Anthropogenic Modification of the natural fire landscape and its consequences for vegetation patterns on the Cape Peninsula

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Abstract

Understanding the spatial probability of fire and how urban development may alter natural patterns is particularly important in areas where alternate ecosystem states occur at fine spatial scales. The Cape Peninsula, South Africa, is a one such region where fire-sensitive forest patches occur interspersed in a sea of fire-dependent fynbos. Fire is believed to be an important determinate of forest distribution, with absence or occurrence of fires potentially allowing patch contraction and expansion. In this thesis I use a series of computer models to determine the extent to which anthropogenic development and land transformation have altered the spatial variation in fire likelihood, or the 'burn probability', and its consequence for the distribution of forest on the Cape Peninsula.

The two multi-model, fire behaviour simulation systems I use are FlamMap and FARSITE. FARSITE is a deterministic simulation package used globally for discrete event simulation. In an effort to assess the viability of using the FARSITE model for fire prediction in fynbos and the determinants of model accuracy, I predicted fire area for a historical fire on the Cape Peninsula using a variety of fuel models and wind conditions. Following this validation, FlamMap was used to simulate the burn probability of the Cape Peninsula under natural conditions – no urban development present – and transformed conditions – where urban areas are mapped as non-burnable fuel models. I then determined changes in forest distribution documented over the last 50 years relative to changes in burn probability as a result of urbanisation. My results show that an increase in urbanisation on the Cape Flats has produced a significant urban shadow effect due to the interruption of natural fire catchments. This urban shadow effect has resulted in an overall increase in area of fire refugia on the Peninsula and expansion of forest, particularly on the more mesic eastern slopes at Kirstenbosch and Newlands. The results strongly support that urban-mediated changes to fire patterns are drivers of forest expansion in this region, and adds further evidence to support the significance of fire in determining biome boundaries in the fynbos.

Contents

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Thanks to the Fire, Fuel, and Smoke Science Program (FFS) of the Rocky Mountain Research Station at the Missoula Fire Sciences Laboratory for making FARSITE, FlamMap and a variety of other fire behaviour platforms available as freeware. Thanks to the City of Cape Town Open Data Initiative, a public access portal though which I got much of my input data. Thanks to SAEON and Jasper Slingsby here too for providing much of the data required. Additional thanks to Zoe Poulson for data sharing and replying so kindly to all of my emails, even though she was busy in the field!

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Figure list:

Chapter 1

Introduction

Fire occurs on over 40% of the world's land surface in a variety of ecosystems (**Chapin et al, 2002**), many of which are considered ‘fire-dependent systems’. In these systems, species diversity is dependent on the regular occurrence of fire (**Bond & van Wilgen, 1996; Keeley et al, 2011b**). Fire-dependent systems are adapted to a particular pattern of occurrence in terms of fire type, intensity, size, severity, frequency and seasonality – termed a fire regime (**Gill, 1975**). Contemporary fire regimes in fire-dependent systems are determined by both natural and human influences, with most having been impacted by humans for thousands of years (**Goren-Inbar et al, 2004**).

While humans have impacted fire regimes throughout their history, significant growth of human populations and changes in land use/management in recent decades have resulted in rapid changes to modern fire regimes in many fire-dependent systems (**Pausas & Keeley, 2009**). This is particularly true in Mediterranean Type Climate regions, where mild climates and great natural beauty are driving high rates of population growth and urbanisation (**Di Castri, 1994; Rundel, 1998**). In the last decade of the 20th century, the total population within Mediterranean Type Climate regions grew by over 34 million people, with urban areas expanding by 13% (roughly 5,480 km^2; **Underwood et al, 2009**). This is problematic as these regions collectively hold over 20% of the world’s floral diversity, despite only occupying 2.2% of the earth’s surface (**Médail & Quézel, 1997; Cowling et al, 1996a**).

The Cape Peninsula, located at the south-western tip of the Western Cape Province of South Africa, is a classic example of the overlap between fire-dependent vegetation and high levels of urbanisation that is characteristic of Mediterranean Type Climate regions. The vegetation on the Cape Peninsula is termed fynbos, a hyper-diverse and fire-dependent sclerophyllous shrubland that is characterised by the dominance of ericoid (fine leaved and shrub-like), restioid (reed-like, aphyllous species of Restionaceae and Cyperaceae) and proteoid (broad-leaved, tall shrubs) growth-forms with a notable lack of tall trees (**Bergh et al, 2014**). There are 2285 indigenous plant species on the Cape Peninsula, 158 of which are endemic (**Trinder-Smith et al, 1996; Helme & Trinder-Smith, 2006**). The area of the Peninsula is only

470 km^2, making this one of the highest concentrations of plant species diversity in any temperate ecosystem in the world (**Cowling et al, 1996b**).

The average fire return interval the Peninsula is approximately 13 years, though return interval varies and many species are resilient to variable return periods of between 10 and 40 years (**van Wilgen & Forsyth, 1992; Forsyth & van Wilgen, 2008**). Many fynbos species exhibit fire survival or fire-stimulated reproductive traits in response to this regular fire regime (**Bond & van Wilgen, 1996**). Fire stimulated flowering is a particularly common trait in geophytes such as *Cyrtanthus spp.*, whose crimson flowers are only visible in the landscape after a fire. Serotiny and consequent heat or smoke-stimulated seed release is also common, particularly in the woody members of the Proteaceae family (**Lamont et al, 1991**), as is heat or smoke-stimulated germination of seed banks. Fire persistence traits such as such as basal sprouting and regeneration from underground lignotubers are also common (**Bond & van Wilgen, 1996**).

Natural variation in the fire regime is key to promoting species co-existence and maintaining diversity at a meta-community scale (**van Wilgen et al, 1992; Bond & van Wilgen, 1996; Le Maitre & Midgley, 1992**), particularly in terms of fire frequency (**Thuiller et al, 2007**). Obligate re-seeders with a longer juvenile period are particularly vulnerable to any shortening of the fire return interval (**van Wilgen & Forsyth, 1992; Forsyth & van Wilgen, 2008**). Many proteoid shrubs are obligate re-seeders and although these often make up only a few species in a stand of fynbos, they may contribute up to 90% of the total plant biomass. Excessively short (<6 year) fire return intervals therefore have the potential to cause large structural changes to the environment (**van Wilgen & Forsyth, 1992; Kraaij & van Wilgen, 2014**).

Fire is additionally thought to be important in delineating the distribution of fire-sensitive forest patches on the Cape Peninsula, where small pockets of broad-leaved and evergreen indigenous forests are surrounded by a fire-prone fynbos matrix (**Cramer et al, 2014**). Sharp boundaries typically occur between neighbouring fynbos and forest patches and are thought to be predominately maintained by fire (**Granger, 1984**). A lack of ladder fuels and high density of tree species with high foliar moisture act as an effective barrier to fire penetration in forest patches. High fire frequency or intensity may however reduce the size of fire-sensitive forest patches with repeated damage to species on the forest margin

(**Schmidt & Vlok, 2002**). Damage to and reduction of these margin species exposes the more fire-sensitive species of the patch interior to fires, which may result in stem death and patch reduction (**Granger, 1984; Manders, 1990**). Conversely, long-term absence of fire or a sustained regime of low intensity fires may allow recruitment of forest species outside of the forest margin, rendering the margin much less defined (**Schmidt & Vlok, 2002**). Forest pioneers are often bird dispersed, with higher densities of seed typically deposited under large woody shrubs that provide natural perches in the fynbos (**Masson & Moll, 1987; Midgley et al. 2003**). In the absence of fire, these scattered dispersion nuclei of forest seedlings may grow and establish into new forest patches with time (**Manders & Richardson, 1992**).

The reliance on fire for system health, diversity and vegetation structure makes the Cape Peninsula very vulnerable to changes in the fire regime. Historical accounts suggest extensive change has occurred to the fire regime over the Cape's relatively short history of urbanisation that began with the first Dutch farms along the Liesbeeck River in 1657 (**Brink, 2008**). Although human use of fire for management on the Peninsula probably began with fire-stick farming by nomadic hunter-gatherers about 10,000 years ago (**Deacon, 1983**), the rapid expansion of pastoral agriculture after Dutch colonisation led to the overutilization of fire for land clearance and excessively short fire returns periods. The short interval regime was subsequently replaced with a policy of total fire suppression that stayed in place until the late twentieth century. The consequent build-up of fuel and increase in ignition sources from population growth resulted in large and well documented fires and a sustained antipathy towards fire (**Pooley, 2014**). This continued until the 1970's, when suppression policies were lifted in line with the growing global awareness of the role of fire in maintaining system health, though only a limited number of prescribed burns between 1970 and 2008 (**van Wilgen, 1996; Forsyth & van Wilgen, 2008**). Contemporary fire management acknowledges the role that fire plays in species diversity of fynbos, with attempts to dynamically manage fire on the Peninsula for both plant species diversity and public safety (**van Wilgen et al, 2010**). Since the 1990's the urban population of the City of Cape Town has increased by 46% to reach over 4 million people in 2016 (**Stats-SA, 2016**) . Urban development now completely encircles Table Mountain National Park, the 265 km^2 conservation area that contains the majority of the remaining natural land on the Peninsula.

Digitized fire records collated since the 1970's suggest the Peninsula is moving towards a higher frequency fire regime, with mean fire return interval having decreased significantly from an average of 31.6 years in the 1970's to 13.5 years in 2007. This decrease in fire frequency is 'almost certainly' attributable to the concurrent increase in human population (**Forsyth & van Wilgen, 2008**).

A less understood impact of urbanisation on the Peninsula is how urban development has impacted the spatially explicit patterns of burn probability. There are areas in a landscape that are naturally more likely to experience fire as a function of spatial variation in local topography, fuels and weather conditions (**Syphard et al, 2008**). For example, the channelling of wind through valleys or around ridges can result in complex changes to the pattern of wind flow, both in terms of direction and velocity (**Forthofer et al, 2014a**). This interaction may create areas that are more difficult for a spreading fire to reach, commonly termed fire refugia. Natural topographic features, such as scree slopes or steep escarpments, can act as barriers to fire flow and halt fire spread, causing shadow areas on the lee side (**Geldenhuys, 1994; Ager et al, 2007; Parisien et al, 2010**). The summary of these varied interactions over a landscape should result in characteristic patterns of spatially explicit fire likelihood or 'burn probability' (**Parisien et al, 2010**). The addition of artificial barriers to the flow of fire through a landscape, such as extensive metropolitan areas where fire is suppressed, may have a similar impact to that of natural barriers; creating large expanses of urban fire shadows (**Geldenhuys, 2000**). High levels of urbanisation may therefore substantially impact natural patterns of fire in a landscape.

The Cape Peninsula is a good case study for exploring the impact of urban expansion on burn probability as the region has experienced extensive but disjoint urban development interspersed among fire-dependent vegetation. Additionally, forest and fynbos exist as alternate stable ecosystem states, with fire important in determining their relative extents. Change to burn patterns has the potential to impact these extents by modifying the spatial occurrence of fire refugia in the landscape. In this thesis I explore the potential impact of anthropogenic land cover change on fire and vegetation patterns on the Cape Peninsula using fire simulation models.

Understanding the impacts of altered landscapes on vegetation structure requires the determination of how fire would naturally flow through both altered and unaltered landscapes. This can only realistically be achieved using models, but ecological models are simplifications of complex realities and may require validation (**Gardner & Urban, 2003**). I validate the modelling approach and parameters used by comparing model projections with a well-documented fire in a fire scar analysis using FARSITE in **Chapter Three**. I then use FlamMap to assess the predicted impact that urbanisation has had on burn probability and compare this to maps of changes in the distribution of fire-sensitive forest. By doing this analysis, I aim to determine if fire models are useful in fynbos and can be used for ecological research, as well as take some initial steps in exploring the feasibility of fire modelling for operational use on the Cape Peninsula. I also aim to evaluate the extent to which urbanization has disrupted the natural fire landscape and whether changes in fynbos and forests distribution have occurred as a result of these changes in fire landscapes.

Chapter Two explores various options for fire behaviour modelling in fynbos and has an in-depth discussion of the software used in Chapters Three and Four. In **Chapter Three**, I use the discrete event simulation system FARSITE to predict the final fire area of a historical fire, using fire scar analysis to determine how accurately fire area can be predicted on the Cape Peninsula. The aim of this chapter is to validate the underlying fire behaviour models for use in Chapter Four, and identify conditions of accuracy in fuel model and wind data for potential operational use in fire management. In **Chapter Four**, I use FlamMap to explore the impact of urbanisation on patterns of fire vulnerability on the Cape Peninsula and how these change the distribution of fire-dependent fynbos and fire-sensitive forest patches. Finally, **Chapter Five** gives an overarching research synthesis, assessing the ecological implications of my results. Limitations of the modelling approach are also discussed, and recommendations made for improving further fire modelling efforts in the fynbos.

Chapter 2

Selecting an appropriate fire behaviour model for fynbos

The ultimate utility of any model is to enable the user to make useful predictions about a phenomenon. This is particularly important for modelling wildfire, as fire spread predictions can aid fire containment and reduce risk to property and life. The success of a modelling attempt is dependent on the use of an appropriate model. Many fire prediction models exist, although these vary regarding which facet of fire behaviour is predicted (e.g. rate of spread, intensity, flame height, and fire area), as well as the model underpinnings, ranging from the purely physical to purely empirical. When choosing an appropriate model for fynbos, both the ecology of the fynbos system as well as the availability of suitable data must be considered. This chapter will briefly discuss some of the important types of wildfire models, before selecting an appropriate model for usage in fynbos.

Types of Models

Fire behaviour models exist as a spectrum of approaches from physical models that are built from theoretical principles to empirical models that are built from statistical correlation between observed variables (**Papadopoulos & Pavlidou 2011; Sullivan, 2009a**). Both physical (those using both physical and chemical principles) and quasi-physical (those using purely physical principles) models use a bottom-up approach to system modelling, and aim to predict fire behaviour based on the fundamental physical and/or chemical underpinnings of combustion and heat transfer. Fire is therefore visualised as the collective outcome of multiple underlying process, each of which needs to be understood and expressed formulaically (**Sullivan, 2009a**). Empirical models however are characterised by the absence of a physical framework and are entirely statistical in nature, whilst quasi-empirical models have some physical framework upon which a statistical model is built (**Sullivan, 2009b**). In contrast to physical models, empirical models use a top down approach and visualise fire as a single entity, making no attempt to understand the physical and chemical processes that underpin it. Empirical models attempt to make statistical correlations between measured fire parameters and easily observable environmental parameters, such as wind conditions, terrain and fuel moisture, which can then be extrapolated for prediction of fire behaviour (**Sullivan, 2009b**).

Physical models tend to be complex and therefore very computationally intensive when used operationally. Long computational times are problematic for managers hoping to use physical models for real-time fire behaviour prediction. In order to speed-up computation, operational physical models are forced to reduce the resolution of the computational domain or make broad approximations of physical processes. This can reduce user confidence and the overall accuracy in final results. This factor, in addition to complex data requirements, often limits the operational use of physical and quasi-physical models. Therefore, empirical and quasi-empirical (henceforth just 'empirical') models make up most of the existing operational fire models due to simplicity, easily measurable input data and efficiency of calculation (**Sullivan, 2009b**).

Empirical models of wildfire behaviour

Many empirical wildfire models exist to predict a variety of fire behaviour parameters, including flame height and length, fire line intensity, and rate of spread. Flames are described in terms of height, a measure of the vertical distance from the ground to the flame tip, and length, the distance from the flame base at the ground to the flame tip (**Butler, 2007**). Flame length is often used to estimate fire line intensity, a notoriously difficult parameter to measure in the field that describes the energy released from a fire front per unit time. Intensity measures the radiant energy released as a function of the heat of combustion, the fuel consumed and the rate of spread (**Byram, 1959**). Intensity is not to be confused with burn severity which is a more general metric measuring the post-fire loss of organic matter (**Keeley et al, 2011a**). Rate of spread (ROS) is primarily used to characterise the speed at which a fire spreads and is a measure of the forward horizontal distance travelled by the flaming front per unit time. Rate of spread is a function of the heat balance between burning and pre-burnt fuels, vectored by the positive radiative impact of wind and slope (**Alexander, 2000; Rothermel, 1972**). ROS is a particularly important fire behaviour parameter owing to predictive ability for a variety of other fire behaviours, including of potential fire size, fire line intensity and flame size (**Scott, 2012**).

Rothermel's (**1972**) surface fire model is perhaps the best known and most widely used empirical fire behaviour model and is used to predict the rate of spread in a contiguous fuel bed. Rothermel's rate of spread can be expressed as the ratio of heat emitted from the source to the heat absorbed by the sink. Fire is visualised as a series of ignitions as potential fuel particles become dehydrated when in the immediate presence of burning fuel, bringing potential fuel to pyrolysis temperature. At this threshold, the fuel will ignite and release combustible gas, causing the fire front to advance to a new position (**Rothermel, 1972**).

Rothemel's (**1972**) surface fire spread is calculated as:

$$Rate\ of\ spread = \frac{[Reaction\ intensity] \times [Propagating\ flux\ ratio] \times (1 + [Wind\ factor] + [Slope\ factor])}{[Overdry\ bulk\ density] \times [Effective\ heating\ number] \times [Heat\ of\ preignition]}$$

In units of:

$$ft/\min = \frac{(\frac{BTU}{ft^2}\min^{-1})\ d^*(1 + d^* +\ d^*)}{(\frac{lb}{ft^3})\ \varepsilon\ (\frac{BTU}{lb})}$$

Where d^* is a dimensionless ratio or coefficient.

Simulation of fire spread

Models, either empirical or physical, typically generate point predictions of fire behaviour (**Perry, 1998**). However, fire prediction for operational use needs to be able to predict fire spread over a landscape as well as fire behaviour at specific points. To achieve this, one dimensional models are converted into two dimensional planar models by the use of propagation algorithms (**Sullivan, 2009c**). Such simulation systems fall into Sullivan's (**2009c**) third category of models; simulation systems and mathematical analogues. A variety of propagation methods exist, resulting in a suite of different simulation software (**Papadopoulos and Pavlidou, 2010**). Fire in these simulation systems is typically constrained to a particular shape (typically elliptical) for mathematical efficiency. A single fire has three regions that differ in behaviour: the flaming front, the backing front and the flanking front (**Alexander, 2000**). The flaming front is the leading front of the fire where the fire is moving into new, unburnt fuels. Rate of spread is fastest here and most fire behaviour models are focused on predicting behaviour in this active region. By constraining fire shape to an ellipse, fire growth on the backing and flanking fronts can be estimated from the rate of forward spread using the mathematical properties of an ellipse (**Fig. 2.1; Richards, 1990**).

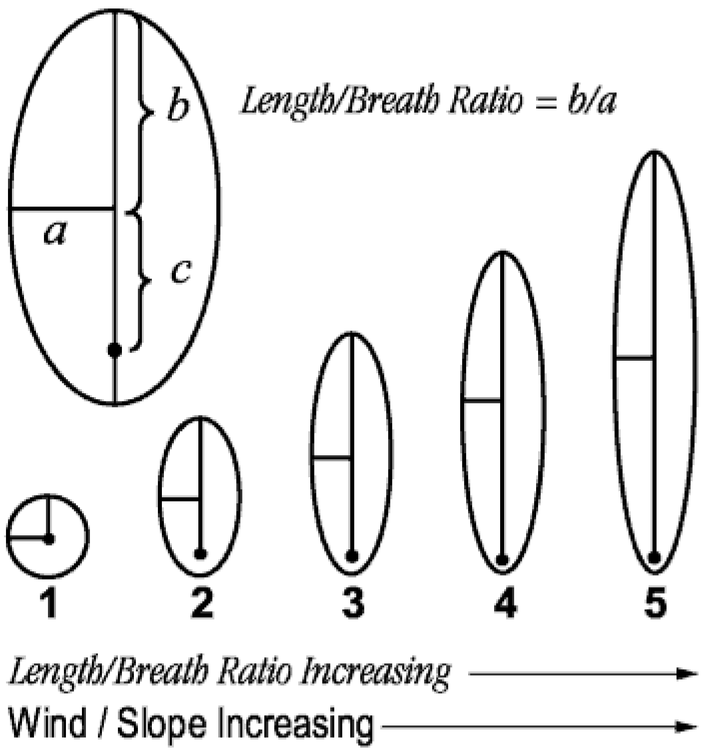

Figure 2.1: The length: breadth method of determining rate of backing and flanking fronts from the forward rate of spread. ɑ represents half the breath of the ellipse, *b* half the length and *c* the distance from ignition point to the centre of the ellipse. The length of the longitudinal axis increases with faster rate of spread, caused by increasing wind/slope coefficients or fuels that support faster combustion (Figure from **Finney, 2008**).

Propagation methods for the fire perimeter are split into raster and vector methods. Raster methods consist of nearest neighbour or direct contact spread models, where the fire environment is split into a regular lattice of cells that may be in one of three states: burnt, burning or unburnt. Fire behaviour parameters are calculated for each burning cell and propagation of the fire front is achieved by the definition of a set of simple rules that govern the state change of a cell when it is exposed to fire by a neighbouring cell. This method of modelling deals well with heterogeneous fuels and topography, and can be less computationally intensive compared to vector propagation depending on resolution (**Sullivan, 2009c**).

Fire spread in vector propagation is primarily achieved using Huygen's wavelet principle, a wave expansion theory first applied to fire spread by Anderson (**1982**), where the fire front is projected as a continuously expanding polygon divided into discrete time steps. Expansion of the flaming front is achieved by using each of a regularly spaced set of vertices on the existing fire perimeter as a potential ignition point for expanding elliptical wavelets, the dimension and orientation of which depends on the underlying topography, fuel and weather (**Fig. 2.2; Anderson et al, 1982; Finney et al, 2004**). The flaming front of each newly formed wavelet is joined to create the new overall fire perimeter for the next time step. As most fire behaviour models are developed specifically for the flaming front (**Rothermel, 1972**), the expansion of the fire on all other fronts is interpolated from the heading rate using the properties of an ellipse (**Fig. 2.1**). The long axis of the ellipse is determined by the calculated forward rate of spread, whilst flank expansion is interpolated using predetermined length to breath ratios (**Mcarthur, 1966; Alexander, 1985**). This is a computationally effective method, as the entire fire perimeter is propagated using only forward rate of spread calculations (**Sullivan, 2009c**).

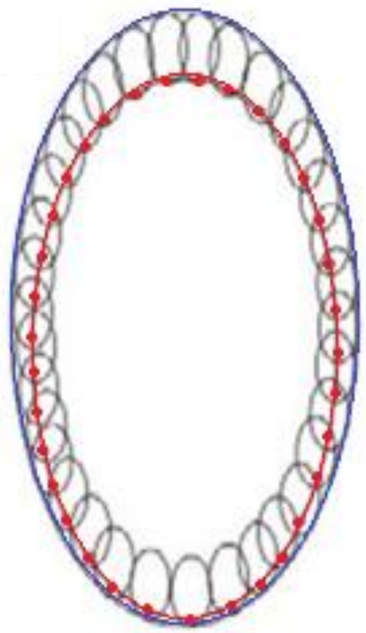

Figure 2.2: Huygens Wavelet Principle, showing the initial fire shape and regular firelet ignition points in red, firelet growth in black and the final shape at the next time step in blue under homogenous fuel conditions, with no wind or slope (Adapted from **Finney, 2004a**).

An appropriate simulation system for fynbos

There are currently no models or simulation systems developed specifically for determining fire behaviour and spread in fynbos. I therefore looked for a simulation system that could be adapted for this purpose. Fynbos in general and the Cape Peninsula in particular is notoriously heterogeneous in both fuel stratum and terrain, necessitating the use of a simulation system that can incorporate significant heterogeneity. Additionally, I required a system that was readily available with abundant online resources and case studies, particularly in Mediterranean Type Climate regions. The system additionally required both discrete event and burn probability functionality to facilitate the planned analyses. The sister-suite of freeware programmes developed by the Fire, Fuel, and Smoke Science Program of the Rocky Mountain Research Station in the United States collectively met these requirements (**Freeware available online at firelab.org**).

Fire Area Simulator (FARSITE) and FlamMap both use the same set of spatial inputs and have the same underlying fire behaviour models (**Finney, 1998**; **Finney, 2004b**; **Finney et al, 2015**). FARSITE is a deterministic modelling system that can predict fire events over long time periods and heterogenous conditions (**Finney, 2004b**). FlamMap is a landscape level fire behaviour mapping and analysis program that has inbuilt burn probability functionality (**Finney, 2006**). These models were developed and are widely used in the United States and there is a large body of research on their use and validation in novel environments throughout the world (**Mistry & Berardi, 2005; Arca et al, 2007; Brakehall, 2013; Dobrinkova et al, 2013; Cai et al, 2014; Jahdi et al, 2014; Hagelin & Culzel, 2016**).

