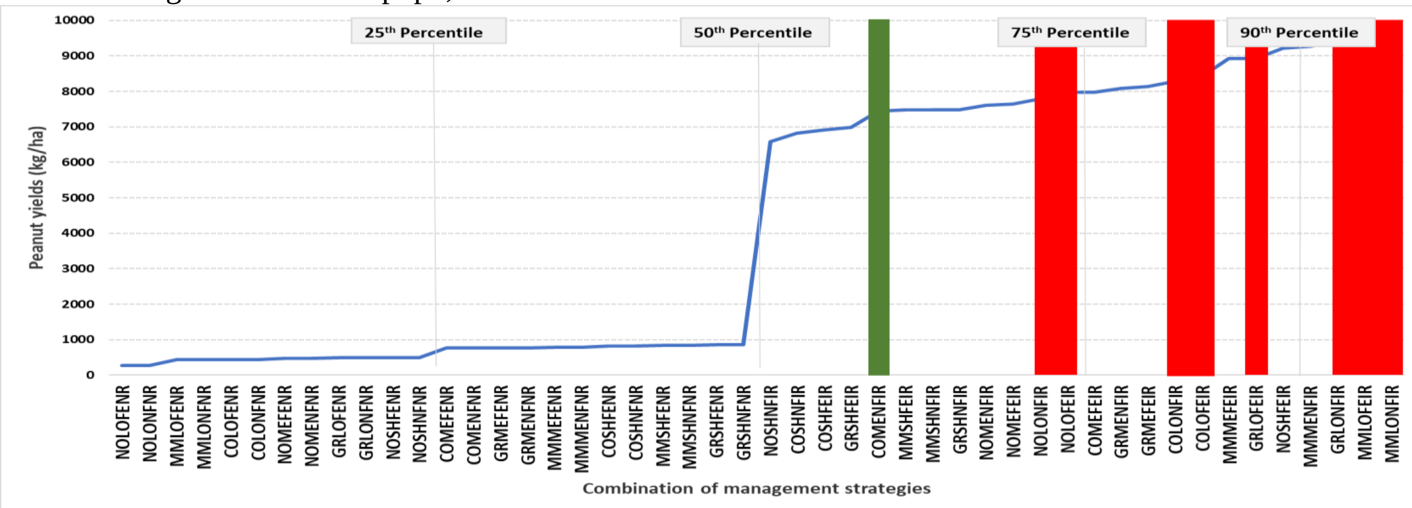
Annexure 5.210: Peanut yield variation amongst the different crop management strategies based on station data for the 2011/12 season for mixed farming farmers in Limpopo, South Africa.



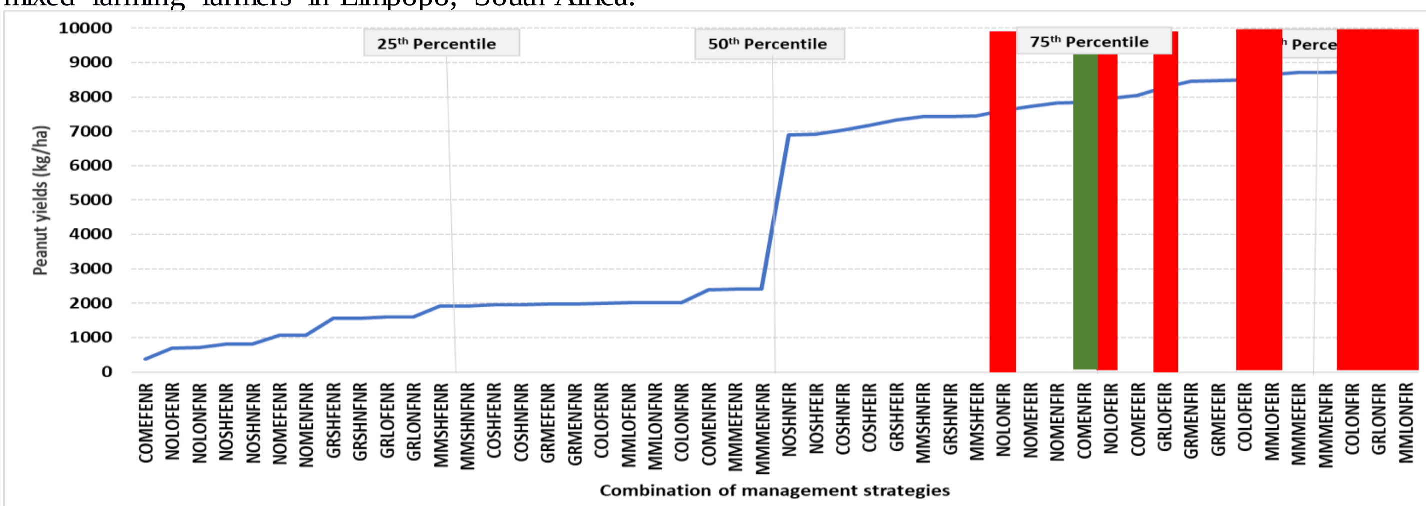
Annexure 5.211: Peanut yield variation amongst the different crop management strategies based on station data for the 2012/13 season for mixed farming farmers in Limpopo, South Africa.



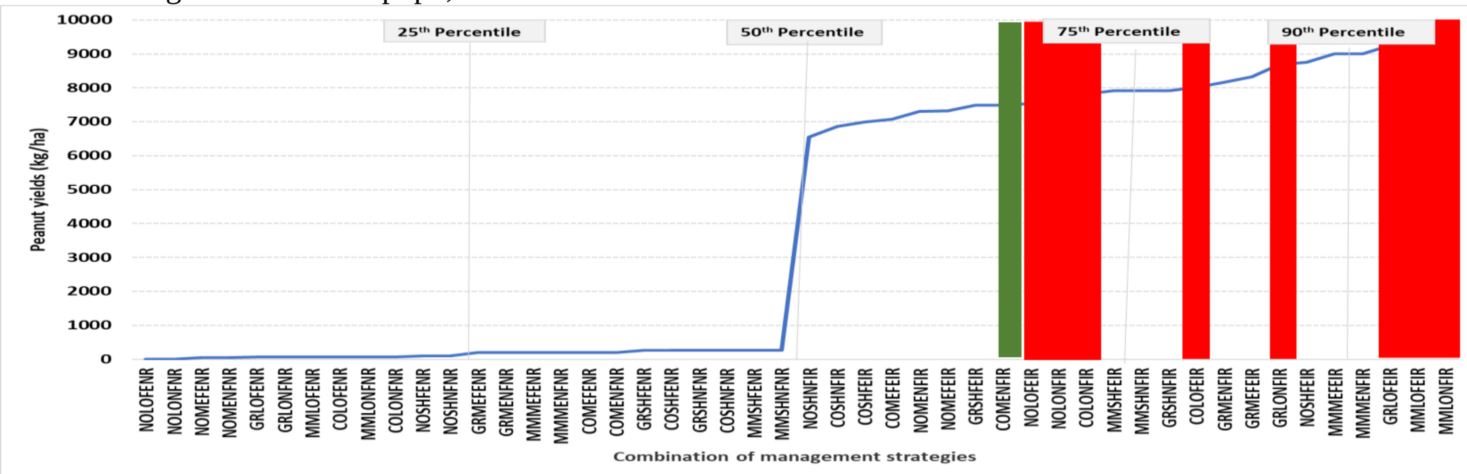
Annexure 5.212: Peanut yield variation amongst the different crop management strategies based on station data for the 2013/14 season for mixed farming farmers in Limpopo, South Africa.



Annexure 5.213: Peanut yield variation amongst the different crop management strategies based on station data for the 2014/15 season for mixed farming farmers in Limpopo, South Africa.