FARSITE

FARSITE is a semi-empirical, deterministic fire modelling system that uses topographical, climatological and fuel input layers to simulate fire behaviour in a landscape (**Finney, 2004a**). FARSITE uses multiple models for fire behaviour; most prominently Rothermel's (**1971**) surface fire spread, Nelson's fuel moisture (**2000**), van Wagner's (**1977**) crown-fire initiation and spread (**Rothermel, 1991**) as well as models for spread via spotting (**Albini, 1979**). Attempts to use FARSITE in Mediterranean type systems (Californian chaparral and Mediterranean marquis) have demonstrated that FARSITE can simulate shrubland fire behaviour reasonably well, but requires custom fuel models and accurate wind data (**Arca et al, 2007**).

FARSITE has extensive input requirements, including the topographical, vegetative and meteorological features of the fire area. Fires are simulated over a landscape file (.lcp), created from GIS raster layers with identical extent and resolutions describing elevation (m), aspect (degrees), slope (degrees), canopy cover (%) and vegetation. Vegetation is described by mapping the landscape into discrete units of fuel type, each of which is associated with a fuel mode. A fuel model is a stylised set of parameters that define the average fuel condition (**Deeming & Brown, 1975**). Fuel models describe living and dead fuel load, surface-area-to-volume ratios, fuel bed depth, extinction moisture, live and dead heat content and fuel moisture content (See **Chapter Three; Table 3.1**). A weather file (.WTR) is used to describe meteorological conditions during the burn and consists of a daily record of total rainfall (mm) as well as the maximum and minimum temperature (°C) and relative humidity (%). A wind file (.WND) is also used, specifying hourly wind speed (m/s) and direction (degrees), as well as cloud cover (%) for the duration of the simulated fire event.

Propagation of the fire perimeter in FARSITE is done using a modified version of Huygens wavelet principle, whereby a series of regularly spaced points on the existing fire perimeters at time t act as ignition points for firelets that expand elliptically over timestep Δt. The shape and direction of these firelets is dependent on wind and slope and the length is determined by the spread rate, calculated using conditions at the ignition point held constant over the time step. The size of the firelets are determined by length and breadth ratios appropriate to flank expansion (**Anderson et al, 1983**). At $t + \Delta t$, the new fire perimeter is drawn from the furthest points of each firelet (**Finney, 2004a**).

FLAMMAP

FlamMap is a landscape level fire mapping system that predicts wildfire behaviour under constant weather and fuel moisture conditions (**Finney, 2006**). FlamMap requires the same raster based input layers as FARSITE, owing to a matching set underlying fire behaviour models that include Rothermel 's surface fire (**1972**) and crown fire (**1991**) spread, van Wagner's (**1977**) crown fire initiation and Nelson's (**2000**) dead fuel moisture. FlamMap is particularly useful for the inbuilt burn probability functionality that uses operator-supplied or random ignitions to simulate thousands of fires across a landscape. The resulting map depicts the spatially explicit relative probability of each pixel burning given a fire under constant fuel, wind and weather conditions.

FlamMap propagates fire using the Minimum Travel Time (MTT) algorithm (**Finney, 2002**), much like that utilized by graph or network theory, where the landscape is visualized as a series of interconnected nodes. MTT interrogates the landscape to identify pathways that minimize the travel time from the ignition source to each node. To do this, a rectangular lattice is superimposed over the landscape at a user-determined resolution with nodes identified at the corners of each lattice cell. Finer resolution lattices produce more nodes and capture more spatial heterogeneity, but increase processing times significantly. The fastest travel time from point of ignition to each node is calculated via the establishment of straight line transects linking nodes. The line transects are composed of multiple short segments created by the intersection of the transect line with the boundaries of each lattice cell. Fire travel time is calculated per cell segment, using the underlying fire behaviour characteristics to give a total fire travel time for the straight line transect. Efficiencies in computation are afforded by stopping the search for the shortest time to a particular node after a specified number of failures occur in the search (in the X- and Y- directions; **Finney, 2002**).

Despite the similarity of FARSITE and FlamMap in both underlying models and shared input format, differences occur between the sister programmes. FlamMap lacks the temporal dimension of fire behaviour prediction and assumes that fuel moisture, wind speed, and wind direction are constant through the entire burn time. This limits its use for discrete fire simulation in an operational setting and so the programme is used more generally to assess landscape-level variation in fire vulnerability. An additional difference lies in propagation method: FlamMap uses Minimum Time Travel whilst FARSITE uses Huygens Wavelet Principle. Minimum Time Travel (MTT) was developed to increase computational efficiency, particularly in heterogenous conditions; MTT FlamMap simulations are up to eight times faster than the same simulation using FARSITE (**Finney, 2002**). Despite these differences in propagation methods, validation exercises have shown resulting fire perimeters and fire behaviour predictions are essentially identical for both MTT FlamMap and FARSITE (**Finney, 2002**).

In this thesis I use FARSITE and FlamMap because both models use the same set of inputs, have matching underlying fire behaviour models and equivalent propagation methods as well as because of their collective ability to perform discrete event simulation and burn probability calculations. In **Chapter Three** I use the discrete event functionality of FARSITE to simulate a historical fire that occurred in April 2007. This chapter serves as a validation exercise, assessing how accurately these simulation systems can predict fire in fynbos. Multiple FARSITE simulations were run to assess the relative performance of a suite of custom fuel models specifically developed for fynbos. Following this validation, I use

FlamMap in **Chapter Four** to explore how urbanisation changes landscape level patterns of burn probability on the Cape Peninsula.

Chapter 3

Evaluating and improving fire models for the simulation of fynbos fire spread on the Cape Peninsula

Introduction

Fire modelling in fynbos is an underdeveloped discipline. This is surprising considering the dependence of fynbos on fire for regeneration in a highly transformed, urban-integrated landscape where fire is considered a threat to property and safety. The most significant fire behaviour modelling in fynbos thus far has been testing Rothermel's (**1972**) surface fire spread model by van Wilgen (**et al, 1985**). The results of this study show that Rothermel's fire spread model can successfully predict rate of spread and flame length for fynbos fires to a reasonable degree of accuracy. The authors were however sceptical as to its applicability to fires in mountainous areas with rugged topography, variable winds and extremely heterogenous fuel loads (**van Wilgen et al, 1985**).

Despite the complexity of the landscape, it is critical to develop methods for wildfire management on the Cape Peninsula that both reduce fire risk to humans while allowing for a natural fire regime. Wildfire modelling is a powerful tool to develop such management methods by addressing uncertainty surrounding fire risk. Currently no model exists which explicitly predicts fire in fynbos, and the development of such a model would be prohibitively expensive and time consuming. Instead, a more reasonable first step would be to assess the validity of adapting existing fire modelling and simulation packages for use in the fynbos. By far the most widely used simulation package globally is the Fire Area Simulator (FARSITE), which was developed in the United States but is used for fire prediction globally (**Finney, 1998; 2004a; Dobrinkova et al, 2013; Brakehall, 2013; Cai et al, 2014; Hagelin & Cluzel, 2016**).

A key component in calibrating FARSITE to novel environments and to enhancing prediction accuracy is the use of custom fuel models; stylized sets of fuel bed characteristics that describe average fuel condition in a system (**Deeming & Brown 1975; Arca et al, 2007; Cai et al, 2014**). The first custom fuel model for fynbos was developed in 1984 using a mixture of field collection and previously published literature (**van Wilgen et al, 1984**). However, owing to significant levels of intra-stand heterogeneity and age-dependent flammability, the fynbos system requires multiple fuel models to more accurately describe spatial variation in fire spread (**van Wilgen, 1985**). A suite of fynbos fuel models were developed in 1995, derived from regression analysis using pre-existing fuel data and age-biomass coefficients to estimate fuel properties for different fynbos types at various ages (**Le Maitre & Marais, 1995**).

In this chapter I assess the accuracy of the custom fynbos fuel models in predicting fire extent in fynbos using fire scar analysis, an approach that compares the spatial differences in simulated versus observed fire scars to calculate an error matrix. I compare prediction accuracy to determine the applicability of the FARSITE fire simulation platform for general use in fynbos while also identifying the most appropriate fuel models for use on the Cape Peninsula. Finally, I use sensitivity analysis to identify important fuel model parameters to guide future fuel model development for the region.

Methods

Study area and fire

The Cape Peninsula is an exceptionally flora-rich region, located at the south-western-most tip of South Africa in the Western Cape (**Simmons & Cowling, 1996**). The 52 km long Cape Peninsula stretches from Moullie Point (-33.901485, 18.399787) at its northern tip to Cape Point (-34.356693, 18.496799) in the south (**Fig. 3.1**). The Peninsula is connected to the rest of the mainland by a low elevation flat sandy platform, the Cape Flats. Table Mountain National Park encompasses most of the remaining natural land on the Peninsula, including much of the Peninsula Mountain Chain, an extremely heterogenous mountain range that exhibits rapid changes in topography over short distances and stretches down the spine of the Peninsula. The Table Mountain National Park is completely encircled by human development, urban areas and bisecting roads which split the park into three distinct sections: the mountainous northern section (that incudes Table Mountain), the central plateau (incorporating Silvermine) and the less rugged southern section that is largely made up of undulating coastal plains at lower elevations (200-400 m), known as the Cape of Good Hope.

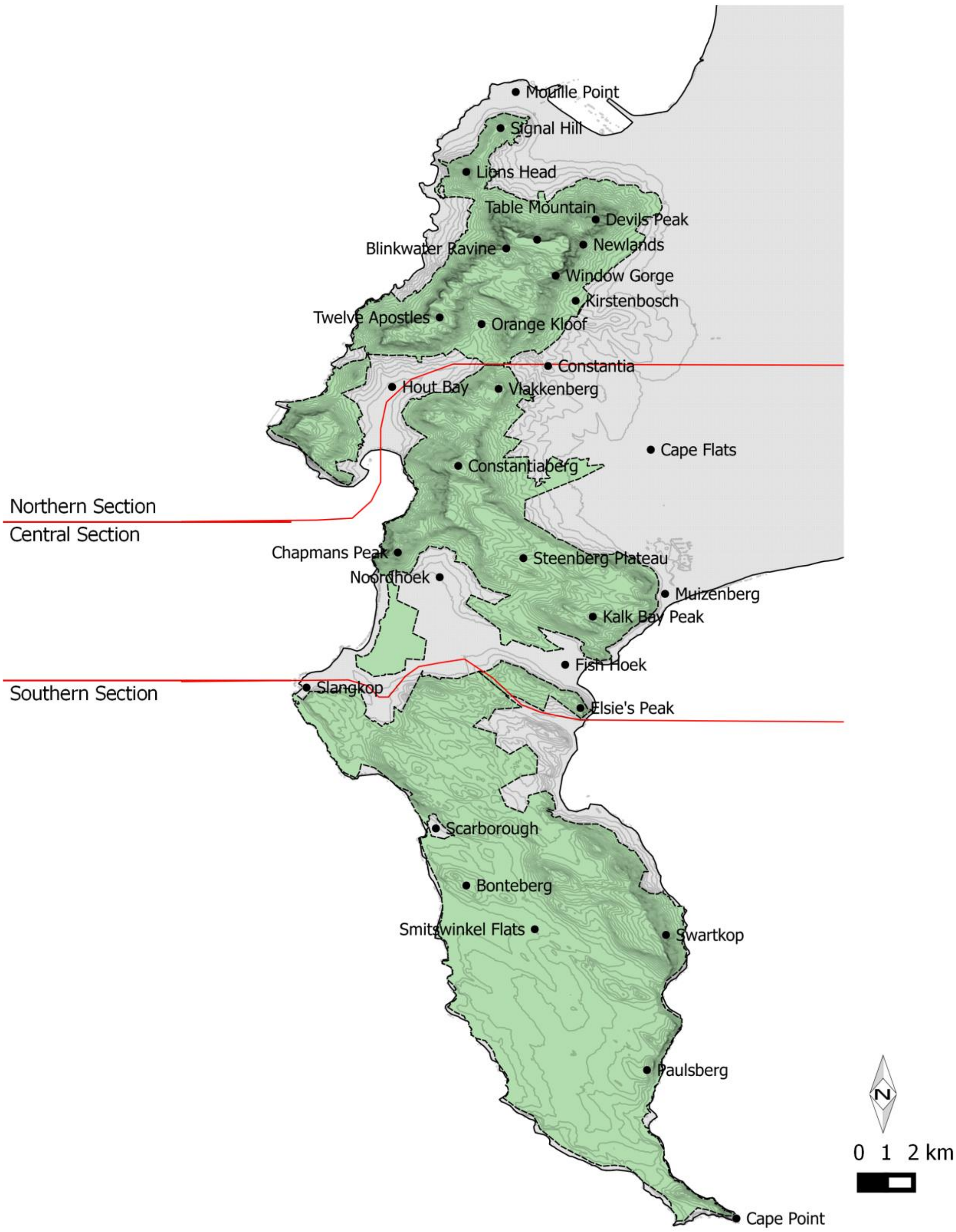

Figure 3.1: Topographic map of the Cape Peninsula, showing the three sections of Table Mountain National Park in green, urban areas in grey and locations relevant to the study are labelled

The Cape of Good Hope reserve, the southern section of Table Mountain National Park, is relatively flat compared to the more mountainous Northern peninsula. The centre of the reserve is dominated by the Smitswinkel flats, a large and flat plateau with occasional rocky outcrops. The Smitswinkel flats is bordered to the North by Bonteberg, to the east by

Paulberg (the highest point in the park at 366 m) and to the west by a gradual escarpment ending in a narrow coastal plain (**Fraser, 2014**). Although the regional climate is Mediterranean, the Cape of Good Hope section of the park receives less annual rainfall and much higher wind speeds than the central or northern sections of the park with the relatively flat terrain reducing wind field complexity. Cape Point, located at the southern tip of the Cape of Good Hope reserve, is the windiest place in South Africa where 42.1% of the wind speeds recorded are greater than 8 m/s with an average wind speed of 6.9 m/s (**SAWS, 2015**).

Vegetation in the southern section of the park is largely made up of peninsula sandstone fynbos, a fynbos subunit that covers much of the Peninsula. Structure and species composition vary spatially as a result of a variety of environmental factors, but sandstone fynbos typically has a tall, moderately dense proteoid overstory with a reasonably tall and dense ericoid understory and prominent restioid elements (**Mucina & Rutherford, 2006**). Regionally dominant species include *Leucospermum conocarpodendron subsp. Viridium, Erica mammosa* and *Thamnochortus lucens*.

A historical fire that was ignited on the 4th of April 2007 in the Cape of Good Hope section of Table Mountain National Park was selected for this analysis. In an effort to limit the scope of uncertainty to differences in fuel models only, it was necessary to select a fire with good data for all other fire behaviour variables. Fire records that have such high quality data in terms of weather, burn time and approximate ignition location are surprisingly rare. Additionally, this specific fire was relatively 'simple', being both short (24 hours before being 'contained' along the flaming front) and occurring under relatively stable wind conditions – a strong south easterly wind. Few such fires exist in the record, and so the study was restricted to a single fire.

The fire was the result of a management burn of 17 year old fynbos ignited on the morning of the 4th of April. Gale force south easterly winds unexpectedly picked up on the evening of the 5th of April and with wind speeds in excess of 65 km/hour, the fire jumped the road defining the boundary of the planned burn. The fire burnt through 1000 hectares of vegetation in 24 hours, before the flaming front was contained late in the afternoon of the 6th of April, 10 km from the coastal town of Scarborough. The fire scar was mapped using GPS tracks recorded by municipal fire fighters.

Fire simulation, input and run parameters

To simulate fire spread and predict burnt area for the 2007 fire, I used the FARSITE (Fire Area Simulator) fire simulation software package (**Finney, 1994; 2004a**). Input requirements include vegetation maps and a topographical description of elevation (m), aspect (°) and slope (°) for the Cape Peninsula. These were accessed through the City of Cape Town Open Data Portal using the Digital elevation model (10 m grid, resampled to 30 m) depicting the elevation of the geographical surface of the Cape Town municipal area (Bare Earth Model; **City of Cape Town, 2016**).

When converting vegetation maps to fuel maps, all urban areas and roads were demarcated as non-burnable fuel models. The urban model (NB1/091), defined as land covered by urban and suburban development, is unable to support wildland fire spread (**Scott & Burgan, 2005**). All periphery roads off the main thoroughfare through the Cape of Good Hope Reserve were not included. The ocean was defined as NB8/098, a standard fuel model used to describe land covered by open bodies of water. The shapefiles for management burns immediately prior to the wildfire event were accessed from the Cape Fire database and mapped as non-burnable model NB9/099, owing to recent removal of the majority of biomass.

The wildland fuel properties of the area are described by the designation of vegetation into fuel models. Parameters required in a standard fuel model are described in **Table 3.1**. I used 19 different fuel models to comparatively assess model fit (described in **Table 3.2**); 9 standard fuel models developed for use in Californian chaparral (**Scott & Burgan, 2005**) and 10 custom fuel models developed for use in fynbos (**van Wilgen, 1984; Le Maitre & Marais, 1995**). The study area was designated as having a homogenous fuel to reduce uncertainty in comparing fire spread and burnt area between fuel models. The area is typically thought to consist of a complex matrix of mesic oligotrophic proteoid fynbos with pockets of wet restioid fynbos (**Cowling et al, 1996**).

Fire suppression by both ground and aerial teams can be accounted for using FARSITE. As little to no information was made available from fire fighter logs, we were unable to construct a coherent and accurate fire suppression map. From what little that could be gleaned from news articles, fire suppression teams were in position to the south of Scarborough. Aerial bombing was also used primarily along this front. However, there is little detailed information on location and intensity of firefighting effort, making it impossible for this to be included in the analysis. It is unlikely that the excessive western spread shown in all of the better fitting simulations was as a result of firefighting efforts. No infrastructure exists between the ignition site and the west coast. I make the assumption that firefighting effort was much more likely to have impacted the spread of the northern front, the front heading for Scarborough town. As such, fire suppression activities were left out of analysis.

Table 3.1: Description of each parameter required within the Rothermel surface fire spread fuel model with associated metric units for FARSITE use.

Parameter Name	**Description**	**Metric Unit**
Dead Fuel Load – 1 Hr, 10 Hr, 100 Hr	The oven dry weight of dead fuel that is potentially available for combustion (**Knapp, 2007**), separated by coarseness into time lag classes[1]; 1 Hour: dead fuel less than 0.635cm in diameter, 10 hour: 0.635-2.54cm, 100 hours: 2.54-7.62cm (**Anderson, 1982**).	metric t/ha
Live Fuel Load – Woody and Herbaceous	The oven dry weight of live fuel that is potentially available for combustion, separated into herbaceous and woody categories.	metric t/ha
Live Surface are to Volume Ratio (SAV) – 1 Hr , 10 Hr, 100 Hr	The surface area of fuel particles per unit volume for each dead timelag category (**Scott, 2007**)	cm^2/cm^3
Dead Surface area to Volume Ratio (SAV) – Woody and Herbaceous	The surface area of fuel particles per unit volume for each live timelag category (**Scott, 2007**)	cm^2/cm^3

[1] Time lag classes in hours indicate the amount of time necessary for a dead fuel particle to lose or gain 63 percent of the difference between its initial moisture content and its equilibrium moisture content at a constant temperature and relative humidity (**Knapp, 2007**).

Fuel Bed Depth (FBD)	Depth of the surface fuel layer measured perpendicular to the slope (**Albini ,1976**)	cm
Moisture of Extinction	The dead fuel moisture content at which the Rothermel's (**1972**) surface fire spread model predicts spread rate will fall to zero (**Scott, 2007**)	%
Live and Dead Heat Content	Heat released from a unitary fuel amount (completely oxidized).	J/Kg
**Moisture Content - 1 Hr, 10 Hr, 100 Hr, Woody and Herbaceous*	Though not defined in the fuel model, each fuel category has an associated moisture content, estimating the mass of water within a fuel particle expressed as a percentage of the particle's oven-dry mass (**Knapp, 2007**)	%

Research on validating FARSITE in Mediterranean Type Climates suggest that fuel models specifically created for chaparral are not specific enough for use in other Mediterranean shrublands (**Arca et al, 2007**). There have however been two studies that define fuel models for fynbos. The first of these was a single fuel model developed from a mixture of field-collected and published data in average to tall open shrubland with a post-fire age of 15 years (**van Wilgen, 1984**). The second effort created multiple fuel models to represent the 15 types of fynbos as defined by Cowling (**1996b**). These fuel models were statistically derived using regression analysis of existing data to predict biomass and fuel bed estimates at different vegetation ages (**Le Maitre & Marais, 1995**). To account for the sigmoidal growth of live biomass and the constant increase of standing dead and litter material, total biomass was assumed to increase logarithmically with time according to:

$$Total\ mass\ (g\ m^{-1}) = A * \log(age\ in\ years) + B$$

*Where A is a group specific coefficient and B a constant (See **Appendix I**).*

After estimating total biomass, biomass was partitioned into five fuel load categories based on field proportions (Dead 1 Hr, 10 Hr, 100 Hr, Live Herbaceous and Live Woody; See **Table**

3.1). Fuel bed depth was estimated for each age class by multiplying stand height by 0.7 (**Le Maitre & Marais, 1995**). The remaining fuel model parameters were based on van Wilgen's (**1984**) custom model (See **Appendix II** for all parameter values used).

Meteorological data requirements for FARSITE include hourly wind speed, wind direction and cloud cover estimates, as well as daily minimum and maximum values for temperature and relative humidity, and total daily rainfall for the entire burn period. Meteorological data for the study area during the week of the 2nd to the 8th April 2007 were acquired from the South African Weather Service archive for the two closest meteorological stations to the burn site; Slangkop Lighthouse (-34.148611,18.319167) and Cape Point (-34.3567 22, 18.497056). Ignition time was set at 16h00 on the 5th of April with the ignition point centred on -34.275500, 18.435097 and the time of containment was set at 18h00 on the 6th. A time step of 30 minutes and a perimeter and distance resolution of 30 m were used with crown fire simulation disabled due to lack of reliable bulk density data.

FARSITE output for each fuel model included 30 m resolution raster layers, detailing rate of spread and flame length as well as shape files of fire perimeter at each 30 minute time step for the duration of burn period and the final fire scar. The models that predicted the best fit relative to the fire scar were used in subsequent simulations with spatially variable wind fields. Topographic maps along with data streams of hourly wind speed, wind direction, temperature and cloud cover were used as input to generate complex wind fields using WindNinja, a program that computes spatially varying, fine-scale wind fields for wildland fire application (**Forthofer et al, 2014b**).

Table3.2: Commonly used acronyms and associated descriptions of each fuel model used in fire prediction runs. Standard fuel models (SH1-9) were developed based on Chaparral data (**Scott & Burgan, 2005**) while custom fuel models were developed for fynbos (**van Wilgen, 1984; Le Maitre & Marais, 1995**).

Abbreviation	*Name*	*Description*
SH1	Shrubland 1	Dry climate shrubland with a low fuel load and relatively shallow (~30 cm) fuel bed in which fire is carried primarily through woody shrubs and shrub litter, although some grass may be present. Spread rate is very low; flame length very

		low
SH2	Shrubland 2	Dry climate shrubland with a moderate fuel load and relatively shallow (~30 cm) fuel bed in which fire is carried primarily through woody shrubs and shrub litter, and no grass is present. Spread rate is very low; flame length very low
SH3	Shrubland 3	Humid climate shrubland with moderate fuel load and low to moderate fuel bed depth (60 – 90 cm). Potential for pine overstory or some herbaceous fuels. Spread rate is low; flame length low
SH4	Shrubland 4	Humid climate shrubland with timber overstory and low to moderate shrub and pine litter load with a moderate fuel bed (>90cm). Spread rate is high; flame length moderate.
SH5	Shrubland 5	Dry climate shrubland with high fuel load and deep (120 - 180 cm) fuel bed. Spread rate very high; flame length very high. Moisture of extinction is high.
SH6	Shrubland 6	Humid climate shrubland with a low fuel load and low to moderate fuel bed depth (~60cm). Fuel is largely densely packed shrubs with little to no herbaceous fuel. Spread rate is high; flame length high.
SH7	Shrubland 7	Dry climate shrubland with a very high load with deep fuel bed (120 - 180 cm). Spread rate lower than SH5, but flame length similar.
SH8	Shrubland 8	Humid climate shrubland with a high load and moderate fuel bed (~90 cm). Fuel is largely dense shrubs with little to no herbaceous fuel. Spread rate is high; flame length high

SH9	Shrubland 9	Humid climate shrubland with a very high load and deep fuel bed (120 - 180 cm). Dense, finely branched shrubs with significant fine dead fuel, about 4 to 6 feet tall; some herbaceous fuel may be present. Spread rate is high, flame length very high
AFM	Asteraceous fynbos	Mainly found in more arid areas or on shallow soils on northern aspects as well as indune and sandplain fynbos. Relatively low total shrub cover (30-70%) with prominent fine-leaved shrubs of the Asteraceae, Thymeleaceae and Rhamnaceae and a relatively high grass cover; includes Protea Savanna (with *Protea nitida*)
DOP	Dry Oligotrophic Proteoid	Typically found on sandstone derived soils and deep (also known as sandplain Proteoid fynbos). Overstory varies from sparse to dense with an understorey of ericoid shrubs with a low cover of Ericaceae
MEM	Moist Ericoid	Mid-high to tall (1.0 to 2.0 m) fuel bed with prominent sedge and restioid element and a high total cover (>75%); dominant shrubs typically Ericaceae
MMP	Moist Mesotrophic Proteoid	Typically found on granites and shale derived soils. High total cover (75-100%) with a dense overstory (50-75% cover) and potential for closed understorey (if Proteoid overstory is not closed) dominated by grasses and fine-leaved sedges. Shrub layer dominated by non-ericoid shrubs *(Searsia, Cliffortia, Brunia, Leucadendron*). Overstorey species include *Protea lepidocarpodendron, P. coronata* and *Leucadendron argenteum*

MOP	Moist Oligotrophic Proteoid	Typically found on sandstone derived soils and deep sands. Total cover is high (50-75%) with a dense overstory and an understorey dominated by ericoid shrubs (Ericaceae, Restionaceae and Cyperaceae) where the overstory is open enough. Typical overstory species include *Protea repens*
MRM	Moist Restioid	Typically found on sandplains and montane plateaus. Total cover is high (75-100%) with mid-high and dense cover of restioids (*Chondropetalum, Hypodiscus, Thamnochortus* species), and fine-leaved sedges (*Tetraria* species)
RM	Renosterveld	Renosterveld is a low to mid-high shrubland, dominated by small-leaved Asteraceae. As with fynbos, trees are sparse, but unlike fynbos grasses are more common. High prominence of geophytes and annuals. Typical genera include *Elytropappus, Pteronia,* and *Anthospermum*.
VW	van Wilgen	Built from collection in a tall open Proteoid shrubland at a post-fire age of 15 years, with a well-developed understory (approximately 7 000 kg/ha of woody shrubs). About 32 % of the woody shrub mass is fine enough to be classified as fuel and roughly 5 000 kg/ha of herbaceous vegetation and dead material (**van Wilgen, 1982; 1984**).
WEM	Wet Ericoid	Occurs on quartzite or high altitude shale bands. Tall (often > 2.0 m) and dense shrubland with >40% cover of ericoid shrubs (usually Ericaceae), bruniaceous shrubs and prominent restioid elements as well as seed-regenerating Proteoid shrub cover (<10%).
WRM	Wet Restioid	Occurs in seasonally moist soils (e.g. streamlines or seepage

plains). Tall (>1.5m) and dense shrubland (100% total cover) with high cover of restioid and sedges (>60% of the total cover). Shrub cover is low and tall Proteoid shrubs are rare.

Fire Scar Analysis

Similarity matrices were calculated for each fuel model output, comparing the extent of the observed relative to the predicted fire scar. Cohen's Kappa Statistic, Sørensen coefficient and the percentage of over- and under-prediction were calculated for each fuel model. Cell by cell statistics such as this are a common method for fire scar comparison (See **Arca et al, 2007; Jahdi et al, 2014, Kalabokidis et al, 2014**).

Cohen's Kappa (**Cohen, 1960**) is a widely used non-parametric measure of accuracy after random agreements by chance are removed, and can be used to assess agreement between spatial model predictions and observations (**Congalton, 1991**). Cohen's Kappa Statistic (K) was calculated using the fmsb package (**Nakazawa, 2015**) in R (**Version 3.2.2; R Core Team, 2015**). Kappa statistics, Z values and P values were reported for all simulations, to test whether the Kappa values differ significantly from zero.

The Kappa statistic (K) is calculated as:

$$\kappa = \frac{Total\ Acuracy - Random\ Acuracy}{1 - \text{Random Acuracy}}$$

where

$$Total\ Accuracy = \frac{TP + TN}{Total}$$

$$Random\ Accuracy = \frac{(TN + FP) * (TN + FN) * (FN + TP) * (FP + TP)}{Total * Total}$$

And TN = 'true negative' when model and negative are both unburnt, TP = 'true positive' when both model and real are both burnt, FP = 'false positive' where model is burnt but real is unburnt and FN = 'false negative' where model is unburnt but actual is burnt.

Sørensen's coefficient is an asymmetrical measure of the exclusivity of association between observed and simulated burnt areas. Sørensen's coefficient can be expressed using the same notation as above by:

$$S = \frac{2 * TP}{2 * TP + FP + FN}$$

The percentage of over-prediction and under-prediction were additionally calculated for each fuel model.

Fuel Model Sensitivity

To aid in future data collection and parameter optimisation exercises, an analysis of model sensitivity to fuel model parameters was conducted. The Morris approach to sensitivity analysis (**Morris, 1991; Campolongo et al, 2007**) was developed to efficiently identify the important factors in models with many factors. Morris analysis uses many individually randomised OAT experiments, each of which consists of a random starting point in a user defined parameter space Ω (a k-dimensional, p-level grid) and consequent random trajectory created by varying one factor at a time in a random order. Along each trajectory, an Elementary Effect (EE) is calculated for each factor, calculated as:

$$d_i(X) = \frac{Y(X_1, \ldots, X_{i-1}, X_i + \Delta, X_{i+1}, \ldots, X_k) - Y(X)}{\Delta}$$

Where Δ is a value in { 1/(p-1), … , 1-1/(p-1)}, and p is the number of user defined levels.

A user defined number of *r* EE are calculated for each factor by randomly sampling *r* points to start *r* trajectories in the parameter space Ω. EE's are aggregated at the factor level, with each factor EE's over *r* trajectories summarised by their mean and the standard deviation as sensitivity indices μ and σ;

$$\mu_i = \frac{1}{r} \sum_{j=1}^{r} d_i(X^{j)})$$

$$\sigma_i = \sqrt{\frac{1}{r-1} \sum_{j=1}^{r} (d_i(X^j) - \mu_i)^2}$$

μ assesses the overall influence of the factor on the output variable, and σ estimates the factors higher order effects such as non-linearity and/or level of interaction with other factors.

The use of both of these indices allows for the identification of factors that have effects that are negligible (low μ and low σ), liner and additive (high μ and low σ) and non-linear interactive with other factors (high σ).

However, this method is prone to type II errors (failing in the identification of a factor of considerable influence on the model) for factors that have a high variance in response (so both strongly positive and strongly negative EE's in different trajectories). Averaging EE's in such a factor may result in cancelling out and a low over all influence (low μ). To navigate this, the average of the absolute values of a factor's EE's is also used (**Camplongo et al, 2007**).

$$\mu_i^* = \frac{1}{r}\left|\sum_{j=1}^{r} d_i(X^{j)})\right|$$

The statistical computing and graphical platform R was used to construct MA trajectories (r = 100) using the 'sensitivity' package (**Pujol, 2009**). These trajectories were modified to form fuel model input files, before being fed into a command line version of FlamMap that produced estimates of Flame Length (m) and Rate of Spread (m/min) for each trajectory. The input factor trajectories and resulting output estimates were then transferred back into R, where values for μ, μ* and σ were calculated for each factor. Linear correlations were explored between sensitive fuel model factors and fire behaviour and model fit estimates.

Results

All fuel models were able to predict burnt areas significantly better than random (p<0.001) (**Table 3.3**) except the arid to semi-arid standard shrubland fuel models (**Table 3.2**: SH1, SH2, SH5 and SH7) which failed to ignite. Humid to sub-humid standard shrubland fuel models (SH3, SH4, SH6, SH8 and SH9) showed a range from poor (SH3; Kappa=0.03, Sørensens=0.05) to moderate fit (SH9; K= 0.54, S= 0.63). Custom fynbos fuel models showed a larger range in fit, from the poor fit of MEM (K=0.01, S=0.02) to the substantial fit of WEM (K= 0.72, S=0.82). The top three models were all custom fuel models (MMP, WRM and WEM) while the bottom three were all standard models (SH1, SH2 and SH5). Most prediction inaccuracy across fuel models was a result of under-predicting fire extent, often by 50% or more (**Table 3.3 & 3.4 & Fig. 3.2**). However, the four fuel models exhibiting the highest level of fit (RM, MMP, WRM, WEM) all over-predicted the historical fire scar extent by 24-41%. These four models cover the historical fire scar near-completely, excluding only the area of the actual fire that jumped the main road on the eastern flank. All four models also show significant spread outside of the historical fire scar, primarily in a western and a northern direction. Western spread is arrested by the Atlantic Ocean in all four cases, although the extent of northern spread varies. The northern over-prediction of the fire front was the least for WEM, where the northern front ends just before a small hill. The northern spread of the other three models is much more extensive, with both MMP and RM reaching the urban boundary of Scarborough (**Fig. 3.2**).

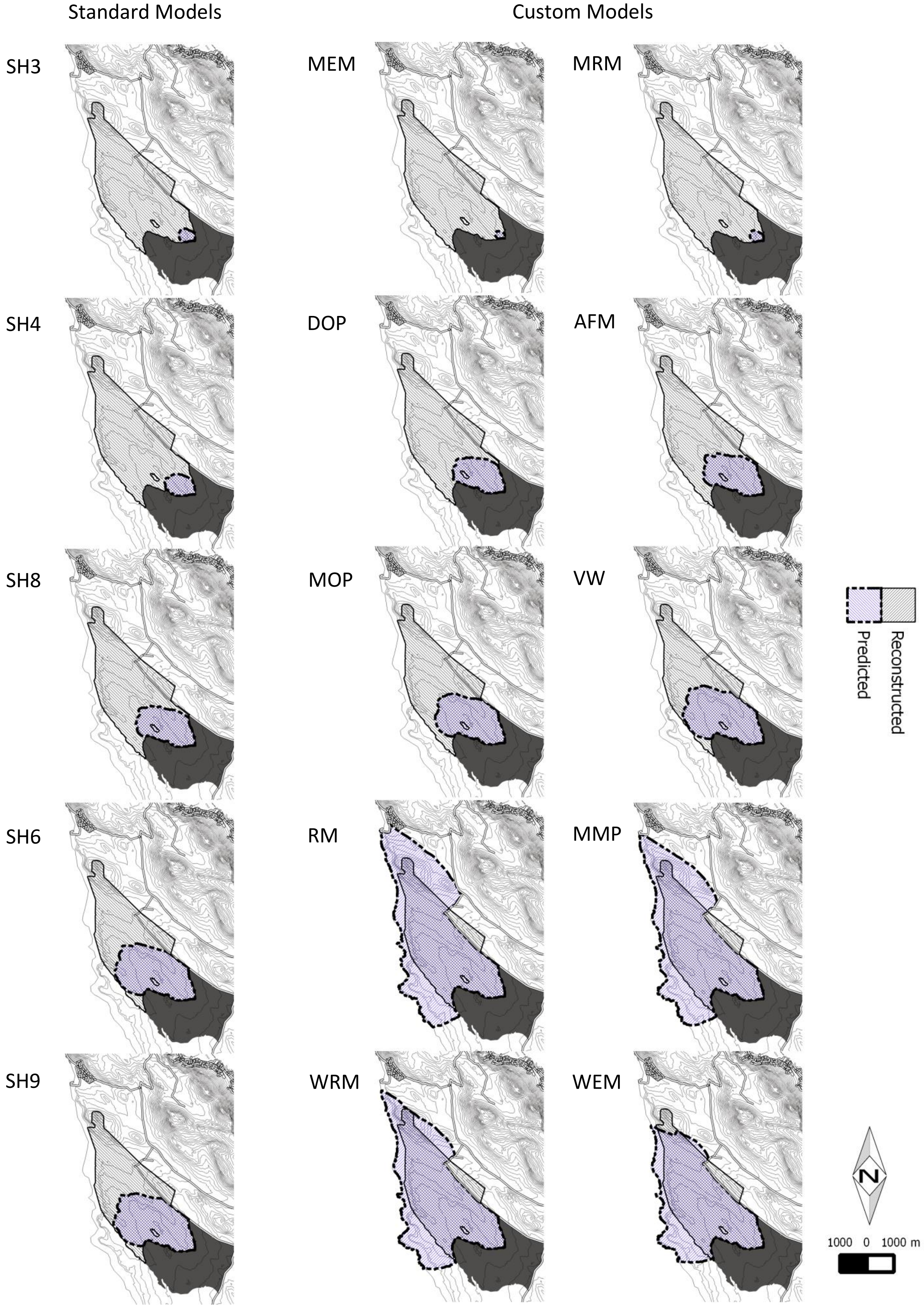

Figure 3.2: Comparison of predicted fire scar extents using simple wind conditions for each of the standard and custom models at 1800h on the 6th of April 2007 with the reconstructed fire scar. All non-burnable area burnt under prior management burn is shown in light grey, with major roads and urban areas outlined in dark grey. Contours shown at 20 m.

Table 3.3: Comparative statistics measuring the goodness of fit of fire area predictions for each standard fuel model, under simple wind conditions. ** indicates all Kappa values significantly different from 0 at a $p< 0.001$.

Fuel Model	Cohens Kappa	Sørensen Coefficient	Over-prediction (%)	Under-prediction (%)
SH1	0.00	0.00	0.00	0.00
SH2	0.00	0.00	0.00	0.00
SH5	0.00	0.00	0.00	0.00
SH7	0.00	0.00	0.00	0.00
SH3	0.03 **	0.05	0.00	97.51
SH4	0.10 **	0.14	0.00	92.65
SH8	0.30 **	0.39	1.63	75.98
SH6	0.52 **	0.61	1.06	55.99
SH9	0.54 **	0.63	1.19	53.66

Table 3.4: Comparative statistics measuring the goodness of fit of fire area predictions for each custom fuel model, under simple wind conditions. All Kappa values significantly different from 0 at a $p< 0.001$.

Fuel Model	Cohens Kappa	Sørensen Coefficient	Over-prediction (%)	Under-prediction (%)
MEM	0.01	0.02	0.00	99.17
MRM	0.02	0.03	0.00	98.27
DOP	0.25	0.33	1.99	80.44
AFM	0.32	0.41	1.51	74.11
MOP	0.43	0.52	1.22	64.67
VW	0.54	0.63	1.23	53.80
RM	0.54	0.71	41.80	7.86
MMP	0.58	0.73	39.38	7.87
WRM	0.66	0.78	32.28	7.93
WEM	0.72	0.82	24.56	11.36

Rate of spread estimates varied temporally with higher rates of spread typically reached later in the burn period and fuel models varied considerably both in terms of average and maximum rate of spread (m/min). The top four best fitting models also had the four highest mean rates of spread (**Fig. 3.3; Table 3.5**).

A slight positive trend existed between models with higher Kappa coefficient and maximum rate of spread (m/min) estimates (R^2=0.3472; **Fig. 3.4B**). Maximum rate of spread correlated strongly with both the fine dead fuel load (R^2=0.8865, **Fig. 3.4A**) and herbaceous fuel load parameters (R^2=0.6983, **Fig. 3.4C**)

Using spatially varying wind fields slightly improved the fit of the models that were more prone to over-prediction under simple wind conditions: MMP (simple wind: K=0.58, S=0.71 & spatially variable: K= 0.60, S=0.75) and RM (simple wind: K=0.54 and S=0.72 & spatially variable: K=0.65, S=0.75) (**Fig. 3.5**). This increased fit was primarily due to arrested northern spread. Concurrently, the southward spread of the fires was emphasised, resulting in a longer tail of fire burning down towards Cape Point around the block burn area (**Fig. 3.5**). While the increase in fit from limited northern spread out-weighed the reduction in fit from the southern spread for MMP and RM models, it resulted in decreasing fit for the top-performing Wet Ericoid model as this model already had limited northern spread under simple wind conditions (WEM, K=0.46, S=0.67).

Elementary effects (in terms of μ* & σ) calculated for each fuel model parameter under Morris Analysis were highest for fuel bed depth, followed by fine fuel load, surface area to volume ratio, herbaceous fuel load and extinction moisture for both flame length (m) (**Fig. 3.6A**) and rate of spread(m/min) (**Fig. 3.6B**).

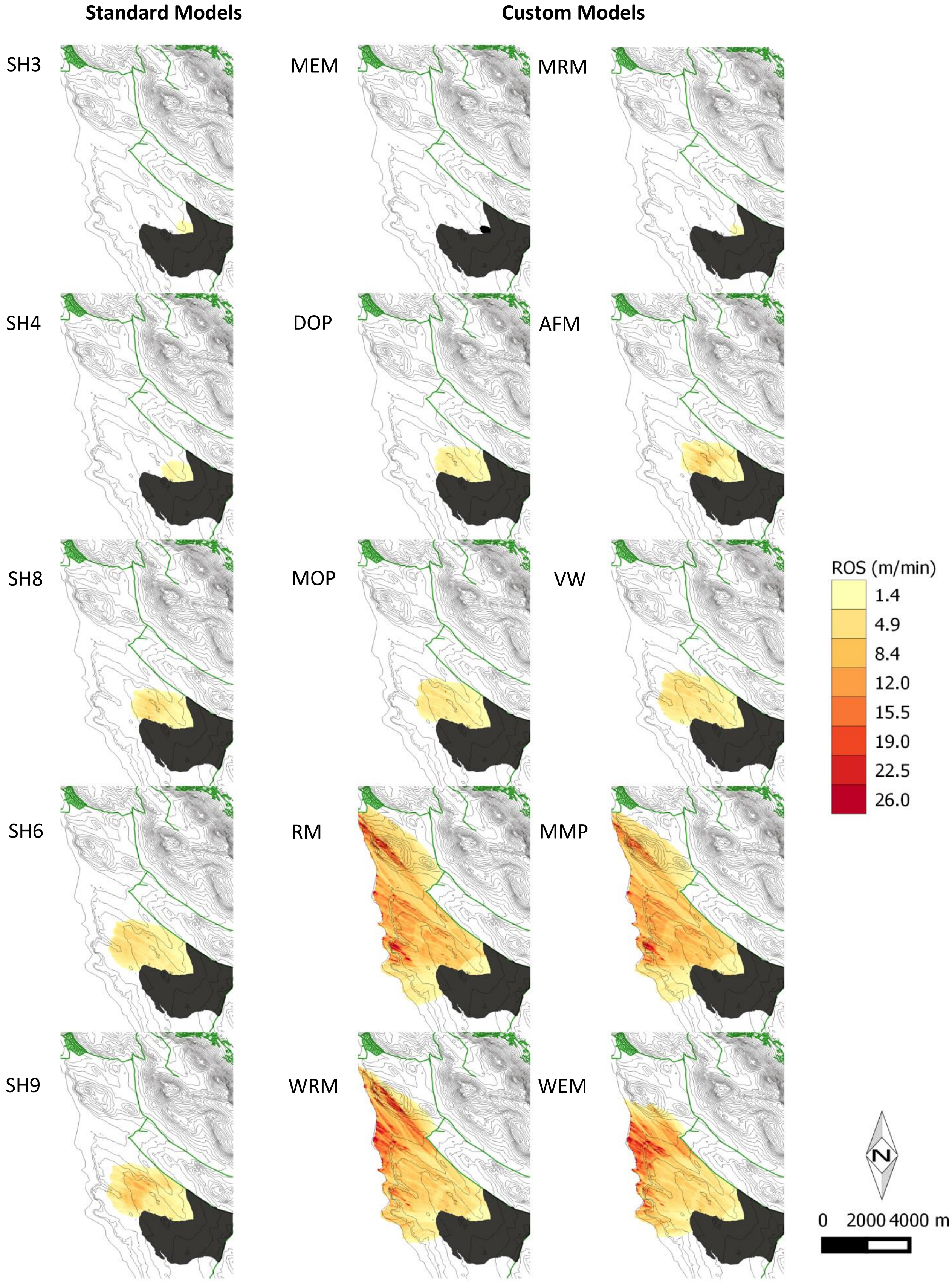

Figure 3.3: Spatial variation in rate of spread (m min-1) for standard versus custom fuel models for April 2007 fire. Simple wind stream conditions used, with all non-burnable area burnt under prior management burn shown in grey, with major roads and urban areas outlined in green. Contours shown at 20 m.

Table 3.5: Maximum, mean, minimum and standard deviation in rate of spread (ROS; m.min-1) predictions for all fuel models in FARSITE for the April 2007 fire. Models arranged in descending order by mean rate of spread.* Error in calculating ROS values occurred for MEM fuel model

Fuel Model	ROS max (m/min)	ROS mean (m/min)	ROS min (m/min)	ROS std dev (m/min)
MEM*	NA	NA	NA	NA
RM	24.98	6.88	0.98	3.87
WEM	40.39	6.73	0.71	4.52
WRM	28.37	6.58	0.62	4.80
MMP	21.52	6.55	0.35	3.51
SH9	10.18	4.05	0.95	0.234
SH6	6.58	3.12	0.50	1.30
VW	6.37	3.07	0.82	1.17
MOP	5.74	2.68	0.76	1.11
AFM	6.10	2.46	0.26	1.31
SH8	4.90	2.32	0.60	1.037
DOP	3.42	2.11	0.70	0.65
SH4	2.85	1.54	0.39	0.67
SH3	0.99	0.66	0.26	0.24
MRM	1.04	0.65	0.20	0.26

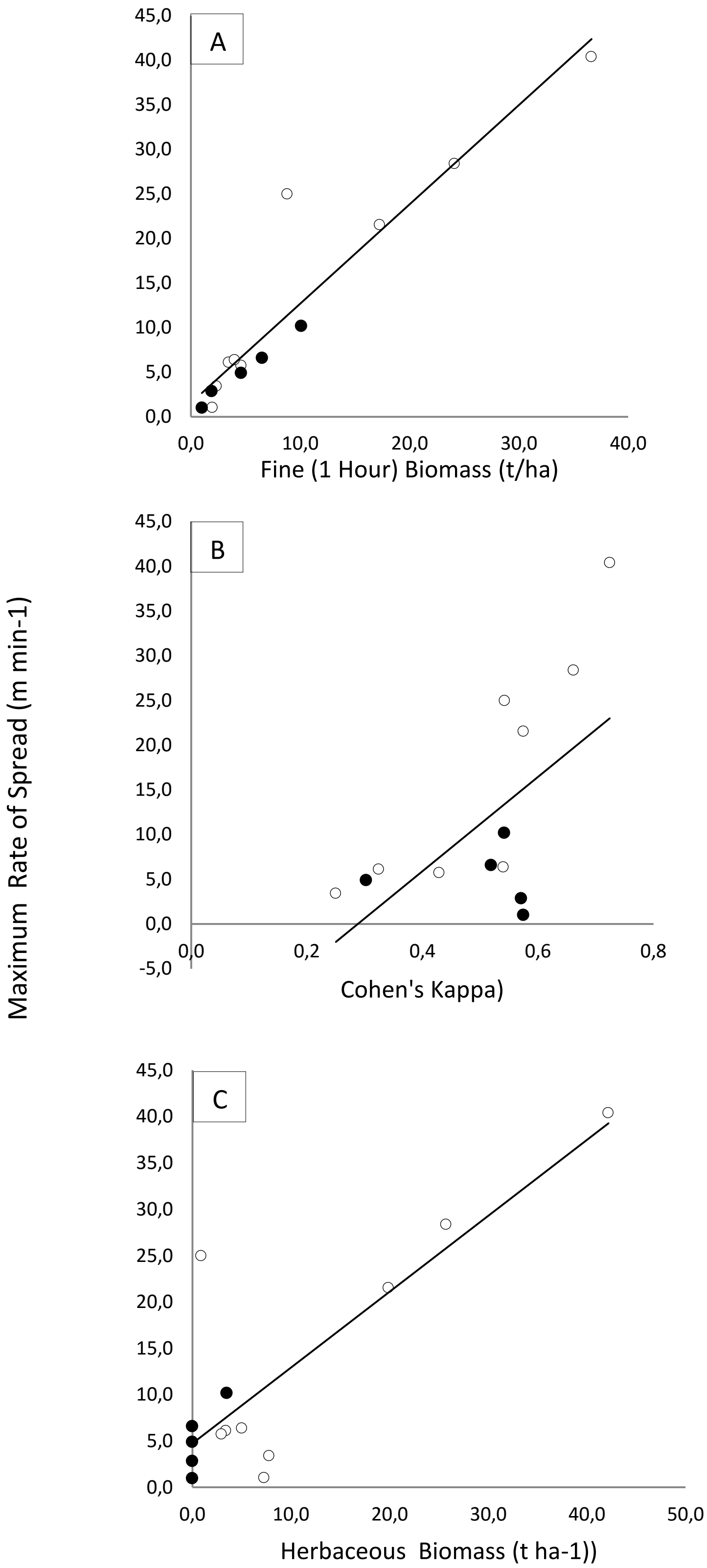

Figure 3.4: Regression analysis showing strongest correlates between measure of prediction accuracy and fuel model parameters. (A) Maximum rate of spread (m min-1) against fine fuel biomass (t ha-1) (R^2 = 0.8865) (B) Maximum rate of spread (m min-1) against Cohen's Kappa (R^2=0.3472) and (C) Maximum rate of spread (m min-1) against herbaceous biomass (t ha -1) (R^2=0.6983) Open circles are custom fuel models and closed circles standard.