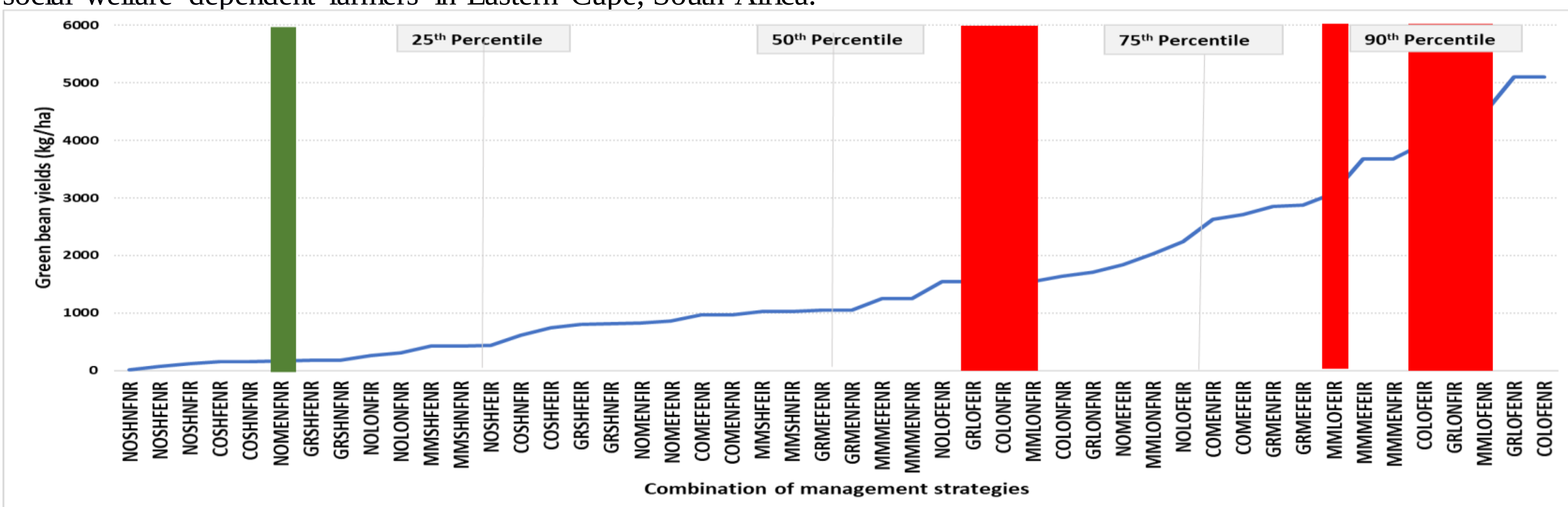


Annexure 5.214: Peanut yield variation amongst the different crop management strategies based on station data for the 2015/16season for mixed farming farmers in Limpopo, South Africa.