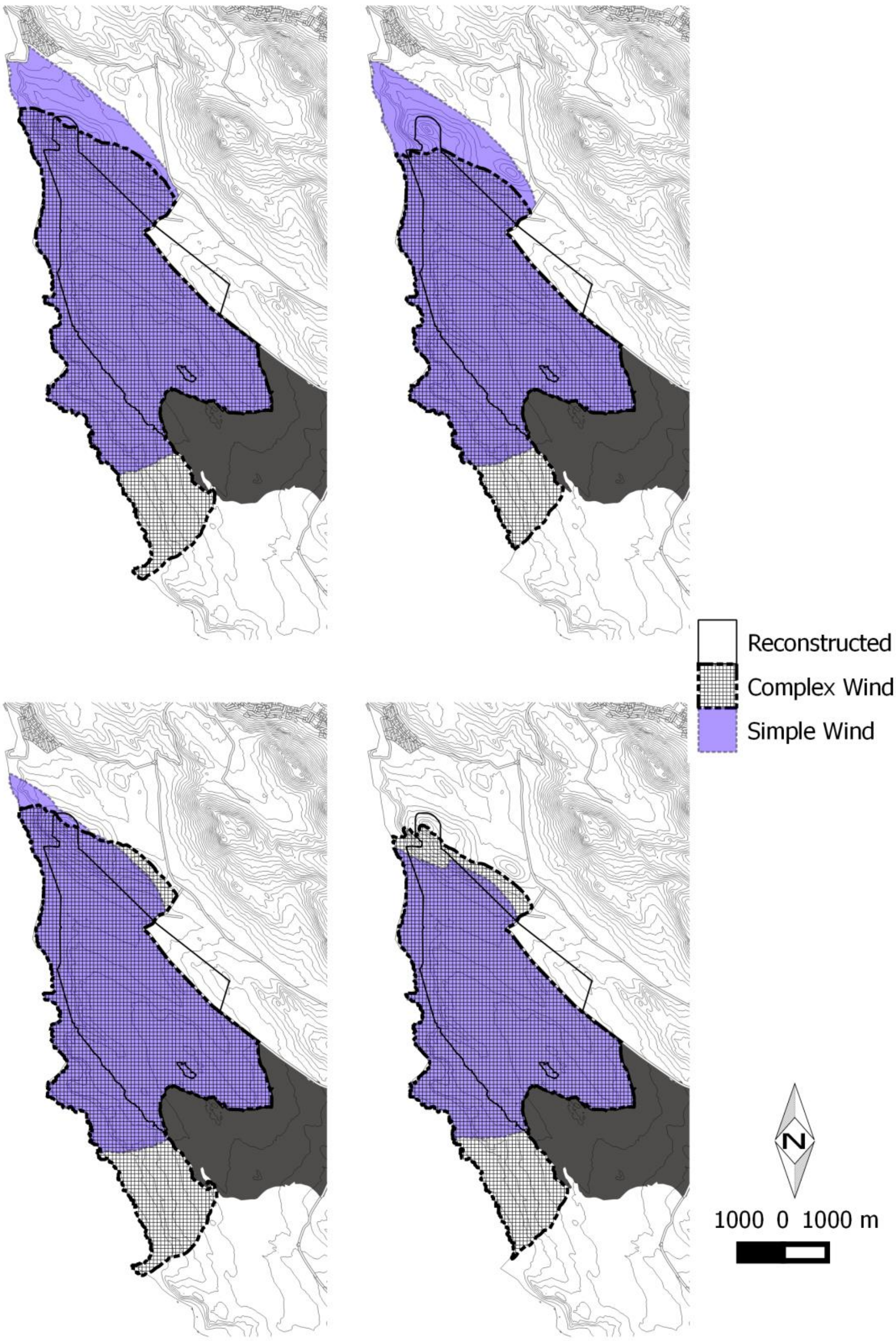

Figure 3.5: Fire scar comparison between simple wind stream conditions and complex, spatially variant winds for the top four performing models (in terms of Kappa). Non burnable area burnt under prior management burn shown in grey, with major roads and urban areas outlined in grey. Contours shown at 20 m.

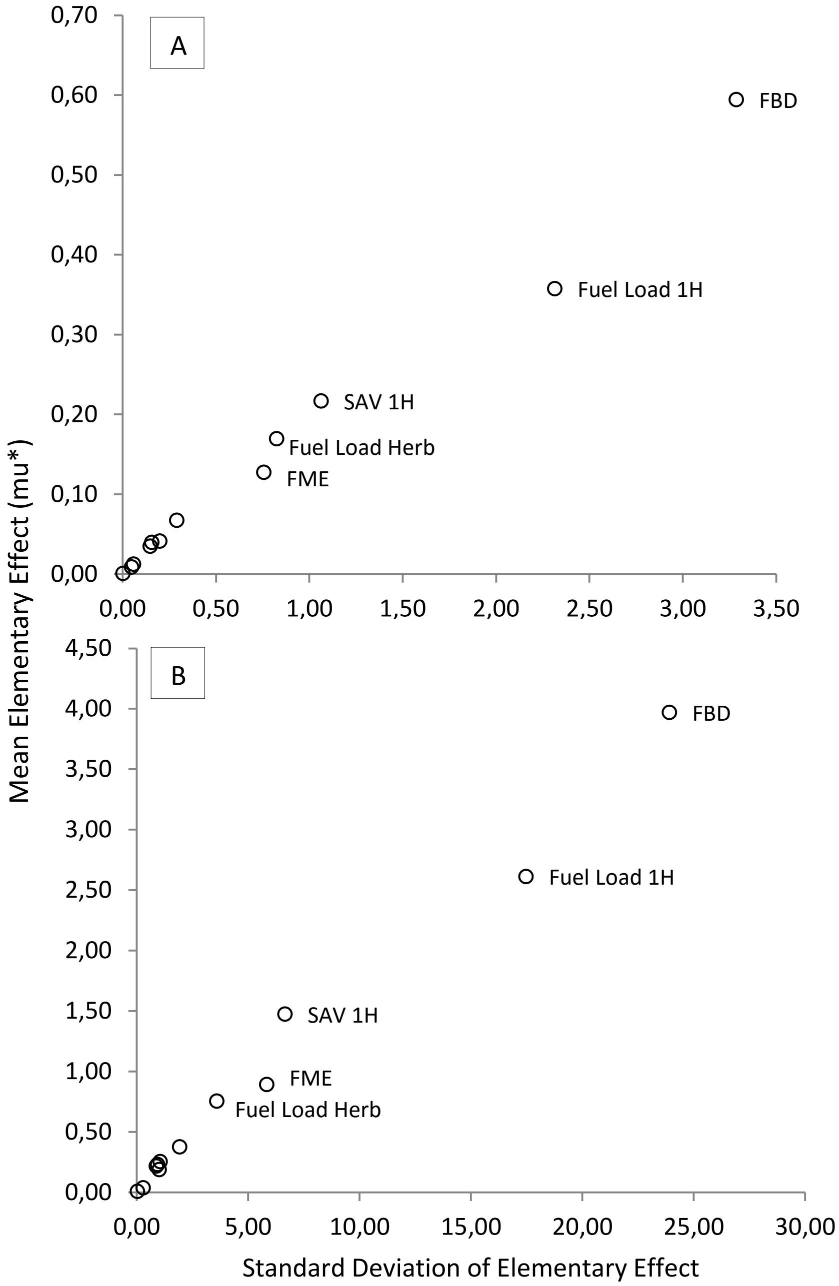

Figure 3.6: Fuel model sensitivity analysis for all parameters in predicting (A) Flame Length (m) and (B) Rate of Spread (m/min) in terms of absolute mean elementary effect and standard deviation. The top five most sensitive parameters are labelled; FBD = fuel bed depth, Fuel Load 1H = fine dead fuel load (1Hr), SAV 1H = surface area to volume ratio of fine dead fuel, FME = moisture of extinction and Fuel Load Herb = herbaceous live fuel load.

Discussion

To assess the viability of using FARSITE for fire prediction in fynbos and the determinants of model accuracy, I predicted fire area for a historical fire on the Cape Peninsula using a variety of fuel models and wind conditions. Multiple custom fuel models exhibited substantial agreement between predicted and actual fire scars, and rate of spread estimates fit with observed data for experimental fires in fynbos, suggesting good potential for the use of these models. Although these results are only the first steps in the process of validation for operational use, they are positive for future expansion.

Prediction accuracy is highly dependent on fuel model choice. A split in goodness of fit between custom and standard fuel models was anticipated, primarily due to the large structural differences between superficially similar fynbos and chaparral vegetation. A prominent difference is the lack of an herbaceous understory in mature chaparral relative to fynbos, which typically has an extensive herbaceous element that burns readily during fire (**van Wilgen, 1984**). This parameter was identified as important during sensitivity analysis, suggesting a high determination power on prediction output. Despite this, there is a large degree of overlap in goodness of fit between custom and standard models.

The best fitting fuel models were those developed for vegetation occurring in wetter soils with higher fine fuel biomass. The Wet Ericoid Model (WEM) was both the best fitting model and the model with the highest fine fuel load, owing to the dominance of tall restioids and high concentration of fine ericaceous and bruniaceous shrubs (**Le Maitre & Marais, 1995**). The next two best fitting models, Moist Mesotrophic Proteoid (MMP) and Wet Restioid (WRM), had similarly high fine fuel biomass with understories dominated by fine leaved restioid and ericoid elements (**Le Maitre & Marais, 1995**). Fine fuel biomass was one of the most sensitive fuel model parameters. It had a strong correlation with maximum rate of spread and the strongest correlation with Kappa out of all the fuel model parameters. This positive effect of fine fuel biomass on fire behaviour output reiterates the importance of fine fuels in driving fynbos fire behaviour, suggesting that the fine biomass in a stand (the ericoid and restioid forms) are important contributors to fire risk. Fire danger in fynbos may therefore be better estimated by the relative amount of fine fuel accumulation rather than by total aboveground biomass or stand age.

Calibration exercises for FARSITE in novel environments find that both custom fuel models and complex wind fields are required to maximize prediction accuracy (**Arca at al, 2007; Jahdi et al, 2014; Cai et al, 2014**). The results of this study are somewhat less conclusive; while complex wind fields improve accuracy in predicting the extent of the northern flaming front in the historical fire, this improvement is often counterbalanced by the over exaggeration of the spread to the south. This reduces the overall fit of models under complex wind conditions. Over exaggeration of southern spread is likely due to error in wind field due to an overemphasis of wind deviation around the gentle hill on the western flank of the burn site. This error highlights the issue with using complex wind fields in relatively flat terrain where these may simply add more uncertainty to the simulation as the accuracy of the complex wind field is not known.

Fine fuel load values for the top performing fuel models are disproportionately large relative to field determined values. An estimate of fuel load as gathered from field data for the VW model is 4 t/ha whereas the regression-derived value of WEM at the same age is 36.64 t/ha – a near 10 fold increase. Fuel models with unrealistically high biomass estimates perform better than field-collected values, suggesting that fynbos may be more inherently flammable than can be simulated by FARSITE without artificial inflation of important fuel model parameters. The inherent flammability of Mediterranean shrublands compared to other vegetation types is widely recognised, with shrublands able to support high intensity fires in moderate fire environments (**Catchpole, 2002; Fernandes, 2001**). Fires in fynbos have been found to spread faster and burn more intensely relative to similar fires in other shrublands (**van Wilgen et al, 1985**). This inherent flammability derives from the chemical and structural traits of fynbos, where flammable compounds are common and the relatively high crude fat content enhance the readiness with which the vegetation will burn (**Bond & Midgley, 1995; van Wilgen et al, 1990**). There is no way to account for this elevated flammability using FARSITE, which may account for the underprediction of fire spread using 'real' fuel loads.

In addition to an unrealistically low spread when using field data, the fire spread pattern in all burn scenarios overemphasises the lateral spread of the fire flanks. By elongating the vertical axis based on wind and slope conditions, the rate of spread at the flaming front is used to infer fire spread in all other directions (**Finney, 2004a**). The underprediction of vertical extent of flaming front in most fuel models and an overemphasis of the lateral spread towards the coast in all of them suggest that the algorithm that infers flank expansion based on heading rate of spread may be unsuitable for fire spread in fynbos. The algorithm does not realistically elongate the vertical axis as a function of the high wind speeds during the fire, suggesting that new flank expansion parameters may need to be developed for fynbos.

A significant limitation to this study is the sample size. A single fire used to ascertain the overarching utility of a fuel model is inappropriate for fires generally, whose behaviour can vary widely even under similar conditions, but also specifically in fynbos where high spatiotemporal fuel heterogeneity means fire behaviour has a strong potential to vary. The limitation of this study to a single fire was data related – the fire record for the Peninsula is poor and though shapefiles of fire scars are recorded, details on basic fire parameters such as ignition location, start time, and containment time are scare. The Scarborough fire was chosen due to media coverage and the relative confidence with which an ignition location could be ascertained (jumped the road from a neighbouring bock burn). Ideally, this fire scar analysis would be repeated for as many of the historical fires as possible. A more exhaustive effort at fire scar analysis on the Cape Peninsula would in all probability emphasise the spatial and temporal variance in the goodness of fit of fynbos fuel models. Deriving regionally accurate fuel models by statistical optimisation is a possible avenue for exploration in order to incorporate the high spatial heterogeneity in fuel.

The result of this exercise should not be seen as an absolute confirmation of suitability of the FARSITE simulator for fynbos, but rather as a starting point for further in-depth analysis. More comprehensive analysis of FARSITE performance using several datasets for historical burns would allow a more in-depth diagnosis of error sources and a more confident commentary on the fundamental suitability of FARSITE and its sister suite of programmes to accurately model fire spread and behaviour in fynbos. However, the lack of high quality input data makes this difficult, primarily in terms of classifying error to inaccuracies in input data or more general error due to poor model suitability. More systematic data collection during fire events, both in terms of real fire behaviour as well as environmental parameters such as wind speed and direction, would improve modelling capabilities. Despite the uncertainty in the data, the results of discrete event simulation in this study are surprisingly positive. Multiple fuel models were able to predict with substantial agreement in terms of actual fire area, and produce realistic rates of spread. This validation exercise justifies the use of sister programme FlamMap in the next chapter, where I use simulation to explore landscape-scale impacts of urbanisation on spatial patterns of fire vulnerability.

Chapter 4

Urban impact on spatial patterns of fire vulnerability on the Cape Peninsula and consequences for the distribution of indigenous forests

Introduction

Human activities are altering contemporary fire regimes and potentially changing the spatial likelihood of fire occurrence (**Syphard et al, 2007; Liu et al, 2012**). Understanding how the spatial probability of fire varies and how urban development has changed these patterns is particularly important in areas where alternate ecosystem states co-occur at fine spatial scales. The Cape Peninsula is one such region, where fire-sensitive forest patches are interspersed in a sea of fire-prone fynbos. Fire is believed to be an important determinant of forest distribution, with absence or occurrence of fires potentially determining patch contraction and expansion over time (**Midgely et al, 2003; Cramer et al, 2014**). Modelling can help assess how anthropogenic land transformation has altered the likelihood of fire at any given point within a landscape, or the 'burn probability'.

The calculation of a per pixel burn probability records areas where fire is more likely to occur within a landscape and this can be calculated in a number of different ways, ranging from temporally explicit likelihood within a single year or month (e.g. FSPro; **Finney et al, 2011**), to a relative measure with no explicit temporal component (e.g. FlamMap; **Finney, 2004b**). The main inputs into burn probability calculations that have strong and distinct impacts on fire behaviour include fuels, weather and topography.

Fuels are important determinates of fire behaviour and affect patterns of burn probability primarily by altering relative spread. The structural and chemical composition of fuel as well as the relative moisture content all affect spread rates, particularly in shrubland fires where a high proportion of both fine dead and fine living fuel is consumed (**Plucinski, 2006**). Structurally important parameters impacting fire behaviour include proportion of dead standing fuel, fuel bed depth and fuel density, all of which are key in promoting fire spread **(Keeley, 2002; Plucinski, 2006**). Chemical composition, such as inorganic mineral content or presence of solvent extractives, is typically more important in heat content and burning rates, with some 34% of heat content explained by solvent presence in some chaparral species (**Philpot, 1977**). Both live and dead fuel moisture are important, with higher moisture contents reducing fuel flammability and rates of spread. Moisture content of fine dead fuel is particularly important, especially in shrublands where much of the fire is carried by dead fine material. Relative moisture content is however the most variable aspect of fuel and is modified by various aspect of the fire environment, including weather and topography, at a variety of scales to produce spatiotemporal variance in fire behaviour throughout a landscape.

Weather, most notably wind conditions, is key determinant of fire behaviour (**Brun et al, 2012**) as it directly correlates with the physics of heat transfer between fuels (**Nelson Jr et al, 1988**). Strong winds increase combustion rates by bending flames towards unburnt fuels, increasing the efficiency of heat transfer (**Catchpole, 2002**). Wind is therefore a crucial element in determining how fast and in which direction fires will travel.

Topography impacts fire behaviour at varying temporal scales. Over longer temporal scales, aspect influences the amount of solar radiation received causing inter-slope differences in fuel moisture and spatially variable fire spread. More short term impacts on fire behaviour are caused by slope, where steep inclines cause acceleration in fire spread uphill by decreasing the angle between the flaming front and the pre-ignition fuel in a similar manner to strong winds (**Rothermel, 1983**). Terrain that is highly complex and topographically disjunct can create multiple natural barriers to fire spread, limiting fire size and distribution (**Falk et al, 2007; Taylor and Skinner, 2003**). Such natural barriers include riparian areas, ravines and mountain ridges, each of which may interact with prevailing winds to determine fire spread rate and direction around the barrier.

Fuel, wind and topography are all important factors to fire spread, and so are likely important in determining wider patterns of burn probability within a landscape. This research introduces the novel concept of a fire catchment, a key concept in understanding burn probability patterns. A fire catchment represents the area in a landscape that will result in a specific location burning. Fire catchments are therefore defined with respect to a point location and will differ for each location in the landscape. The size and shape of a fire catchment depends on the topography, wind direction and fuel properties in the areas surrounding the point of interest (See **Fig. 4.1**). The larger the location's catchment, the higher the overall probability it will burn, irrespective of where the fire starts, as there is more areas of ‘catch’ fire over. Burn probability maps such as those developed by FlamMap (e.g. **Fig. 4.3**) represent the aggregation of the fire catchments for all point locations. Such burn probability maps reveal areas where many adjacent point have large fire catchments and are more likely to burn (fire pools) and areas where many adjacent point have small fire catchments and are less likely to burn (fire shadows).

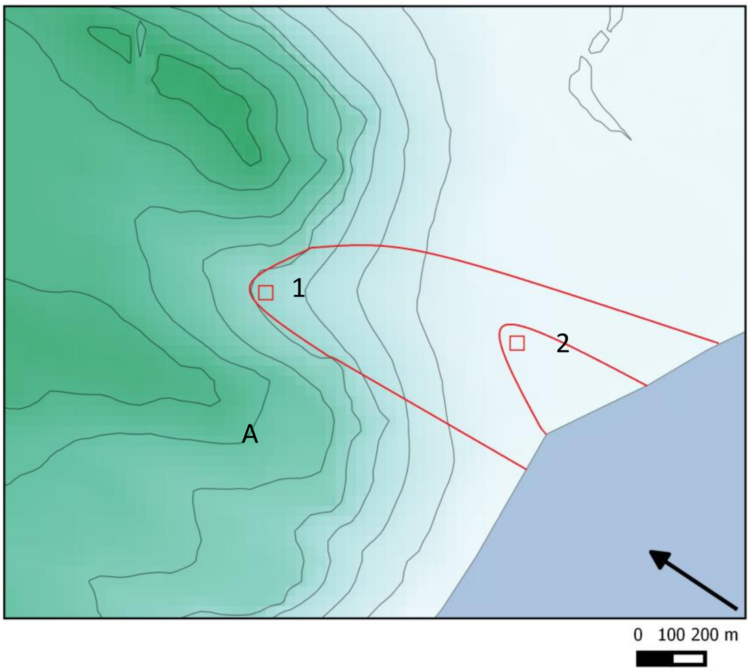

Figure 4.1: Comparison of the fire catchments of 2 spatially disjunct pixels under a south easterly wind. The topography surrounding pixel 1 impacts the fire catchment shape, most significantly the southern fire catchment boundary which is narrower due to bluff A obstruction fire flow. Pixel 2 has a much smaller fire catchment area due to its proximity to the sea.

The location of fire pools, as concentrations of high fire likelihood and fire shadows, as concentration of low fire likelihood, is likely to be strongly determined by natural barriers such as a rocky outcrop, steep slopes or water courses. The impenetrability of the barrier to fire flow creates fire shadows on the lee side while creating fire pools on the windward side, trapping fire and preventing further movement. In a similar way to that of natural barriers, artificial barriers may also interrupt the natural flow of fire through a landscape. Vast urban areas may create artificial barriers owing to both lack of fuel and active suppression of fire. The addition of such barriers may interrupt natural patterns of fire flow through a landscape, resulting in changes to the locations of fire pools and shadows. The most obvious effect may be urban fire shadows, cast along the lee side of suitably impassable urban areas.

The casting of urban fire shadows may have tangible impact on vegetation structure on the Cape Peninsula, where fire is thought to be key in maintaining the boundary between fynbos and isolated patches of indigenous forest that occur in fire refugia throughout the Peninsula (**Campbell & Moll, 1977; McKenzie et al, 1977; Manders, 1990; Midgely et al, 2003; Cramer et al, 2014**). When fire is excluded, forest species with fleshy, bird-dispersed fruits are able to establish outside of forest margins. Given the prolonged absence of fire, these recruitment patches may expand and extend the forest boundary (**Masson & Moll, 1987; Manders & Richardson, 1992**). As fynbos is shade intolerant, the potential to colonise established forest patches is low (**Manders & Richardson, 1992**). If urban development can alter the natural pattern of burn probability and therefore the location of fire refugia, it has the potential to alter the fynbos-forest boundary.

Previous studies have looked at spatiotemporal changes in contemporary fire regimes on the Cape Peninsula (**Forsyth & van Wilgen, 2008**) but few have explicitly examined the spatial pattern of burn probability to identify which areas of the Cape Peninsula are most vulnerable to fire and how this pattern changes with urbanization. In this chapter I use FlamMap (**Finney et al, 2015**), a fire behaviour mapping and analysis program, to simulate natural patterns of burn probability under typical fire conditions. I then add urban areas to the landscape and assess urbanisation-mediated changes to spatial patterns of fire vulnerability on the Cape Peninsula. I hypothesise that fire vulnerability in the landscape determines forest distribution, and that urbanization has allowed forest to spread beyond its natural boundaries by altering landscape patterns of fire vulnerability.

Methods

Study Area

The Peninsula is dominated by fynbos - a fire-dependent, sclerophyllous shrubland characterised by a diversity of shrubs of the ericoid (fine leaved and shrub-like), restioid (reed-like, aphyllous species) and proteoid (broad-leaved, tall shrubs) growth forms (**Bergh et al, 2014**). This vegetation type correlates strongly with the nutrient poor granite or sandstone derived soils. Small (~5%) patches of Renosterveld, a fire-prone, microphyllous shrubland, are found on more nutrient rich shale soils. Patches of fire-sensitive Afrotemperate forest exist as islands in this fire-prone matrix. The forest patches are split into Southern Afrotemperate forest, which is typically confined to steep-sided ravines, and

Coastal Milkwood forests, which occur on well-drained, sandy coastal soils. Although both are fire-sensitive, they differ in structure: Southern Afrotemperate forest has a tall, multi-layered canopy dominated by Yellowwoods (Podocarpaceae; *Podocarpus* or *Afrocarpus*) while the coastal forests are dense and of medium to low height with relatively simple mono-layered canopies dominated by *Sideroxylon inerme* (White Milkwood) (**Bergh et al, 2014**).

The Peninsula has a Mediterranean-type climate with a hot, dry season and a cool wet season, although seasonal temperature fluctuations are ameliorated somewhat by the surrounding Atlantic Ocean (**Cowling et al, 1996b**). Temperatures do however vary considerably in response to elevation, slope, aspect, exposure to the wind and proximity to the coast, with minimum temperatures of -7 °C recorded on the top of Table Mountain and maximum temperatures as high at 50 °C recorded on north facing slopes at sea level (**Slingsby, pers. comm.**). Large gradients in rainfall exist across the Peninsula, both laterally from north to south (2270 mm at Maclear's Beacon on Table Mountain to 402 mm at Cape Point in the south) as well as vertically, with higher elevation areas of the region typically receiving more rainfall. Rain shadows result in the eastern-facing slopes of the Peninsula Mountain Chain receiving more rain than the Cape Flats areas further east (**Cowling et al, 1996b**). Summer is dominated by south easterly winds that commonly reach gale force. Mean wind speeds in this season range from 20 km/h on the Cape Flats to 40 km/h at Cape Point. There is a strong interaction between the wind and topography, resulting in a complex spatiotemporal pattern of wind still and wind dominated areas, particularly in the southern Peninsula (**Cowling et al, 1996b**).

The topography of Peninsula is dominated by the Peninsula Mountain Chain, running from Table Mountain in the north to Swartkopberge in the south. Resistant granite and sandstone makes up much of the plateaux and ridges, while the softer shales underlie the valleys. Soils derived from the relatively inert and quartz-rich sandstones create nutrient-poor, shallow soils while those derived from the mineral-rich granite and shale are deeper and more nutrient rich (**Compton, 2004**). Soil nutrient status and drainage are both important in delineating different types of fynbos, with the vegetation assemblages found on the nutrient-poor sandstone plateaus and peaks distinct from those found in the more fertile colluvial slopes and lowlands (**Simmons and Cowling, 1996**).

The three sections of Table Mountain National Park and associated topography are shown in **Figure 3.1**. **Appendix III** describes the topography of the Peninsula more intimately and is a good guide to locations mentioned later in this chapter for international readers.

FlamMap

Though FlamMap utilises the same underlying fire behaviour models as its sister program FARSITE, the simulation package differs in its method of two dimensional propagation, using Minimum Time Travel (MTT) rather than Huygens Wavelet Principle. MTT involves a search for the minimum time for fire to travel among a grid of theoretical nodes in two-dimensional space. The paths resulting in the shortest possible internode travel time is then interpolated to produce instantaneous fire perimeter positions. MTT produces minimal distortion to fire shapes because there are no limits on angles or distances for searching and is computationally efficient for the large numbers of simulations involved in Burn Probability mapping. MTT closely replicates patterns in fire spread as predicted by Huygens' Wavelet Principle in FARSITE (**Finney, 2002**).

FlamMap's inbuilt burn probability function simulates a user-specified number of random ignitions across a landscape to build a map detailing probability of a pixel burning. Burn Probability is calculated as:

$$BP = \frac{F}{n}$$

Where F is the number of times a pixel burns and n is the number of simulated fires.

The BP for a given pixel is an estimate of the likelihood that a pixel will burn given a random ignition within the study area and similar burn conditions (**Ager et al. 2012**). This is not an annual probability; it rather acts as a relative index of burn probability across a given landscape.

Input data

FlamMap relies on a series of inputs describing topography, fuel distribution, and meteorological data. Topographic input requires five GIS raster themes describing elevation (meters), aspect (degrees), slope (degrees), vegetation cover (in term of fuel model number) and canopy cover (percent) to describe the landscape of interest. The digital elevation model (accessed through the City of Cape Town Open Data Portal with a 10m grid, resampled to 30m) depicts the elevation of the geographical surface of the Cape Town municipal area (Bare Earth Model; **City of Cape Town, 2016**) and was cropped to the extent of the Peninsula including the Cape Flats (18.2752, 18.51992; -34.41661, -33.88054). Additional files required for crown fire and spotting functionality (primarily canopy bulk density) were unavailable for this study resulting in the disabling of both. These files are incorporated into a single landscape (.lcp) file which forms a base onto which fire events are projected. Landscape files are interchangeable between the FARSITE family of simulators.

Fuel properties are represented by fuel models that summarize the key properties of the vegetation necessary to predict fire behaviour (**Chapter Three, Table 3.1**). Fuel model parameters are an average representation of the fuel mass, shape and spatial configuration, and by creating a set of accepted standard fuel models, fire researchers do not have to repeatedly measure these parameters (**Rothermel, 1972**). Custom fuel models for fynbos have been developed from field collection (**van Wilgen, 1984**) and regression analysis (**Le Maitre & Marais, 1995**) and these were tested in **Chapter 3**. These same fuel models were used to map and describe the vegetation of the Cape Peninsula. In addition to the custom fuel models used to describe the fuel properties of fynbos, some standard fuel models (**Scott and Burgan, 2005**) were used, primarily to describe urban landscapes.

Meteorological data

FlamMap allows only very simple inputs for meteorological data. A single average value is used for each of temperature, wind direction and wind speed, and these values are kept static for the entire duration of a single fire (i.e. no temporal variation in meteorological conditions is allowed). However, spatial variation in wind field is allowed, and is recommended for topologically complex regions.

Spatially variant wind fields are created using WindNinja (**Forthofer et al, 2014b**), a mass consistent wind model programme developed for wildland fire application. Input required to create spatially variant wind field in WindNinja are 'fire environment' - point measures of temperature, wind speed and wind direction from multiple points in the landscape. To create these fire environments , the SANParks public access fire database was sampled. The SANParks Peninsula fire database records the dates and shapefile of all fire events on SANParks land from 1970 – 2008. Fires were randomly sampled from the record, the dates of which were then cross referenced to the South African Weather Service climate record.

Only 100 fires which had climate records for at least two of the five weather stations on the peninsula were used to create fire environments. These 100 fire environments were then used as input to WindNinja to create 100 90 m resolution, spatially variant wind fields for the entire Peninsula.

Final meteorological input to the FlamMap burn probability simulator was one of 100 weather scenarios, with each scenario consisting of at least two measures of daily average temperature and humidity from different locations in the landscape, and a spatially variant wind field, with one layer for wind direction and one for wind speed.

Landscape Treatments

To investigate the impact of urban areas, two levels of transformation were used; pre-transformed and transformed. The pre-transformed treatment contained no roads or urban areas, whilst the transformed treatment mapped all urban areas and major roads as of 2014 at a 30 m resolution. All urban areas were demarcated using the non-burnable urban fuel model (NB1/091), defined as land covered by urban and suburban development that is unable to support wildland fire spread (**Scott and Burgan, 2005**). No existing forest were mapped onto the landscape.

An additional treatment was added to the landscapes to explore the impact of fuel model choice on burn probability output. The homogenous treatment applied van Wilgen's (**1984**) field fuel model to all vegetation in the study area. The heterogeneous treatment used the set of fuel models tested in the previous chapter (**Le Maitre & Marais, 1995**) and mapped according to Campbell's (**1985**) spatial distribution of major fynbos structural classes (**Fig. 4.2**, **Table 4.1**).

To summarize, the four landscape scenarios used in the scope of this study are:

1. Homogenous Pre-transformed – Single custom fuel model #85 (**van Wilgen, 1984**) used to describe all vegetation on the peninsula with no urban areas mapped.
2. Homogenous Transformed – Single fuel model #85 (**van Wilgen, 1984**) used to describe all vegetation on the peninsula with urban areas represented by non-burnable fuel model 091 (**Scott & Burgan, 2005**).

3. Heterogeneous Pre-transformed – multiple custom fuel models (**Le Maitre & Marais, 1995**) used to describe vegetation groups as mapped by Campbell (**1985**) with no urban areas represented (See **Fig. 4.2, Table 4.1**)
4. Heterogeneous Transformed – multiple custom fuel models (**Le Maitre & Marais, 1995**) used to describe vegetation groups as mapped by Campbell (**1985**) with urban areas represented by non-burnable fuel model 091 (**Scott & Burgan, 2005**).

For each of the four landscape treatments, burn probability landscapes were generated 100 times – one for each fire weather scenario created.

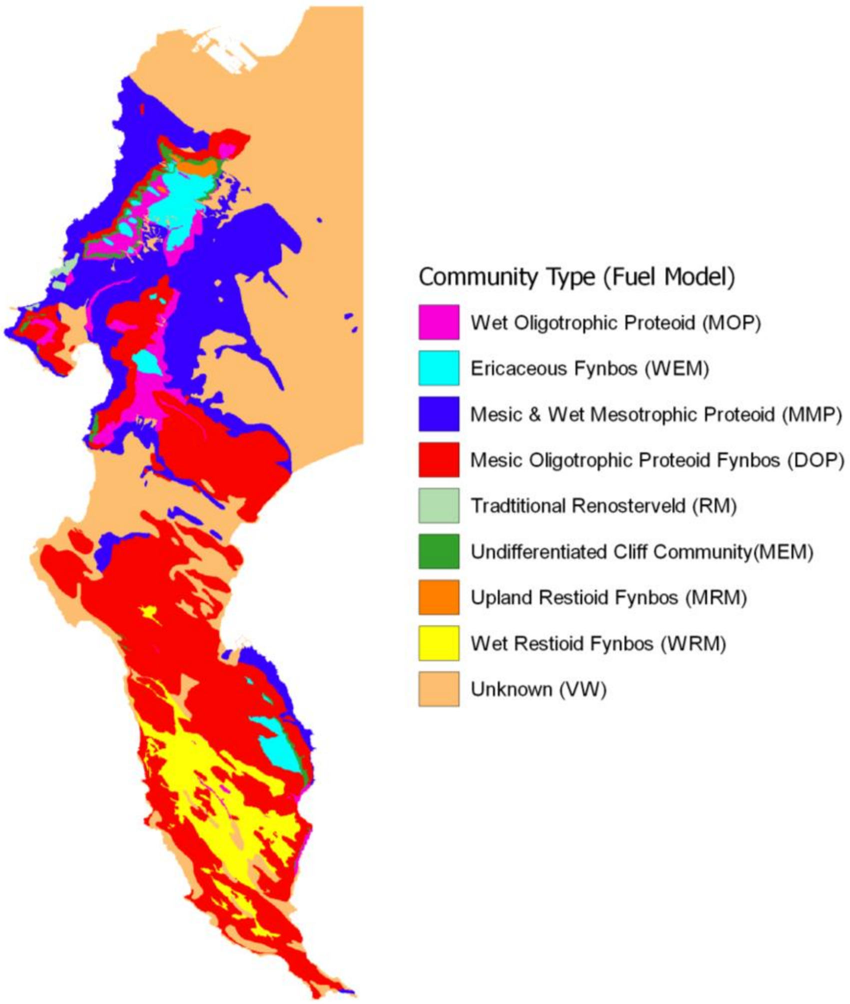

Figure 4.2: Spatial distribution of Le Maitre & Marais (**1995**) fuel models (with associated fuel model code) used for heterogenous landscapes. Based on vegetation map according to Campbell's (**1985**) spatial distribution of major fynbos structural classes.

Table 4.1: Plant communities of Table Mountain with corresponding fuel models (from Le **Maitre & Marais, 1995**).

Cowling (1996) Fynbos Communities	Le Maitre & Marais (1995) Fuel model	Fuel Model Code
Wet Mesotrophic Proteoid	Moist Mesotrophic Proteoid	MMP
Mesic Mesotrophic Proteoid	Moist Mesotrophic Proteoid	MMP
Wet Oligotrophic Proteoid	Moist Oligotrophic Proteoid	MOP
Mesic Oligotrophic Proteoid	Moist Oligotrophic Proteoid	MOP
Sandplain Proteoid	Dry Oligotrophic Proteoid	DOP
Ericaceous	Wet Ericoid	WEM
Upland restioid Fynbos	Moist Restioid	MRM
Wet Restioid	Wet Restioid	WRM
Undifferentiated Cliff	Moist Ericoid	MEM
Dune Asteraceous	Asteraceous	AFM
Coastal Scree Asteraceous	Asteraceous	AFM
Renosterveld & Grassland	Renosterveld	RM

Crown fire

The primary impact of disabling crown fire is the inability to include fire spread by spotting. Spotting is a behaviour typically observed in crown fires when sparks or embers are produced that are carried by the wind to create a new fire in unburnt vegetation ahead of the main fire (**Andrews, 1996**). The disabling of crown fire was judged to have little potential to impact this particular study, based on the height of vegetation, duration of simulated burns and resolution of output in FARSITE simulations. Spotting is of primary concern in crown fire systems such as the conifer forests of North America, with much work done on calculating potential spotting distances (seminal work by **Albini, 1979**; **Rothermel, 1991**). Fynbos is also considered a crown fire system, as fire is carried in the shrub canopy that is elevated above ground fuel. Though both the *Pinus* forests of North America and fynbos are classified as crown fire systems, Northern American forests are much higher – anywhere from 15 – 30 m (**Scott & Reinhardt, 2002**) while fynbos canopies have an average height of 2 – 3 m (**Van Wilgen & Van Hensbergen, 1992**). Local crowning and short range spotting in fynbos is restricted to orange class fire conditions when flame lengths are between 2 and 5 m and ROS between 25 and 35 $m.min^{-1}$. The resolution of simulation output at 90 m means that any fire bands that travel short term – i.e. less than 90 m - would have no impact on the fire perimeter, reducing the impact of not simulating these firebrands. Long-range spotting is rare in fynbos and is only presumed to occur in red class, or extreme fire conditions when flame lengths are between 5 and 15 m and ROS can exceed 60 $m.min^{-1}$ (**Forsyth & Bridgett, 2004**). However, such extreme fires only comprise a small proportion of the total Peninsula fire records - only 40 out of 373 since 1973 burned greater than 300 ha under extreme fire conditions (**Forsyth and Van Wilgen, 2008**). As 100 fires were selected randomly from the fire record, it is likely that very few extreme fire conditions are being simulated in this study, limiting the impact of disabling crown fire. Furthermore, other agents of spotting, such as stands of invasive vegetation or naturalised aliens in plantations were not included in the landscape, further reducing the requirement for spotting capability. The only practical concern is the ability of fires to jump roads. However, only major roads are included in the transformed landscape for the peninsula, and these would typically be used by firefighters to prevent further spread, mimicking the barrier effect of the road as simulated in FlamMap.

Run Parameters

During burn probability simulations, output resolution was set at 90 m to match the resolution of the complex wind fields. 10,000 random ignitions were used for each simulation run, with maximum simulation time set to 240 minutes (a proxy for maximum fire size). Of the 373 fires in the Peninsula fire record, 58% are 'small' fires (<25 ha) and only 40 fires on the record burnt over 300 ha (**Forsyth & van Wilgen, 2008**). Although these large fires dominate in terms of cumulative area burnt, computational load of simulating 10,000 large fires of 24 hours or more for each of the 100 weather scenarios for each of the 4 landscape conditions was unrealistic given the computational power required. A compromise was reached by trial and error: increasing ignition points per simulation and decreasing the individual burn time to minimise computational time while still obtaining a landscape with a low prevalence of zero values in burnable cells (**Seli et al, 2015**). To limit how long the MTT algorithm interrogates different pathways to compute a faster arrival time (and hence computational time), a lateral and vertical search depth was set to the default values of 6 and 4.

Aggregated burn probability landscapes and relative change

Burn probability landscapes for each of the four landscape scenarios were generated 100 times; once for each of the 100 wind fields. These 100 layers were then aggregated by four prevailing wind directions (SW, SE, NW and NE, proportion of wind scenarios falling into each were 8:74:3:15) into four burn probability average layers per landscape scenario. These four prevailing wind direction layers were then also averaged into a single aggregate layer where the average pixel value was weighted according to the overall proportional occurrence of each wind direction out of the 100 wind scenarios. To assess the impact of urbanisation on burn probability, pixel values for the aggregated transformed burn probability layer were subtracted from those of the pre-transformed layer for both homogenous and heterogenous landscapes, generating two landscapes of change.

Forest Occurrence

The distribution of Afrotemperate forest patches on the Peninsula in 1944 and 2008 have been mapped as digital GIS layers using aerial photography (**Poulson & Hoffman, 2015**). To map the spatial occurrence of growing, contracting and static forest patches, I overlaid the 1944 and 2008 distribution maps and classified each patch as expanding, contracting or static based on change in mapped forest extent. Plantations and established stands of alien trees were not included in this analysis.

This forest change map was then overlaid onto the change in burn probability layers for homogenous and heterogenous fuel landscapes. Burn probability was extracted for forests that decreased in size (8 patches) and forests that have expanded (68 patches) to examine the distribution of burn probability change values in each scenario.

Statistical Association

Two statistical analyses were attempted. Binomial logistic regression in R was performed on (1) current fynbos versus forest extent and (2) fynbos sites that transitioned to forest versus those that remained fynbos as a function of change in burn probability and other input parameters (aspect, elevation, TIP, fuel type, wind angle and speed) for both homogenous and heterogenous fuel conditions. Input variables were randomly sampled (n=1000 for each binomial category) and Moran I (ad4e package**, Dray & Siberchicot, 2016**) and Mantel (ape package; **Paradis et al, 2011**) tests were performed to assess the extent of spatial autocorrelation in burn probability landscapes.

Results

Pre-transformed patterns in burn probability

Although all wind scenarios show a gradient in burn probability from relatively high in the north to relatively low in the south, patterns of burn probability are heavily dependent on prevailing wind direction (**Fig. 4.3**). The northern region of the Peninsula in particular has dramatic differences in burn probability between wind conditions, with 'pooling' of high fire probability at downwind barriers emphasizing the importance of wind-driven fires. In this context, pooling occurs when wind-driven fires move with the direction of the prevailing wind until reaching a barrier to fire flow, such as the end of the land mass or topographical barriers such as cliff faces and mountain ridges. The NW wind condition showed high burn probabilities pooled at the SE extent of the northern Peninsula, with the eastern lower faces of the Constantiaberg slopes all the way down to Kalk Bay Peak experiencing heightened burn probabilities. The NE wind pushes fires to the SW, showing pooling around the central regions of Constantia Neck, including the escarpments from Devil's Peak down to Vlakkenberg. The SE condition results in the concentration of high burn probability at the city bowl in the northern Peninsula.

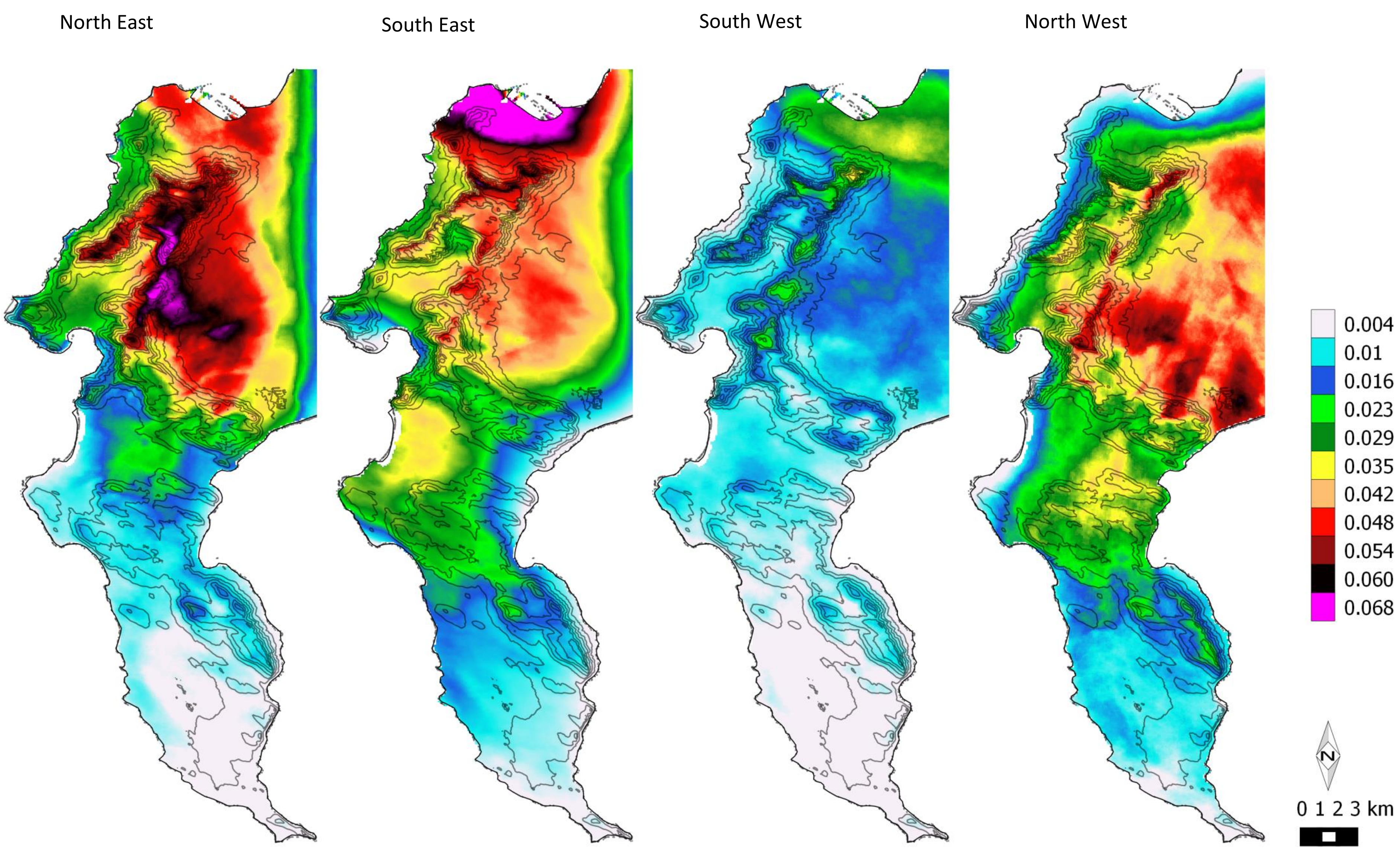

Figure 4.3: Burn probability landscapes for the Cape Peninsula under each wind condition (North East, South East, South West and North West) with homogenous fuel treatment. Contours **are shown at 100m**

The mountain ridges from Devil's Peak down to Vlakkenberg again have a high concentration of burn probability, as fire movement from the Cape Flats is interrupted by the mountain ridges. Though much lower landscape burn probability is experienced in the SW wind condition, the relative concentration of higher burn probability pixels to the NE is still present. These patterns are evident without considering meteorological factors that are associated with certain wind conditions, such as rain that might be associated with a north westerly wind.

The aggregate burn probability landscape for homogenous fuel is dominated by the SE wind condition, which made up 74 of the 100 wind scenarios sampled (**Fig. 4.4**). As with the SE-only landscapes, the southern Peninsula is less likely to burn than the north, largely due to the edge effect of the ocean. In the northern Peninsula, the western slopes of the mountains are less likely to burn than those on the eastern side. A large fire pool occurs over much of the eastern faces of the Peninsula Mountain Chain, where fires that ignite on the flats are driven by the primarily SE winds up the lower slopes of the eastern facing mountains. Fires accelerate uphill but their flow is interrupted by the rocky faces and steep slopes of the mountain ridges, resulting in fires pooling along the steep cliffs while creating the fire shadow that engulfs most of the west coast around Camps Bay. The prominent band of lower burn probability at the eastern extent of the Cape Flats is an edge effect, created by the boundary of the study landscape used, which largely coincides with freshwater bodies such as Zeekoevlei that would naturally inhibit the flow of fire.

There was a large difference in the spatial pattern of burn probability between homogenous and heterogenous fuel treatments in the aggregated landscape (**Fig. 4.4**). Differences in fire behaviour in each of the nine fuel models results in a spatially variant pattern of fire spread compared to the homogenous landscape. The northern Peninsula in the heterogenous landscape had generally lower burn probabilities relative to the homogenous landscape, largely owing to excessively low spread rates in the regionally dominant fuel model 83, Dry Oligotrophic Proteoid. Spatial impacts of fuel models are further seen in the south of the Peninsula, where areas described by models with higher spread rates (fuel model 87, Wet Restioid Model, on the west coast and small pockets of fuel model 81, Wet Ericoid Model on the east) are easily distinguishable embedded in the less flammable 83 (Dry Oligotrophic Proteoid).

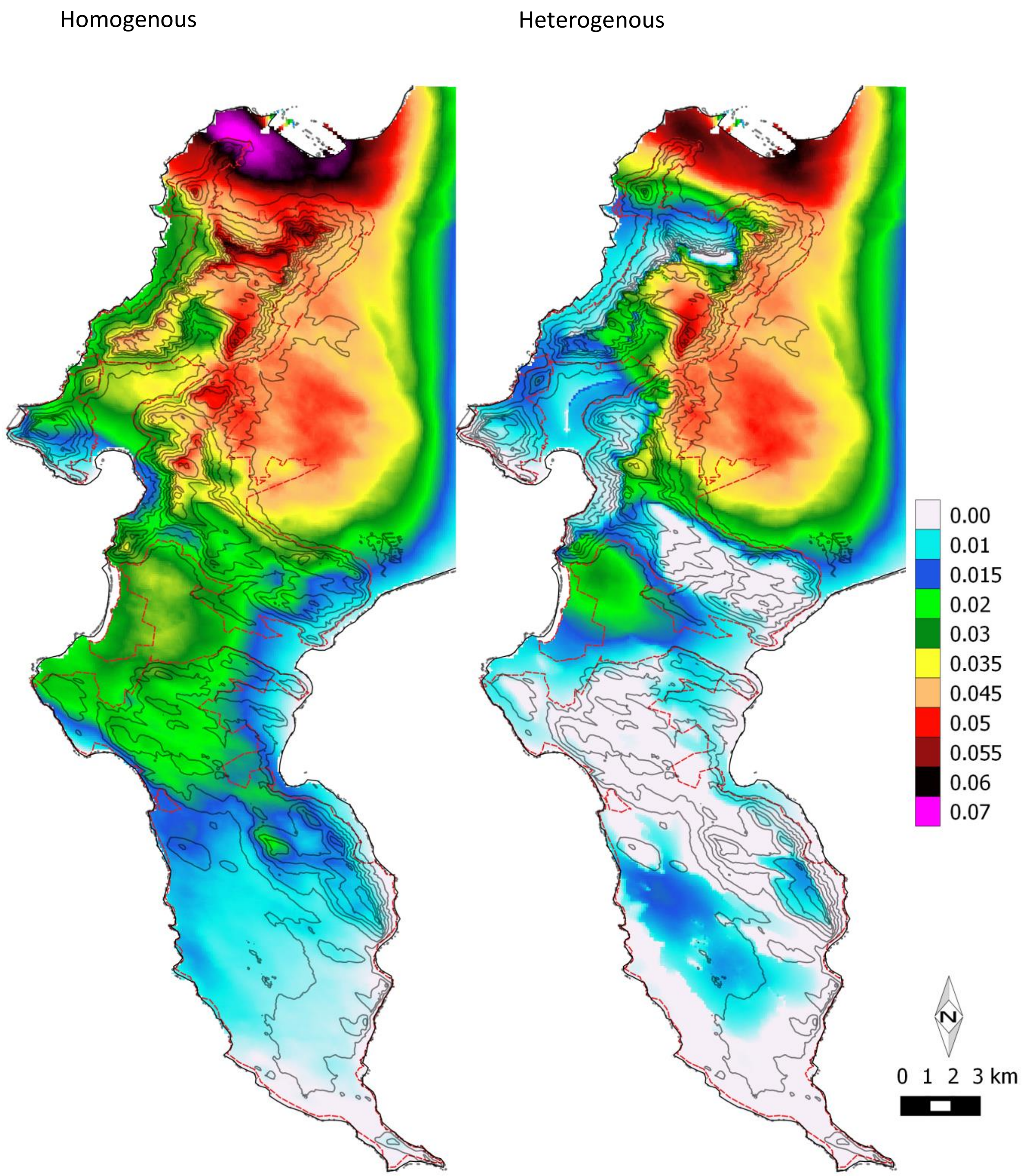

Figure 4.4: Aggregated burn probability for the Cape Peninsula, with per pixel burn probability calculated as a proportional average of each of the four wind categories (NE, SE, SW and NW) for homogenous and heterogenous pre-transformed landscapes. 100 m contour lines are in black and the 2014 extent of Table Mountain National Park indicated in dashed red.