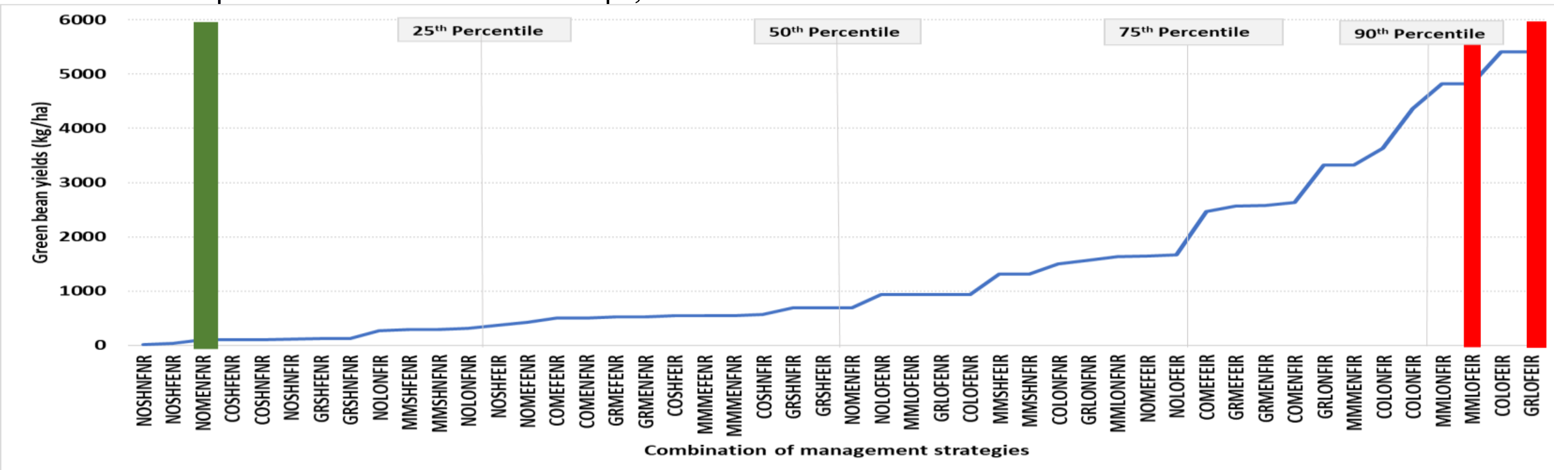


Green bean

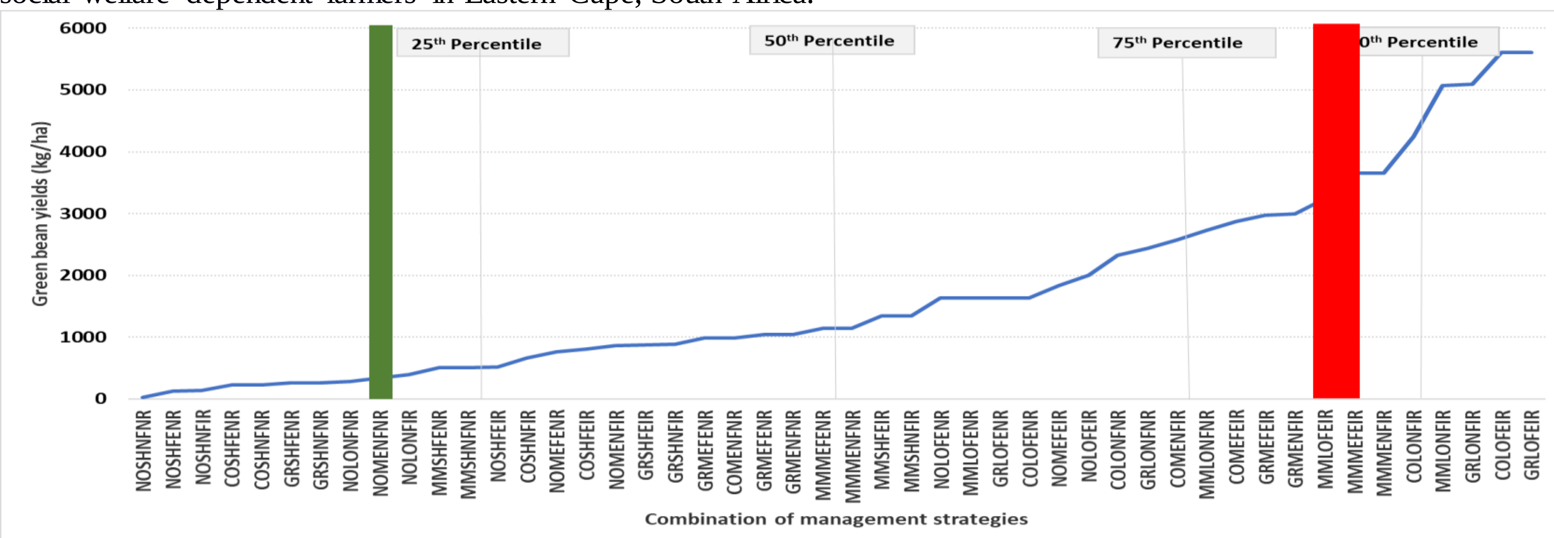
Annexure 5.215: Green bean yield variation amongst the different crop management strategies based on station data for the 2011/12 season for social welfare dependent farmers in Eastern Cape, South Africa.



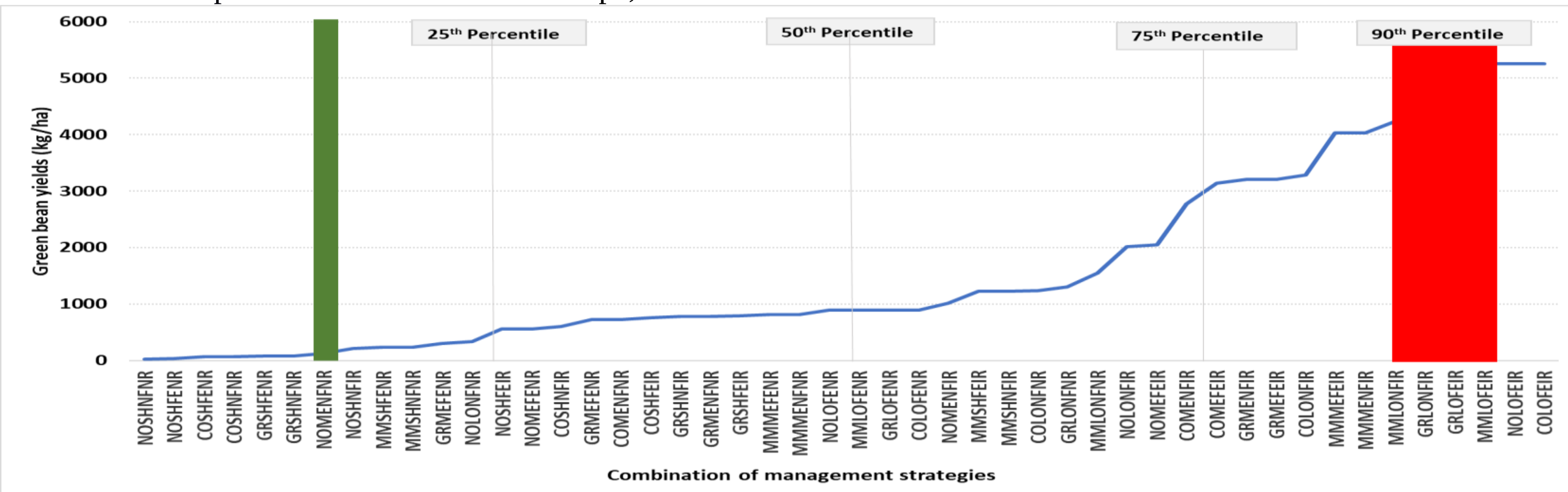
Annexure 5.216: Green bean yield variation amongst the different crop management strategies based on station data for the 2012/13 season for social welfare dependent farmers in Eastern Cape, South Africa.



Annexure 5.217: Green bean yield variation amongst the different crop management strategies based on station data for the 2013/14 season for social welfare dependent farmers in Eastern Cape, South Africa.



Annexure 5.218: Green bean yield variation amongst the different crop management strategies based on station data for the 2014/15 season for social welfare dependent farmers in Eastern Cape, South Africa.



Annexure 5.219: Green bean yield variation amongst the different crop management strategies based on station data for the 2015/16 season for social welfare dependent farmers in Eastern Cape, South Africa.