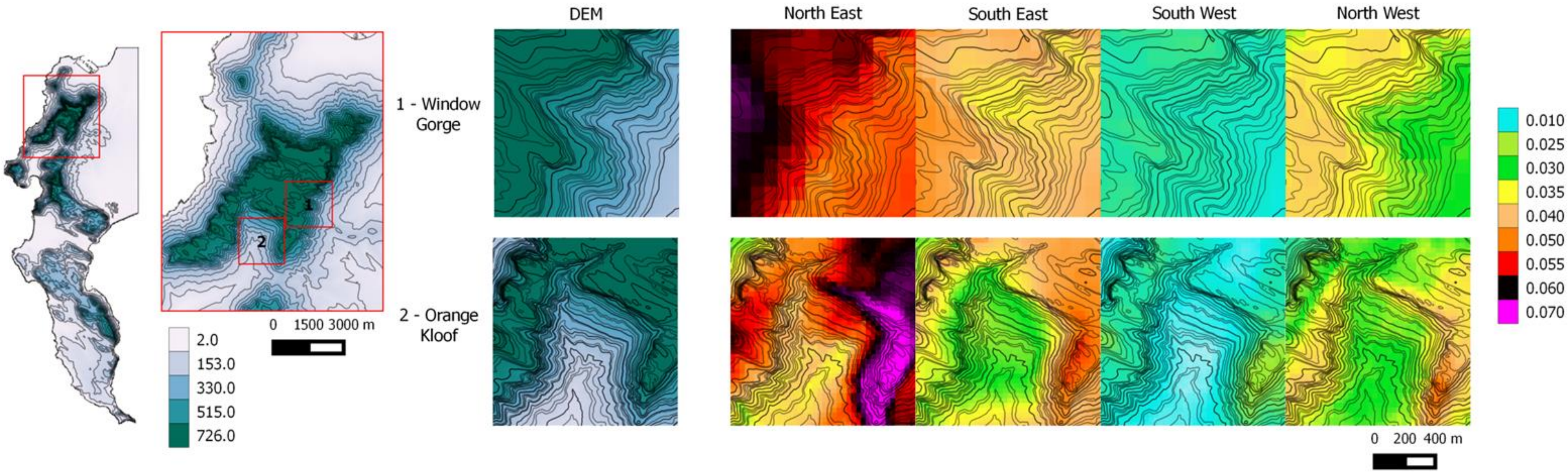

Figure 4.5: Fire refugia comparison, showing two refugia and their variance with wind condition. (1) Window Gorge (on the east facing slopes pf the northern Peninsula Mountain Chain) and (2) Oranjekloof (to the North East of Hout Bay Valley, in the northern Peninsula Mountain Chain). The first column of panels shows a digital elevation model describing the topography of the area, while the following four column show refugia effect predicted under the four wind directions (NE, SE, SW and NW respectively). 30 m contour lines in grey.

Peninsula Mountain Chain interacts strongly with fire-bearing winds, even at the relatively coarse scale of these simulations, to produce a network of fire refugia in the landscape (Fig. 4.5). In the aggregated homogenous landscape, the pre-transformed landscape shows a fire refugium effect most obviously at Orange Kloof, Blinkwater Ravine above Camps Bay and Window Gorge above Kirstenbosch. However, refugia are not static and a change in wind direction can reduce or even remove the refugium from the landscape. Orange Kloof is sheltered by steep valley walls on three sides but variation in wind direction changes the degree of sheltering the valley receives, with both NW and SE prevailing winds (the most common) creating a refugium effect but the NE wind reducing it, concentrating high burn probability on the bluffs above the valley (Fig. 4.5).

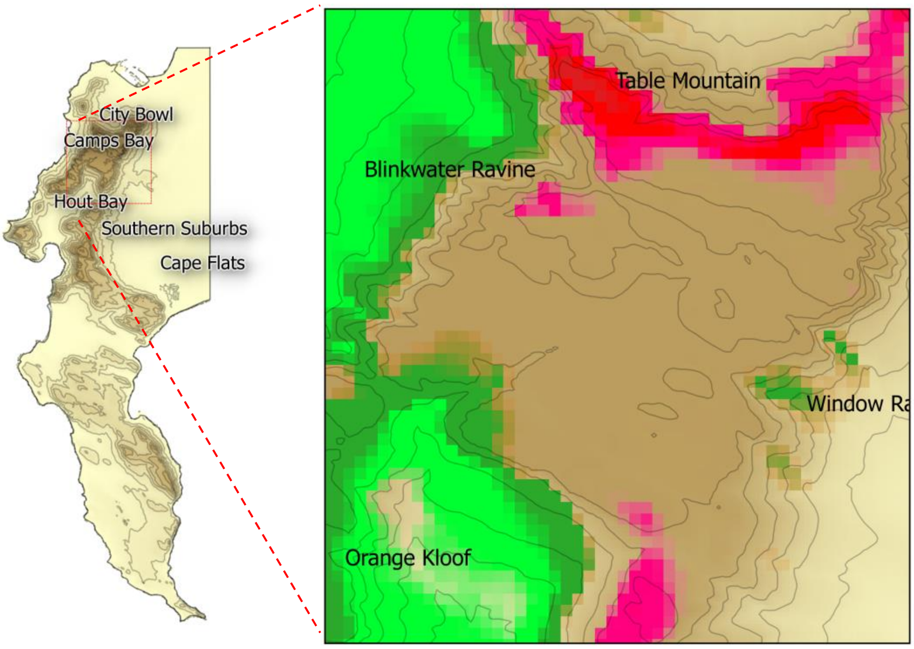

Figure 4.6: Figure outlining fire pool (Pink) and fire shadow (green) areas created in the Northern Peninsula with place names to aid in the discussion.

Changes in burn probability with land transformation

Urban development of the Peninsula fragments the natural landscape into three separate regions, coinciding with the north, central and south sections of Table Mountain National Park. This fragmentation results in three near-discrete fire systems created, one in each section of the park (**Fig. 4.7**). The broad patterns of burn probability created in the pre-transformed landscapes (i.e. the strong SE signal with fires pooling at topographical obstacles to the NW of the land) are evident at finer scales within each of these systems.

Predictions indicate that urban areas to the north-west of large expanses of wildlands – i.e. at the top of a fire system – have increased fire risk, including at Slangkop/Kommetjie (NW extent of the southern Peninsula System), at Chapmans Peak, the southern side of Hout Bay (NW extent of Mid-Peninsula System) and at the Twelve Apostles (Western extent of North Peninsula System) (**Fig. 4.8**). Conversely, there is an urban shadow effect on land to the west of urban areas in each fire system, with these regions generally experiencing a decrease in fire vulnerability (**Fig. 4.8**). This effect is shown strongly along the eastern slopes of the northern section of Table Mountain National Park, from Devils Peak all the way down to Silvermine. This urban shadow effect is strong in both homogenous and heterogenous fuel maps, even though natural and urban burn probability predictions vary between the two fuel scenarios (**Fig. 4.8**).

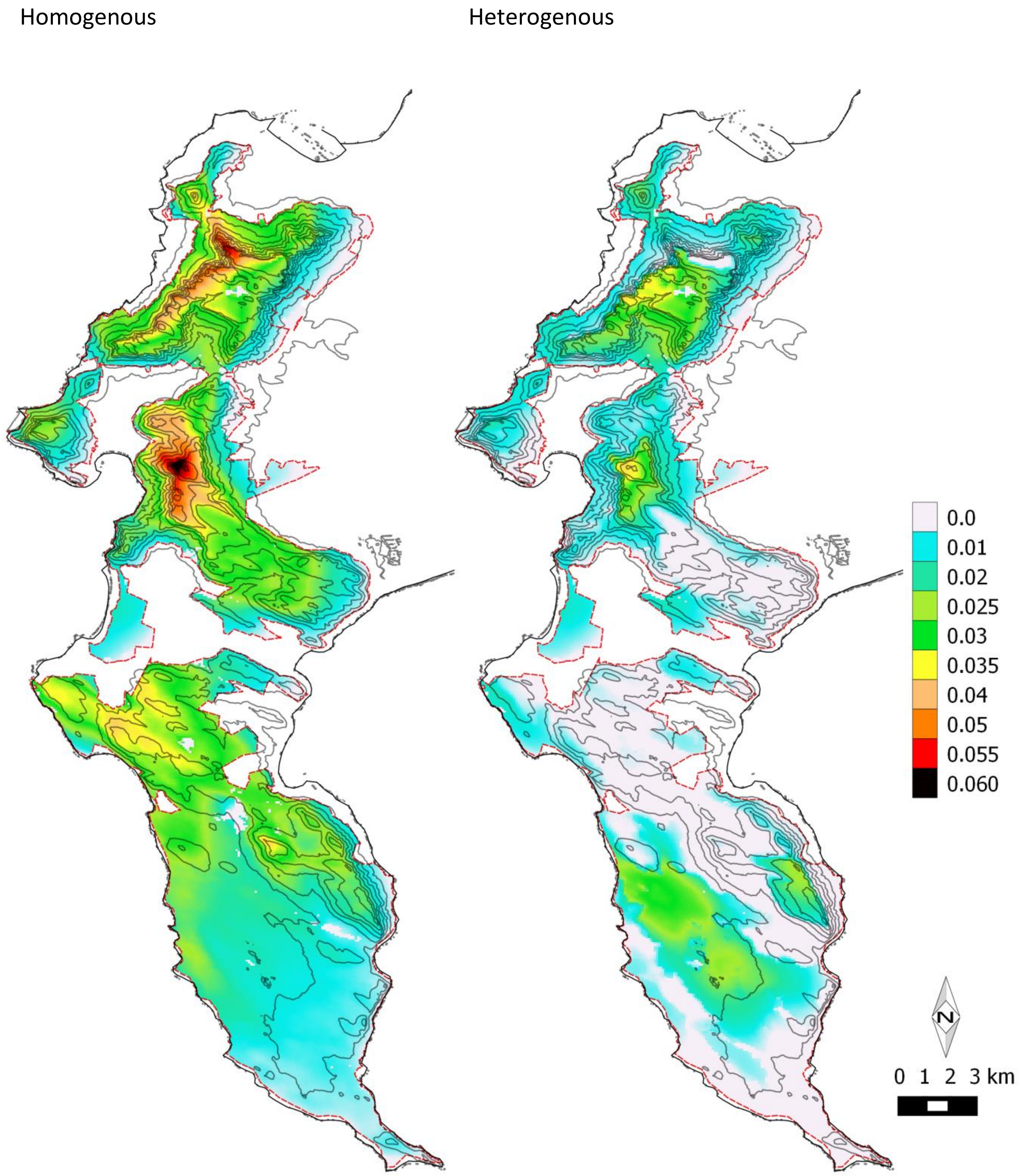

Figure 4.7: Aggregated burn probability for the Cape Peninsula, with per pixel burn probability calculated as a proportional average of each of the four wind categories (NE, SE, SW and NW) for homogenous and heterogenous transformed landscapes. Urban areas indicated in white, 100 m contour lines in black and the 2014 extent of TMNP indicated in dashed red.

Homogenous Heterogenous

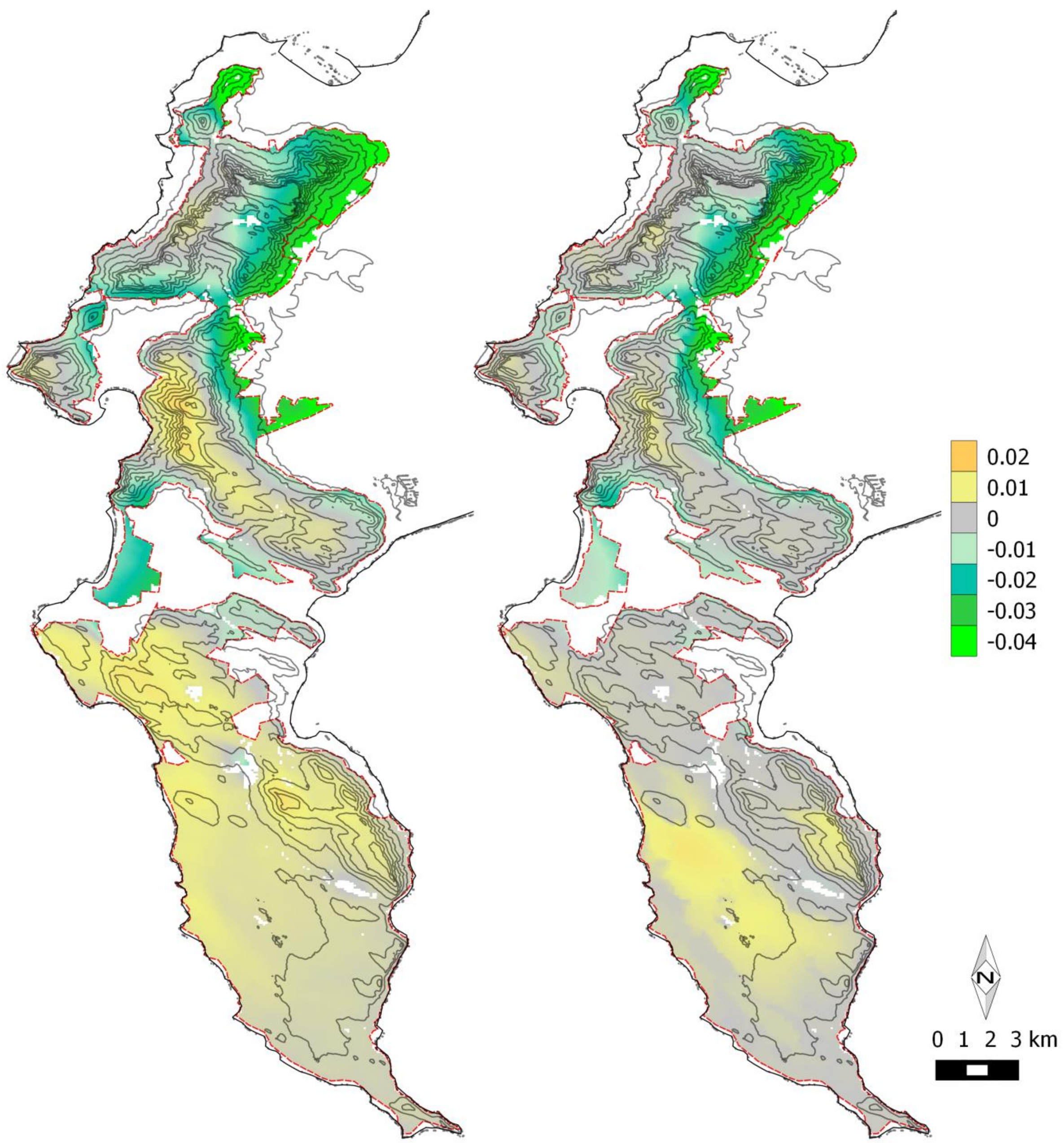

Figure 4.8: Change in Burn Probability, calculated as a per pixel value of transformed minus the per pixel value of pre-transformed for each of the homogenous and heterogenous fuel treatments. Urban areas indicated by white, with black 100 m contour lines and the 2014 extent of TMNP indicated in red dashed.

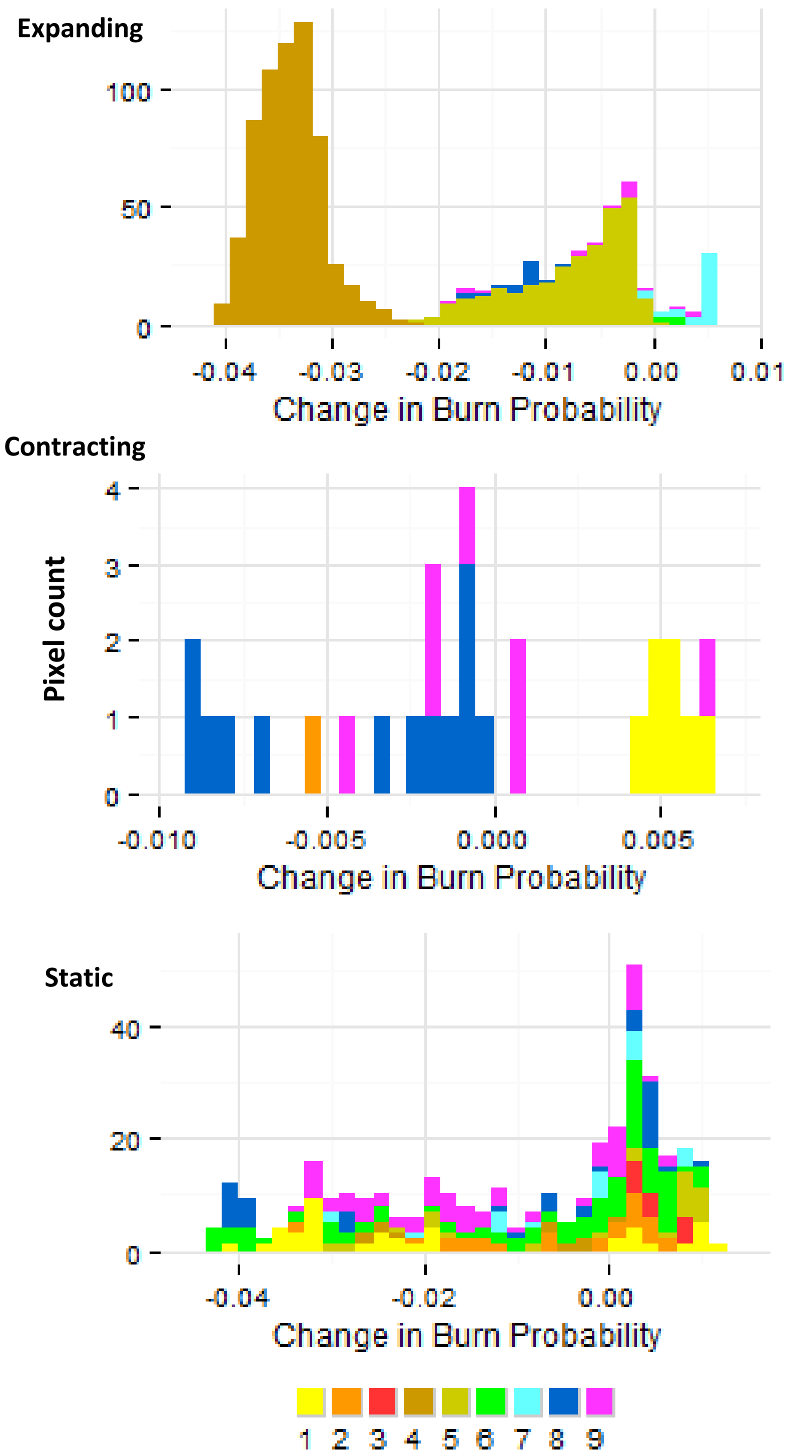

Figure 4.9: Change in burn probability associated with Peninsula forest patches as mapped by Poulson & Hoffman for expanding, contracting and static forest patches from 1944 to 2008, partitioned by forest location; 1. Chapman's Peak 2. Constantiaberg 3. Karbonkelberg 4. Newlands/Kirstenbosch 5.Orange Kloof 6.South Peninsula 7. Steenberg 8.Table Mountain 9. Twelve Apostles.

Table 4.2: Binomial logistic regression and ANOVA summary of coefficients estimates, Z test p values, residual covariance and chi2 test p values for all input parameters on both homogenous and heterogenous fuel landscapes for prediction current forest occurrence

	B Estimate	Error	Pr(>|z|)	Res. Deviance	Pr(>Chi)
Heterogenous	-0.48626	2.34381	0.8356	2760.1	
slope	-0.01415	0.00647	0.0288	2699	5.34E-15
aspect	-0.00195	0.00091	0.0317	2663.4	2.47E-09
TPI	-0.15781	0.02441	1.02E-10	2579.4	2.20E-16
vegClass	0.061096	0.02621	0.0198	2543.3	1.83E-09
windAngM	0.020532	0.00492	2.96E-05	2523.2	7.24E-06
windAngSD	-0.06087	0.00742	2.33E-16	2495.2	1.23E-07
windVelM	-0.45887	0.02849	2.00E-16	1304	2.20E-16
bpHet	27.33195	5.91838	3.87E-06	1282.7	3.87E-06
Homogenous	7.53E+00	8.65E-01	2.00E-16	2760.1	
slope	-2.15E-02	6.31E-03	0.00064	2699	5.34E-15
aspect	-3.73E-03	9.18E-04	4.83E-05	2663.4	2.47E-09
TPI	-1.47E-01	2.45E-02	1.75E-09	2579.4	2.20E-16
windAngM	2.36E-02	5.29E-03	8.34E-06	2560.7	1.50E-05
windAngSD	-7.37E-02	7.31E-03	2.00E-16	2522.5	6.44E-10
windVelM	-5.72E-01	2.90E-02	2.00E-16	1311.1	2.20E-16
bpHom	-1.90E+01	7.82E+00	0.01512	1305	0.01385

Table 4.3: Binomial logistic regression and ANOVA summary of coefficients estimates, Z test p values, residual covariance and chi2 test p values for all input parameters on both homogenous and heterogenous fuel landscapes for prediction of change from fynbos to forest

	Estimate	Std. Error	Pr(>|z|)	Resid. Dev.	Pr(>Chi)
Heterogenous	1.0117851	1.8627506	0.587	2383	
Slope	-0.0062072	0.0041749	0.137	2382.5	0.479763
Aspect	-0.000481	0.0005072	0.343	2381.9	0.42953
TPI	0.0063144	0.0137653	0.646	2381.9	0.829974
Vegetation Type	0.0132932	0.0217786	0.542	2381.7	0.667379
Mean wind angle	0.0033178	0.003168	0.295	2380.8	0.351885
Wind angle SD	-0.0006154	0.0048504	0.899	2380.8	0.866007
Mean wind velocity	-0.0232538	0.0093646	0.013	2372.2	0.003407
Change in burn probability	1.8052138	5.2668557	0.732	2372.1	0.7317
Homogenous	0.0750369	0.4291252	0.8612	2383	
slope	-0.006892	0.0040096	0.0856	2382.5	0.479763
aspect	-0.0004322	0.0005044	0.3916	2381.9	0.42953
TPI	0.0061943	0.0137686	0.6528	2381.9	0.829974
Mean wind angle	0.0032123	0.0031633	0.3099	2381	0.354575
Wind angle SD	-0.0005687	0.0048298	0.9063	2381	0.831627
Mean wind velocity	-0.0206882	0.0093593	0.0271	2372.6	0.003908
Change in burn probability	3.6907759	4.3239485	0.3933	2371.9	0.39291

Forest change

Expanding forest patches largely co-occur with decreasing burn probability that ranges from 0.040 to 0.005 (**Fig. 4.9**). The bulk of this co-occurrence is driven by Kirstenbosch/Newlands and Orange Kloof, where large decreases in the burn probability have occurred. Only a few small forest patches are expanding in areas where there is a slight predicted increase in fire probability, including Milkwood forests of the south Peninsula, the new forest patches at Steenberg, Kalk Bay and an isolated patch along the coast below the Twelve Apostles.

Statistical analysis suggests all predictor inputs are important in determining current forest occurrence on homogenous landscapes (**Table 4.2**), burn probability being the least significantly implicated and wind angle, mean and standard deviation of wind velocity being the most important. All additional input parameters result in a significant decrease in residual deviance from a null of 2760.1, though mean wind velocity results in the largest drop in residual deviance from 2522.5 to 1311.1. Similarly for a heterogonous landscape

(Table 2.4), all input parameters are significantly implicated in determining forest distribution, however, slope, aspect and vegetation class are the least significant. Burn probability is more significant in determining forest distribution in a heterogonous landscape than in a homogenous one.

Statistical association between changing burn probability and expanding forest patches is weak for both homogenous ($Z=0.854$, $p=0.39$) and heterogonous ($z=0.343$, $p=0.732$) landscapes, with the only significant predictor input being mean wind velocity (homogenous, $Z= -2.21$, $p>=0.05$; heterogonous, $Z= -2.48$, $p>=0.05$; **Table 4.3**).

Discussion

The use of fire simulation systems considerably expands our understanding of how spatially explicit patterns of fire likelihood vary across the Peninsula and how these have been altered through urban transformation. Prevailing wind during a fire is altered by local topography to create a mosaic of high and low fire risk regions. Urbanisation produces a significant urban shadow effect due to the interruption of natural fire flow. There is an overall increase in area of fire refugia but little loss of existing fire refugia with urbanisation, suggesting that the main impact of urban mediated changes to the burn probability landscape is not the loss of existing fire refugia, but the creation of expansive new ones.

Prevailing wind direction is an important determinant of burn probability on the Cape Peninsula. The impact of prevailing wind in driving fires is evident in the pre-transformed landscape, with pooling of high burn probability at the leeward land extremes or on the windward side of topographical barriers. It is also evident in the transformed landscapes, where fires pool at the leeward extent of each of the three main wildland fragments. The SE wind is the dominant signal in these landscapes, in line with the dominance of this wind direction during a typical fire season (**van Wilgen, 1981**). The SE effect is evident in both homogenous and heterogenous fuel treatments, despite differences in fire spread rate between fuel models. The impact of fuel models that produce lower rate of spread is visible at Maclears Beacon and the City Bowl, where the use of fuel model 83 significantly reduced the burn probability of the area compared to the homogenous landscape. The large-scale impact of the SE winds is however still strong, suggesting a macro-scale importance of wind over spatial fuel patterns in determining burn probability. Though fires used in this simulation study were short duration, there still a visible impact of wind on burn probability landscapes, strongly support of the overall importance of wind direction on burn probability within the Peninsula.

The shape and complex topography of the Peninsula interacts strongly with prevailing wind to determine patterns of burn probability. The elongated shape of the Peninsula and the encompassing Atlantic Ocean is largely responsible for the low burn probability of the South Peninsula compared to the North. The driving of fire with the prevailing wind and the consequent slow spread of back burns against strong SE winds means that the southern and south-eastern extreme of the Peninsula will only experience fires that ignite in the immediate vicinity. Regions further to the western and northern extreme of the Peninsula will experience fires not only from ignitions in the immediate area but also the spread of fires that have been driven from further upwind. The narrow South Peninsula provides relatively little land where ignition can occur, with no 'catchment' area further south or south east from which to draw fires, supporting the idea that burn probability is dependent on the upstream properties of the landscape (**Finney, 2002; Finney, 2005**). The fire pool that is visible across the eastern faces and ridges of the mountains above the Cape Flats remains largely unchanged by the spatial variation in fuel type, suggesting again that the wind/topography interaction may overrides fuel layout in a suitably flammable system.

Fine scale interaction between topography and prevailing winds create strong refugium effects in various valleys and gorges of the northern Peninsula. Fire refugia , identified on burn probability maps as contained areas of lower burn probability encircled by areas of higher burn probability, are predicted for Orange Kloof and Window Gorge, as well as the western coast from Oudekraal to Camps Bay. All of which can be attributed to abrupt changes in slope associated with steep-sided ravines. Such breaks create more turbulence in the air passing over them, increasing the tendency for airflow to separate from the ground and form vertical eddies in the opposite direction to the prevailing wind. The divergence of wind flow can then protect areas on the lee side from the wind-driven fire path. The formation of these eddies protects valleys and basins from the prevailing wind as a function of their confining topography (**Geldenhuys, 1994; Whiteman, 2000**). This finding supports years of speculation as to the fire protected status of areas such as Orange Kloof (**Masson & Moll, 1987; McKenzie et al, 1977; Poulson & Hoffman, 2015**), and offers the first data-driven support for topographically created refugia within the Peninsula Mountain Chain.

The addition of urban areas results in large changes to patterns of burn probability. Urban development to the windward side of wildlands results in a decrease in fire vulnerability at the leeward urban-wildland boundary, creating artificial shading or an 'urban shadow' effect. The urban shadow effect is most evident on the eastern facing slopes of the mountain from Kirstenbosch to Devil's Peak where the addition of urban areas on the Cape Flats interrupts fire flow up the slopes, casting large urban shadows of decreased burn probability. This shadow effect has long been suspected to be operating on the eastern slopes of the Peninsula Mountain Chain (**Geldenhuys, 2000**), however this study is the first data driven evidence supporting an urban fire shadow effect for the Cape Peninsula.

The prediction of an urban fire shadow is strongly corroborated by forest expansion data over the past 50 years. Aerial photography shows that the forests of the Peninsula have expanded by 65.3% since 1944, with development of closed-canopied forests at Orange Kloof and ecotonal expansion into the fynbos at Kirstenbosch/Newlands (**Poulson & Hoffman, 2015**). This expansion is regardless of a recorded decrease in fire return intervals in the last 50 years (**Forsyth & van Wilgen, 2008**). The concordance between expanding forest patches on the eastern slopes of Kirstenbosch and Newlands and areas of decreasing burn probability in the urban shadow provides strong support for urban mediated changes to fire patterns as a driver for forest expansion in this region of the Cape Peninsula. However, larger scale statistical significance of burn probability on forest occurrence is harder to discern owing to high spatial autocorrelation and the the relatively small number of forest patches. Spatial autocorrelation makes statistical comparison of limited use in this study owing to the violation of the independence assumption between data points.

Both the potential and the actual distribution of forest patches in South Africa are influenced by a variety of factors, with fire only one of the significant determinants. Burn probability was not a notably strong statistical determinant of current forest distribution in this study, despite current academic thought on the overarching importance of fire on forest distribution. Edaphic determination is currently thought to be less important in controlling forest distribution, with increasing evidence of niche construction as a driver behind differing nutrient levels between neighbouring fynbos and forest patches (**Coetsee et al, 2015**). Another important control of South African forests is moisture availability (**Masson & Moll, 1987**) with forests only occurring in areas of the Peninsula receiving more than 650 mm/ year (**Trinder-Smith et al, 2006**). Regional-scale biome modelling in South Africa suggests that in the absence of fire, forests will only expand at the expense of fynbos in the more mesic areas (**Bond et al, 2003**). The association between lower burn probability areas and expanding forest patches is largely driven by forest patches along the eastern facing slopes (Kirstenbosch and Newlands) and Orange Kloof, relatively more mesic regions of the Peninsula. The lack of strong correlation between current forest distribution as well as forest expansion with burn probability variables, suggests that fire is only one control that interacts with other drivers such as available moisture to control forest growth over time to determine forest discussion and change.

Mesic regions of the Peninsula with reduced fire probability may therefore be at heightened risk to forest expansion. Although Afromontane forest is indigenous to the Peninsula, forest patch expansion (particularly in the northern Peninsula) is an undesirable management outcome in a biodiversity hotspot and world heritage site. This is because Afrotemperate forest patches are species poor compared to fynbos (although they are extremely diverse for temperate forest) and have a status of least concern. Conversely, the Peninsula Granite fynbos that occupies much of the northern Peninsula has high floral diversity, contains many Red Data List species and is classified as an endangered National Vegetation type (**Rebelo et al, 2006**). To maximise biodiversity in a National Park that is part of a world heritage site because of its biodiversity, areas above Kirstenbosch should be burned. The close proximity of urban areas in this region complicates management, as authorities responsible for managing the Table Mountain National Park have to balance losses in biodiversity with public safety. A public safety mandate may find forest expansion advantageous, with indigenous forests forming natural fire breaks to protect human interest at the urban wildland interface.

Topography, weather and fuel interact to form spatially complex patterns of fire vulnerability on the Cape Peninsula. Urbanization has further altered this complex landscape, impacting patterns of burn probability by interrupting fire flow and casting large areas of artificial refugia. The fire-dependent nature of the natural vegetation and fire-averse nature of intermixed forests means that alteration of burn probability translates into altered vegetation patterns, facilitating the expansion of forest patches in the more mesic regions of the Peninsula. These finding have implications for informing fire management as well as adding evidence to the importance of fire in determining the boundary between forest and fynbos. This will be further discussed in the following **Chapter Five**.

Chapter 5

Synthesis

Fire is critical in maintaining ecosystem function in the fynbos vegetation of the Cape Peninsula, but the significant anthropogenic-derived reduction in the average fire return interval over the last 40 years represents a significant threat to community structure and composition, with re-seeding species particularly vulnerable (**Forsyth & van Wilgen, 2008**). Using simulation software, I have shown that urbanisation can have unforeseen remote impacts on vegetation structure and distribution in fire-dependent systems such as the Cape Peninsula, suggesting that urban areas can alter such systems simply as a function of being there. Urbanisation is not only a threat in terms of its ability to alter fire return intervals but also has remote impacts by interrupting fire pathways, causing wide scale changes to spatial patterns of fire probability. These changes have tangible impacts on the relative distribution of fire-prone fynbos and fire-sensitive forest in more mesic regions of the Peninsula, with the exclusion of fire facilitating the ecotonal expansion of forest into fynbos.

These findings demonstrate that artificial barriers such as urban development represent significant obstacles to fire flow with wide-scale impact on patterns of burn probability. This is particularly evident along the eastern slopes of the northern Peninsula Mountain Chain, where fire catchments of the points in the area are interrupted by transformation of the Cape Flats, which would naturally act as a collection plain for fires. During typical south-easterly wind conditions of the fire season, fires would have driven to the slopes of the Peninsula Mountain Chain. Fire would then accelerate upslope before pooling at the series of natural barriers created by the high ridges and steep escarpments of the Peninsula Mountain Chain.

The urban fire shadow created by development of the Cape Flats is supported by forest expansion of the Kirstenbosch/Newlands forests, which has undergone ecotonal expansion (**Poulson & Hoffman, 2015**). Forests patches that would have previously been limited by fire occurrence to the relative refugia created by steep-sided gorges such as Window Gorge, Skeleton Gorge and Nursery Ravine are now expanding into and replacing fynbos. This contemporary expansion of forest in the response to the absence of fire provides support for a naturally disjointed distribution of Cape Peninsula forests controlled by fire occurrence.

The vegetation into which these forest patches are expanding is termed peninsula granite fynbos, an endangered vegetation type of which over 57% has been transformed (a further 17% classed as restorable, i.e. currently under plantation or indigenous forest with the potential of being restored to fynbos) (**Rebelo et al, 2011**). The mandate under which the Cape Floral Kingdom was declared a UNESCO World Heritage site is based on plant species diversity, with Table Mountain National Park being a notable regional node of floral diversity. Afrotemperate forest patches are species poor relative to fynbos and have a conservation status of Least Concern. To maintain diversity, park management may have to consider controlled burns in areas such as that above Kirstenbosch to prevent forest from further colonising the fynbos.

The simulation systems used in Chapter Three and Four demonstrate that even with relatively coarse-scale fuel and meteorological data, substantial predictive ability for fires in fynbos is achievable. Considerable agreement between observed and predicted fire area as well as reasonable rate of spread estimates are both positive indications of the future utility of simulation systems to predict fire spread in fynbos. Key findings from this study are helpful in guiding the further use of simulation in fynbos, namely that fuel model choice is critical in maximising prediction accuracy, and also that the current suite of custom fynbos fuel models vary widely in their goodness of fit. Significant effort needs to be put into developing and mapping regionally accurate fuel models on the Peninsula. Optimization methods for refining fuel models, in which random combinations of fuel model parameters are iteratively generated, run and validated against observations to create the most accurate fuel model, have proved to be an efficient method of creating regionally specific fuel models (**Cruz & Fernandes, 2008; Ascoli et al, 2015**). Developing a protocol for refining regional models of best fit for management in fynbos could allow fuel model parameters to vary in both space and time. This may be achieved by repeating the fire scar analysis performed in Chapter Three to identify a regional custom fuel model of best fit, and then optimising this model to refine parameters of best fit for a given fire event. The optimised fuel model could then be used for the next fire to occur in the same area given the same environmental and climate conditions. To reduce computational load and ground optimised fuel models in reality, accurate data should be collected for those parameters that do not vary excessively in space, while optimisation methods should be used for those parameters that are highly variable.

As with any modelling exercise, the strength of predictions is dependent on the validity of the assumptions made in the underlying model, as well as the quality of input data used. These need to be explored extensively before management use and recommendations can be made. As with any model of a complex phenomenon, FARSITE makes multiple assumptions to enable simulation, many of which are realistically violated by fires in spatially and temporally variable environments. The elliptical constraint on fire shape as assumed by Huygens Wavelet Principle allows for the spread of all fire flanks to be inferred from a single forward rate of spread (**van Wagner, 1969**). Although the elliptical shape of fire burning under homogenous conditions has some support, field observation suggests fire shape in heterogenous environments such as the Cape Peninsula may not conform to a specific shape (**Green, 1981**). Another assumption of the model is the independence of ignition points on the fire perimeter as sources of new wavelets. As fire front shape affects radiative heat transfer (**Byram, 1959**), there will realistically be spatial variation in ignition probability along any fire line that is not straight, violating the independence of sources (**Finney, 2004**). There has been little research into the impact of these violations on simulation accuracy (**Finney, 2004**) and future research should focus on comparatively assessing alternative methods of fire front propagation, such as cellular automata, to circumnavigate some of the violated assumptions of Huygens Wavelet Principle.

There are also several problems related to either a lack of flexibility in FARSITE input data, or a lack of high quality data available for simulation. Wind data was particularly problematic in the context of this study. Wind speed and direction can only be input to FARSITE as hourly averages. For areas such as the Cape Peninsula, where wind speed and direction are known to change on a much finer scale, hourly averages do not capture subtle nuances of wind condition. Additionally, for the discrete event simulation of Chapter Three, the nearest wind station was ~ 18 km away. This is too far from the front to be fire-specific, as strong interaction often occurs between wind and fire on the flaming front, creating convectional in-drafts that can radically change wind condition (**Roxburgh & Rein, 2008**). A potential solution to this issue is the use of anemometers mounted on fire response vehicles to remotely record fire specific meteorological conditions. A Peninsula wide study on spatial variation in wind microclimate would be of great use to future fire simulation efforts. As no such data was available for this study, complex wind maps generated by the fluid dynamic model WindNinja (**Forthofer**, 2014b) were assumed to be accurate.

The representation of fuel in FARSITE input data is also problematic for heterogenous environments. Fuel is restricted to discrete fuel models, the extent of which must be mapped. These are essentially artificial delineations and developing fuel models in this way is problematic in fynbos which is characterised by extreme fuel heterogeneity, even on small spatial scales (**van Wilgen et al, 1984**). The discrete system can therefore only hope to capture fuel heterogeneity by increasing numbers of fuel models to describe vegetation. The greater the number of fuel models, the more expensive and exhaustive fuel mapping exercises will be: an exercise that is already considered difficult owing to high fuel variability across time and space. Novel methods need to be considered. One such method could be to use remote sensing to characterise fine scale spatial variance in fuel abundance and structure (e.g. using LiDAR, NDVI, NDWI for fuel moisture; **Keane et al, 2001**), with statistical optimisation to create novel fuel models of best fit from the most sensitive and the most spatially variant fuel model parameters (**Ascoli et al, 2015**).

The data limitations in these models were not restricted to input data. Very little high resolution data exists for comparative fire scar analysis, as required in Chapter Three. There is a digitized fire record for the Cape Peninsula recording the fire scars for most fires since the early 1970's (**Forsyth & van Wilgen, 2008**). This record is very basic however, with no specific fire behaviour parameters such as rate of spread or flame height recorded, making the validation of simulated behaviour difficult and limiting the depth of comparative analysis. Even basic data such as fire duration, approximate ignition time and containment time are unavailable for public access and difficult to obtain from the relevant authorities. This results in ambiguity of these parameters, making diagnosing error and improving simulation accuracy difficult. Furthermore, it restricts fire scar analysis to only the final scar, even though fire simulation becomes less accurate with time due to accumulation of error (**Finney, 1998**). Fire scar comparison at various time steps during the fire event is a better measure of prediction accuracy, allowing researchers to establish how simulator accuracy changes over time (**Kelso et al, 2015**). This requires remote sensing and satellite imagery to define a series of interim fire scars, something that has not yet been done for the Cape Peninsula. To combat this, a more integrated data collection protocol needs to be established for fire teams working on Peninsula fires, with a mind to future fire simulation efforts.

Ignition patterns in Chapter Four were assumed to be random owing to lack of detailed data on contemporary ignition pattern. However, even in natural systems, ignition patterns are unlikely to be random. Chances of lightning strikes and rock falls as sources of natural ignition are concentrated in certain areas (high elevation or high rock cover with steep slopes). Human variables, such as distance to anthropogenic features (towns, roads etc.) have large impacts on ignition probability in transformed landscapes (**Syphard et al, 2008**). The location of ignition can significantly impact the subsequent patterns of wildfire spread (**Syphard et al, 2007**) and so the use of random ignitions over non-random ignitions can substantially alter the burn probability landscape (**Massada et al, 2011; Lowery, 2012**). Future expansions on the work of Chapter Four should include spatial ignition probability models, using biophysical and anthropogenic variables to construct spatially variable ignition scenarios to identify the effect of ignition locality.

A final consideration is the selection of typical fire weather. In Chapter Four, the 100 real fire weather scenarios were sampled randomly from the fire record. However, a strong argument can be made to select extreme fire events – extensive and intense fires that occur during hot, dry and strong wind (**van Wilgen et al. 1990**). The influence of fuel type on fire spread is diminished under extreme weather conditions (**Moritz, 2003; Nunes et al, 2005**) and can overcome age-dependent flammability of vegetation. Some researchers suggest fynbos requires at least 6 years of post-burn growth to become suitably flammable (**van Wilgen, 1982; Brown et al, 1991**), but under extreme weather conditions stands as young as 3 years post-burn may carry fire (**Bands, 1977**). The majority of burnt area on the Cape Peninsula since the 1970's was burnt by a small number of extreme fires (**Forsyth & van Wilgen, 2008**), suggesting that extreme fire weather should be used to understand burn probability, fire risk and ecological impacts of fire on the Peninsula.

Conclusions

I have demonstrated that anthropogenic impacts on fire-dependent systems are not only limited to direct actions, such as changes to ignition patterns or fire suppression, but also indirectly though creating artificial barriers that interrupt fire catchments and alter natural patterns of burn probability. In systems such as the Cape Peninsula, where fire is important in maintaining a balance between alternate stable ecosystem states, this anthropogenic change to burn probability can have tangible impacts on vegetation structure. That a change in fire probability can tip the balance and help facilitate fire-sensitive forest expansion into fynbos adds further evidence to a growing consensus that fire is an important determinant of biome boundaries, over the traditional notion of edaphic or climatic determination. This study presents positive initial steps in adapting existing global simulators for use in fynbos, with substantial agreement between predicted and actual fire scars for some custom fuel models, although further validation is required before operational use can be recommended for the Cape Peninsula. Improved quality and quantity of appropriate data is essential for future fire modelling which suggests the need for managers and scientists to work together to ensure the appropriate data are collected.

References

Ager, A. A., Finney, M. A., Kerns, B. K., & Maffei, H. (2007). Modeling wildfire risk to northern spotted owl (*Strix occidentalis caurina*) habitat in Central Oregon, USA. *Forest Ecology and Management*, 246(1): 45-56.

Ager, A. A., Vaillant, N. M., Finney, M. A., Preisler, H. K. (2012) Analyzing wildfire exposure and source-sink relationships on a fire prone forest landscape. *Forest Ecology and Management.* 267, 271–283.

Albini, F. A. (1979). Spot fire distance from burning trees - a predictive model. *General Technical Report INT-56.* Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. Ogden, UT: U.S.

Alexander, M. (1985). Estimating the length to breadth ratio of elliptical forest fire patterns. In *Proceedings of the Eighth Conference on Forest and Fire Meteorology*. Society of American Foresters . 287–304.

Alexander, M. E. (2000). Fire behaviour as a factor in forest and rural fire suppression. *Forest Research Bulletin No. 197, Forest and Rural Fire Scientific and Technical Series*, National Rural Fire Authority, Wellington, 5, 30.

Andrews, P.L. (1996). Fire behavior. In: Pyne, S.J.; Andrews, P.L.; Laven, R.D. *Introduction to Wildland Fire*. 2d ed. New York, NY: John Wiley and Sons.

Anderson, H. E. (1982). Aids to determining fuel models for estimating fire behavior. *General Technical Report INT-122*. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. Ogden, UT: U.S. 22, 143.

Arca, B., Duce, P., Laconi, M., Pellizzaro, G., Salis, M., Spano, D. (2007). Evaluation of FARSITE simulator in Mediterranean maquis. *International Journal of Wildland Fire* 16, 563–572.

Ascoli, D., Vacchiano, G., Motta, R., & Bovio, G. (2015). Building Rothermel fire behaviour fuel models by genetic algorithm optimisation. *International Journal of Wildland Fire*, 24(3), 317-328.

Bergh, N., Verboom, G., Rouget G. A., & Cowling, R. M. (2014). Vegetation types of the greater cape floristic region. In *Fynbos: Ecology, Evolution, and Conservation of a Megadiverse Region* (pp. 26-46). Oxford University Press, Oxford.

Bond, W. J., & van Wilgen, B. W. (1996). *Plants and fire*. Chapman and Hall, London, UK.

Bond, W. J., & Midgley, J. J. (1995). Kill thy neighbour: an individualistic argument for the evolution of flammability. *Oikos*, 73(1), 79-85.

Bond, W. J., Midgley, G. F., Woodward, F. I., Hoffman, M. T., & Cowling, R. M. (2003). What controls South African vegetation—climate or fire? *South African Journal of Botany*, 69(1), 79-91.

Brakeall, J., (2013). Wildfire Assessment Using FARSITE Fire Modeling: A Case Study in the Chihuahua Desert of Mexico. *Florida International University Electronic Theses and Dissertations*. Paper 923. http://digitalcommons.fiu.edu/etd/923

Brink, Y. (2008). *They came to stay: Discovering meaning in the 18th century Cape country dwelling*. African Sun Media, Johannesburg.

Brown, P. J., Manders, P. T., Bands, D. P., Kruger, F. J., and Andrag, R. H. (1991). Prescribed burning as a conservation management practice: a case history from the Cederberg mountains, Cape Province, South Africa. *Biological Conservation* 56, 133-150.

Brun, C., Artées, T. A., Margalef, T. A., Cortées, A. (2012). Coupling wind dynamics into a DDDAS forest fire propagation prediction system. *Procedia Computer Science* 9(0), 1110-1118.

Butler, B. (2007) Flame length. Definitions In: *FireWords: Fire Science Glossary [electronic]*. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fire Sciences Laboratory (Producer). Available: http://www.fs.fed.us/fmi

Byram, G. M. (1959). Combustion of forest fuels. In Davis, K. P. (Ed.) *Forest fire: control and use*. McGraw Hill, New York, NY. Catchpole, pp. 61–89.

Cai, L., He, H. S., Wu, Z., Lewis, B. L., & Liang, Y. (2014). Development of standard fuel models in boreal forests of northeast China through calibration and validation. *PloS one*,9(4), e94043.

Campbell, B. M., & Moll, E. J. (1977). The forest communities of Table Mountain, South Africa. *Vegetatio*, 34(2), 105-115.

Campbell, B. M. (1985). A classification of the mountain vegetation of the fynbos biome. *Memoirs of the Botanical Survey of South Africa* 50, 1–115.

Campolongo, F., Cariboni, J., & Saltelli, A. (2007). An effective screening design for sensitivity analysis of large models. *Environmental modelling & software*, 22(10), 1509-1518.

Catchpole, W. (2002). Fire properties and burn patterns in heterogeneous landscapes in: Bradstock, R. A., Williams, J. E., & Gill, M. A. (eds). *Flammable Australia: the fire regimes and biodiversity of a continent*. Cambridge University Press, pp 49-75.

Chapin, F. S., Matson, P. A., Mooney, H. A. (2002). *Principles of Terrestrial Ecosystem Ecology*. Springer. New York, USA.

City of Cape Town (2016). Digital Elevation Model for the Cape Peninsula (10 m) Bare Earth Model. Accessed via Open Data Portal at https://web1.capetown.gov.za/web1/OpenDataPortal/

Coetsee, C., Bond, W. J., & Wigley, B. J. (2015). Forest and fynbos are alternative states on the same nutrient poor geological substrate. *South African Journal of Botany*, *101*, 57-65.

Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement 20*(1):37-46.

Compton, J. S. (2004). *The rocks and mountains of Cape Town*. Juta and Company Ltd. Cape Town.

Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote sensing of environment*, 37(1), 35-46.

Cowling, R. M., Rundel, P. W., Lamont, B. B., Kalin Arroyo, M., Arianoutsou, M. (1996a) Plant diversity in Mediterranean-climate regions. *Trends in Ecology and Evolution*. 11(9):362-6.

Cowling, R. M., Macdonald, I. A. W., & Simmons, M. T. (1996b). The Cape Peninsula, South Africa: physiographical, biological and historical background to an extraordinary hot-spot of biodiversity. *Biodiversity & Conservation*, 5(5), 527-550.

Cramer, M., West, A., Power, S., Skelton, R., & Stock, W. D. (2014). Plant ecophysiological diversity. In Allsopp, N. (eds.) *Fynbos: ecology, evolution, and conservation of a megadiverse region*. Oxford University Press, USA.

Cruz, M. G., & Fernandes, P. M. (2008). Development of fuel models for fire behaviour prediction in maritime pine (*Pinus pinaster* Ait.) stands. *International Journal of Wildland Fire*, 17(2), 194-204.

Deacon, H. J. (1983). The peopling of the fynbos. in Deacon, H.J. Hendley, Q.B. & Lambrechts, J.J.N (Eds.) *Fynbos Palaeoecology: A Preliminary Synthesis*, South African National Scientific Programmes, CSIR, Pretoria, South Africa. 183-204.

Deeming, J. E., & Brown, J. K. (1975). Fuel models in the national fire-danger rating system. *Journal of forestry*, 73(6), 347-350.

Di Castri, F. (1994) Politics and environment in Mediterranean-type climate regions. *Noticiero de Biologia* 2, 16.

Dray, S., and M. A. Siberchicot. (2016). "Package 'ade4'." ftp://r-project.org/pub/R/web/packages/ade4/ade4.pdf

Dobrinkova, N., Hollingsworth, L., Heinsch, F. A., Dillon, G., & Dobrinkov, G. (2013). Bulgarian fuel models developed for implementation in FARSITE simulations for test cases in Zlatograd area. In Wade, D. D., Fox, R. L., Robinson, M. L. (eds.)(E-proceeding) *Proceedings of 4th Fire Behaviour and Fuels Conference*, 18-22.

Falk, D. A., Miller, C., McKenzie, D., & Black, A. E. (2007). Cross-scale analysis of fire regimes. *Ecosystems*, 10(5), 809-823.

Fernandes, P. M. (2001). Fire spread prediction in shrub fuels in Portugal. *Forest Ecology and Management* 144, 67-74.

Finney, M. A. (1994). Modelling the spread and behaviour of prescribed natural fires. In: *Proceedings of the 12th conference on fire and forest meteorology,* 138 – 143.

Finney, M. A. (1998). FARSITE: Fire Area Simulator-- Model Development and Evaluation. *USDA Forest Service Research Paper RMRS-RP-4*. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, 47.

Finney, M. A. (2002). Fire growth using minimum travel time methods. *Canadian Journal of Forest Research*, 32(8), 1420-1424.

Finney, M. A. (2004a). 'FARSITE: Fire Area Simulator–model development and evaluation'. *USDA Forest Service Research Paper RMRS-RP-4*. Ogden, UT: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 1 – 47.

Finney, M. A. (2004b). Landscape fire simulation and fuel treatment optimization. *Methods for integrated modeling of landscape change*, 117-131.

Finney, M. A. (2005). The challenge of quantitative risk analysis for wildland fire. *Forest Ecology and Management,* 211(1), 97-108.

Finney, M. A. (2006). 'An overview of FlamMap fire modeling capabilities'. In: *Fuels management—how to measure success: conference proceedings*. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station: 213-220.

Finney, M. A (2008). *FARSITE Online Help* (Version 4.1.005). Available from within the application.

Finney, M. A., Brittain, S., & Seli, R. (2004b). FlamMap. *Joint Fire Science Program*. Rocky Mountain Research Station, US Bureau of Land Management.

Finney, M. A., Grenfell, I. C., McHugh, C. W., Seli, R. C., Trethewey, D., Stratton, R. D., & Brittain, S. (2011). A method for ensemble wildland fire simulation. *Environmental Modeling & Assessment*, 16(2), 153-167.

Finney, M.A., Brittain, S., Seli, R. C., McHugh, C.W., and Gangi, L. (2015). FlamMap: Fire Mapping and Analysis System (Version 5.0) [Software]. Available from http://www.firelab.org/document/flammap-software

Forsyth, G., and Bridgett, J. (2004) Table Mountain Fire Management Plan, CSIR Report ENV-S-C-2004-043. Accessed online via https://www.sanparks.org/docs/parks_table_mountain/library/fire_management.pdf

Forsyth, G. G., & van Wilgen, B. W. (2008). The recent fire history of the Table Mountain National Park and implications for fire management. *Koedoe*, 50(1), 3-9.

Forthofer, J. M., Butler, B. W., Wagenbrenner, N. S. (2014a). A comparison of three approaches for simulating fine scale surface winds in support of wildland fire management. Part 1: model formulation and comparison against measurements. *International Journal of Wildland Fire,* 23, 969-981.

Forthofer, J. M., Butler, B. W., Wagenbrenner, N. S. (2014b). WindNinja V 2.5.2 [Software]. Available at http://firelab.github.io/windninja/

Fraser, M. (2014). Birds of the Cape of Good Hope Nature Reserve, South Western Cape, South Africa. *Ornithological Observations*, 5, 139-247.

Gardner, R. H., & Urban, D. L. (2003). Model validation and testing: past lessons, present concerns, future prospects. In: Lauenroth, W. K. (Ed). *Models in ecosystem science*. Princeton University Press. 184-203.

Geldenhuys, C. J. (1994). Bergwind fires and the location pattern of forest patches in the southern Cape landscape, South Africa. *Journal of Biogeography*, 49-62.

Geldenhuys, C. J. (2000). Conservation management of Afromontane forest pockets on the Cape Peninsula. *Report FW 01/00*, Afromontane Information Forum, Table Mountain National Park. WWF South Africa.

Gill, A. M. (1975). Fire and the Australian flora: a review. *Australian Forestry,* 38, 4–25.

Goldblatt, P. (1978). An analysis of the flora of southern Africa: its characteristics, relationships, and origins. *Annals of the Missouri Botanical Garden*. 67, 369-436.

Goldblatt, P., & Manning, J. C. (2002). Plant diversity of the Cape region of southern Africa. *Annals of the Missouri Botanical Garden*, 281-302.

Goren-Inbar, N., Alperson, N., Kislev, M. E., Simchoni, O., Melamed, Y., Ben-Nun, A., & Werker, E. (2004). Evidence of hominin control of fire at Gesher Benot Yaaqov, Israel. *Science*, 304(5671), 725-727.

Granger, J. E. (1984). Fire in Forest. In: Booysen, P. V., & Tainton, N. M. (Eds.) *Ecological Effects of Fire in South African Ecosystems*, Springer-Verlag, New York, USA.

Green, L. R. (1981). Burning by prescription in chaparral. *General Technical Report PSW-51*. U.S. Department of Agriculture, Forest Service, Pacific Southwest Forest and Range Experiment Station. Albany, CA.

Hagelin, H., & Cluzel, M. (2016). Applying FARSITE and Prometheus on the Västmanland Fire, Sweden (2014): fire growth simulation as a measure against forest fire spread: a model suitability study. *Student thesis series,* Institute of Energy and Process Systems Engineering, Technische Universität Carolo-Wilhelmina.

Helme, N. A., & Trinder-Smith, T. H. (2006). The endemic flora of the Cape Peninsula, South Africa, *South African Journal of Botany*. 72, 205-210.

Jahdi, R., Salis, M., Darvishsefat, A. A., Mostafavi, M. A., Alcasena, F., Etemad, V., Lozano, O., & Spano, D. (2015). Calibration of FARSITE simulator in northern Iranian forests. *Natural Hazards and Earth System Sciences*, 15, 443-459.

Keane, R. E., Burgan, R. E., van Wagtendonk, J. (2001). Mapping wildland fuel for fire management across multiple scales: Integrating remote sensing, CIS, and biophysical modeling. *International Journal of Wildland Fire* 10, 301-319.

Keeley, J. E., Bond, W. J., Bradstock, R. A., Pausas, J. G., & Rundel, P. W. (2011a)*. Fire in Mediterranean ecosystems: ecology, evolution and management*. Cambridge University Press.

Keeley, J. E. (2002). Fire management of California shrubland landscapes. *Environmental Management* 29:395–408.

Keeley, J. E., Pausas, J. G., Rundel, P. W., Bond, W. J., & Bradstock, R. A. (2011b). Fire as an evolutionary pressure shaping plant traits. *Trends in plant science*, 16(8), 406-411.

Kelso J. K., Mellor, D., Murphy, M. E., Milne, G. J. (2015). Techniques for evaluating wildfire simulators via the simulation of historical fires using the AUSTRALIS simulator. *International Journal of Wildland Fire,* 24, 784–797.

Knapp, E. (2007) Fuel Load. Definitions In: *FireWords: Fire Science Glossary [electronic]*. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fire Sciences Laboratory (Producer). Available: http://www.fs.fed.us/fmi

Knapp, E. (2007) Timelag. Definitions In: *FireWords: Fire Science Glossary [electronic]*. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fire Sciences Laboratory (Producer). Available: http://www.fs.fed.us/fmi

Knapp, E. (2007) Moisture Content. Definitions In: *FireWords: Fire Science Glossary [electronic]*. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fire Sciences Laboratory (Producer). Available: http://www.fs.fed.us/fmi

Kraaij, T., & van Wilgen, B. W. (2014). Drivers, ecology, and management of fire in Fynbos. In: Allsopp, N. (eds.) *Fynbos: ecology, evolution, and conservation of a megadiverse region*. Oxford University Press, USA.

Lamont, B., Le Maitre, D., Cowling, R., & Enright, N. (1991). Canopy Seed Storage in Woody Plants. *Botanical Review, 57*(4), 277-317.

Le Maitre, D. C., & Midgley, J. (1992). Plant Reproductive Ecology. In: Cowling, R. M. (ed). *The Ecology of Fynbos: Nutrients, Fire and Diversity*. Oxford University Press, Cape Town, South Africa.

Le Maitre, D. & Marais, C. (1995). Proposed standard vegetation and fuel model classification for Cape fynbos and non-fynbos communities*. Report for Department of Environmental Affairs*; 890.

Lowery, J. (2012). The effect of random and spatially explicit lightning and human-caused ignitions on simulated burn probabilities at small scales. U*niversity of Montana: Theses, Dissertations, Professional Papers*, 992. http://scholarworks.umt.edu/etd/992

Liu, Z., Yang, J., Chang, Y., Weisberg, P. J., & He, H. S. (2012). Spatial patterns and drivers of fire occurrence and its future trend under climate change in a boreal forest of Northeast China. *Global Change Biology*, *18*(6), 2041-2056.

Manders, P. T., & Richardson, D. M. (1992). Colonisation of Cape fynbos communities by forest species. *Forest Ecology & Management*, 48, 277-293.

Manders, P. T., (1990). Fire and other variables as determinants of forest/fynbos boundaries in the Cape Province. *Journal of Vegetation Science*, 1(4), 483-490.

Massada, A. B., Syphard, A. D., Hawbaker, T. J., Stewart, S. I., & Radeloff, V. C. (2011). Effects of ignition location models on the burn patterns of simulated wildfires. *Environmental Modelling & Software*, 26(5), 583-592.

Masson, P. H., & Moll, E. J. (1987) The factors affecting forest colonisation of fynbos in the absence of fire at Orange Kloof, Cape Province, South Africa. *South African Forestry Journal*, 143, 5-10.

McArthur, A. G. (1966). Weather and grassland fire behaviour. *Leaflet No. 100*. 23, Department of National Development, Forestry and Timber Bureau, Forestry Research Institute, Canberra.

McKenzie, B., Moll, E. J., & Campbell, B. M. (1977). A phytosociological study of Orange Kloof, Table Mountain, South Africa. *Vegetatio* 34, 41-53.

Médail, F., & Quézel, P. (1997). Hot-spots analysis for conservation of plant biodiversity in the Mediterranean Basin. *Annals of the Missouri Botanical Garden*. 84:112–127.

Midgley, J. J., Cowling, R. M., Seydack, R. M., & van Wyk, G. F. (2003). Forest. In: Cowling, R. M., Richardson, D. M., & Pierce, S. M. (Eds.) *Vegetation of Southern Africa*, Cambridge University Press, United Kingdom, 278-299.

Mistry, J., & Berardi, A. (2005). Assessing Fire Potential in a Brazilian Savanna Nature Reserve. *Biotropica*, 37(3), 439-451.

Moritz, M. A. (2003). Spatiotemporal analysis of controls on shrubland fire regimes: age dependency and fire hazard. *Ecology,* 84, 351–361.

Morris, M. D. (1991). Factorial sampling plans for preliminary computational experiments. *Technometrics*, 33(2), 161-174.

Mucina, L., & Rutherford, M. C. (2006). *The Vegetation of South Africa, Lesotho and Swaziland*, Strelitzia 19, South Africa.

Nakazawa, M (2015). fmsb: Functions for Medical Statistics Book. R package version 0.5.2. http://CRAN.R-project.org/package=fmsb

Nelson Jr, R. M., Adkins, C. W. (1988). A dimensionless correlation for the spread of wind-driven fires. *Canadian Journal of Forest Research,* 18(4), 391-397.

Nelson, R. M. (2000). Prediction of diurnal change in 10-h fuel stick moisture content. *Canadian Journal of Forest Research,* 30, 1071-1087.

Nunes, M. C. S., Vasconcelos, M. J., Pereira, J. M. C., Dasgupta, N., Alldredge, R. J., and Rego, F. C. (2005). Land cover type and fire in Portugal: do fires burn land cover selectively? *Landscape Ecology,* 20, 661–673.

Papadopoulos, G. D., & Pavlidou, F. N. (2010). Software tools for wildfire monitoring. In: *Proc. of the 5th International Conference Interdiciplinarity in Education (ICIE)*.

Papadopoulos, G. D., & Pavlidou, F. N. (2011). A comparative review on wildfire simulators. *Systems Journal*, 5(2), 233-243.

Paradis E, Bolker B, Claude J, Sien Cuong H, Desper R, Durand B, Durand B, Dutheil J, Gascuel O, Heilbl C, Lawson D, Lawson D, Lefort V, Legrande , Lemon J, Noel Y, Nylander J, Opgen-Rhein R, Popescu A A, Schliep K, Strimmer K, de Vienne D (2011) Package 'ape': Analysis of Phylogenetics and Evolution. URL [http://cran.r-project.org/web/packages/ape/ape.pdf].2011, 1-222

Parisien, M. A., Miller, C., Ager, A. A., & Finney, M. A. (2010). Use of artificial landscapes to isolate controls on burn probability. *Landscape Ecology*, 25(1), 79-93.

Pausas, J. G., & Keeley, J. E. (2009). A burning story: the role of fire in the history of life. *BioScience*, 59(7), 593-601.

Perry, G. L. W. (1998). Current approaches to modelling the spread of wildland fire: a review. *Progress in Physical Geography*, 22(2), 222-245.

Perry, G. L., Sparrow, A. D., & Owens, I. F. (1999). A GIS-supported model for the simulation of the spatial structure of wildland fire, Cass Basin, New Zealand. *Journal of Applied Ecology*, *36*(4), 502-518.

Philpot, C. W. (1977). Vegetative features as determinants of fire frequency and intensity. In: *Proc. of the symposium on the environmental consequences of fire and fuel management in Mediterranean ecosystems*. Washington DC, USA. Available at: https://archive.org/stream/CAT78696401#page/12/mode/2up

Plucinski, M. P. (2006). Fuel Dynamics in Shrub-Dominated Landscapes. *Proceedings of Bushfire Conference Paper No. 0049,* Brisbane.

Pooley, S. (2014). *Burning Table Mountain: An Environmental History of Fire on the Cape Peninsula*. Springer, Cape Town.

Poulsen, Z. C. & Hoffman, M. T. (2015). Changes in the distribution of indigenous forest in Table Mountain National Park during the 20th Century. *South African Journal of Botany*, 101: 49-56.

R Core Team (2015). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Rebelo, A. G., Boucher, C. A., Helme, N., Mucina, L., & Rutherford, M. C. (2006). Fynbos biome. In: Mucina, L., & Rutherford, M. C. (Eds.). *The vegetation of South Africa, Lesoto and Swaziland*. Strelitzia 19. South African National Biodiversity Institute, Pretoria.

Rebelo, A. G., Holmes, P. M., Dorse, C., & Wood, J. (2011). Impacts of urbanization in a biodiversity hotspot: conservation challenges in Metropolitan Cape Town. *South African Journal of Botany*, *77*(1), 20-35.

Richards G. D. (1990). An Elliptical growth models of forest fire fronts and its numerical solution. *International Journal for Numerical Methods in Engineering*. 30, 1163-1179.

Rothermel, R. (1983). How to predict the spread and intensity of forest and range fires. *General Technical Report INT*, USDA Forest Service, Intermountain Forest and Range Experiment Station, 143 – 161.

Rothermel, R. C. (1972). A mathematical model for predicting fire spread in wildland fuels. *USDA Forest Service Research Paper, INT*-115.

Rothermel, R. C. (1991). Predicting behavior and size of crown fires in the northern Rocky Mountains. *USDA Forest Service Research Paper, INT*-438.

Roxburgh, R., & Rein, G. (2008). Study of wildfire in-draft flows for counter fire operations. *WIT Transactions on Ecology and the Environment*, 119.

Rundel, P. W., (1998). Landscape disturbance in Mediterranean-type ecosystems: an overview. In: Rundel, P. W., Montenegro, G., & Jaksic, F. M. (eds). *Landscape disturbance and biodiversity in Mediterranean-type ecosystems*. Springer-Verlag, Berlin. 3–22.

Schmidt, A. G & Vlok, M. (2002) Post fire indicators of fire intensity at indigenous forest margins in the Southern Cape, South Africa, *South African Journal of Forestry*, 194, 59-64.

Scott, J. H., and Reinhardt, E. D. (2002). Estimating canopy fuels in conifer forests. *Systems for Environmental Management*, 62(4)

Scott, J. (2007) Surface area to volume ratio. Definitions In: *FireWords: Fire Science Glossary [electronic]*. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fire Sciences Laboratory (Producer). Available: http://www.fs.fed.us/fmi

Scott, J. (2007) Moisture of Extinction Definitions In: *FireWords: Fire Science Glossary [electronic]*. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fire Sciences Laboratory (Producer). Available: http://www.fs.fed.us/fmi.

Scott, J. H. (2012). Introduction to Wildfire Behaviour Modeling. *National Interagency Fuels, Fire, & Vegetation Technology Transfer*. Available: www.niftt.gov

Scott, J. H., & Burgan, R. (2005). Standard fire behavior fuel models: a comprehensive set for use with Rothermel's surface fire spread model. *General Technical Report* RMRS-GTR, USDA Forest Service, Rocky Mountain Research Station*,* 153, 72.

Seli, R. C., Brittain, S., and McHugh, C.W. (2015). *FlamMap Online Help* (Version 5.0). Available from within the application.

Simmons, M. T., & Cowling, R. M. (1996). Why is the Cape Peninsula so rich in plant species? An analysis of the independent diversity components. *Biodiversity and Conservation.* 5, 551–573.

Stats-SA (2016) Community Survey 2016: Provinces at a Glance. Report 03-01-03, Statistics South Africa.

Sullivan, A. L. (2007a). Wildland surface fire spread modelling, 1990-2007. 1: Physical and quasi-physical models. *International Journal of Wildland Fire*, 18, 349-368.

Sullivan, A. L. (2007b). Wildland surface fire spread modelling, 1990-2007. 2: Empirical and quasi-empirical models. *International Journal of Wildland Fire*, 18, 369-386.

Sullivan, A. L. (2007c). A review of wildland fire spread modelling 1990-2007. 3: Simulation and mathematical analogue models. *International Journal of Wildland Fire*, 18, 387-403.

Syphard, A. D., Radeloff, V. C., Keele, J. E., Hawbaker, T. J., Clayton, M. K., Stewart, S. I., Hammer, R. B. (2007). Human influence on California fire regimes. *Ecological Applications* 17, 1388–1402.

Syphard, A. D., Radeloff, V. C., Keuler, N. S., Taylor, R. S., Hawbaker, T. J., Stewart, S. I., & Clayton, M. K. (2008). Predicting spatial patterns of fire on a southern California landscape. *International Journal of Wildland Fire*, *17*(5), 602-613.

Taylor, A. H., & Skinner, C. N. (2003). Spatial patterns and controls on historical fire regimes and forest structure in the Klamath Mountains. *Ecological Applications*, 13(3), 704-719.

Thuiller, W., Slingsby, J. A., Privett, S. D., & Cowling, R. M. (2007). Stochastic species turnover and stable coexistence in a species-rich, fire-prone plant community. *PloS One*, 2(9), e938.

Trinder-Smith, H., Cowling, R. M., & Linder, H. P. (1996). Profiling a besieged flora: endemic and threatened plants of the Cape Peninsula, South Africa. *Biodiversity & Conservation*, *5*(5), 575-589.

Trinder-Smith, T. H., Kidd, M. M., & Anderson, F. (2006). *Wild flowers of the Table Mountain National Park* (Vol. 12). Botanical Society of South Africa.

Underwood, E. C., Viers, J. H., Klausmeyer, K. R., Cox, R. L., & Shaw, M. R. (2009). Threats and biodiversity in the Mediterranean biome. *Diversity and Distributions*, 15(2), 188-197.

van Wagner, C. E. (1977). Conditions for the start and spread of crown fire. *Canadian Journal for Forest Research.* 7:23-24.

van Wagner, C.E. (1969). A simple fire growth model. *Forestry Chronicle*. 45:103-104.

van Wilgen, B. W. (1982). Some effects of post-fire age on the above-ground plant biomass of fynbos (macchia) vegetation in South Africa. *Journal of Ecology,* 70, 217-225.

van Wilgen, B. W. (1984). Adaptation of the United States Fire Danger Rating System to Fynbos Conditions. *South African Forestry Journal*, 129:1, 61-65.

van Wilgen, B. W. (1996). Management of the natural ecosystems of the Cape Peninsula: current status and future prospects. *Biodiversity & Conservation*, 5(5), 671-684.

van Wilgen, B. W., Le Maitre, D. C. & Kruger F. J. (1985). Fire Behaviour In South African Fynbos (Macchia) Vegetation and Predictions From Rothermel's Fire Model. *Journal of Applied Ecology*, 22, 207-216.

van Wilgen, B. W., Higgins, K. B. and Bellstedt, D. U. (1990). The role of vegetation structure and fuel chemistry in excluding fire from forest patches in the fire-prone fynbos shrublands of South Africa. *Journal of Ecology* 78, 210-222.

Van Wilgen B. W., & Forsyth G.G. (1992). Regeneration strategies in fynbos plants and their influence on the stability of community boundaries after fire. In: van Wilgen, B.W., Richardson, D. M., Krugerand, F. J., & van Hensbergen, H. J. (eds). *Fire in South African Mountain Fynbos: Species, Community and Ecosystem Response in Swartboskloof*. Springer-Verlag, Heidelberg. 55–80

Van Wilgen, B. W., & Van Hensbergen, H. J. (1992). Fuel properties of vegetation in Swartboskloof. In: van Wilgen, B.W., Richardson, D. M., Krugerand, F. J., & van Hensbergen, H. J. (eds). *Fire in South African Mountain Fynbos: Species, Community and Ecosystem Response in Swartboskloof*. Springer-Verlag, Heidelberg. 55–80

van Wilgen, B. W., Bond, W. J., & Richardson, D. M. (1992). Ecosystem management In: Cowling, R.M. (ed) *The Ecology of Fynbos: Nutrients, Fire and Diversity*. Oxford University Press, Cape Town. 345–371.

van Wilgen, B. W., Forsyth, G. G., De Klerk, H., Das, S., Khuluse, S., & Schmitz, P. (2010). Fire management in Mediterranean-climate shrublands: a case study from the Cape fynbos, South Africa. *Journal of Applied Ecology*, 47(3), 631-638.

Whiteman, C. D. (2000). *Mountain meteorology: fundamentals and applications*. Oxford University Press.

Appendix I:

Table A.1: Derived coefficient and constant values for each fynbos category as derived by (**Le Maitre & Marais, 1995**) to develop age classes in custom fynbos fuel models.

Community	Coefficient (A)	Constant (B)
Moist Mesotrophic Proteoid	4765.93	-970.82
Dry Mesotrophic Proteoid	1853.87	188.97
Moist Oligotrophic Proteoid	2394.47	253.6
Dry Oligotrophic Proteoid	1365.85	-186.95
Wet Ericoid	9541.32	-636.39
Moist Ericoid	932.27	-108.07
Dry Ericoid	1132.68	296.63
Wet Restioid	4824.2	-575.32
Dry Restioid	372.27	22.36
Asteraceous	1081.18	141.24
Renosterveld	1270.58	229.73
Acacia Thicket	9607.33	-480.81

Appendix II:

Table A.2: Values used for each fuel model used in this study

Fuel Model	Dead Fine (1 Hour) Biomass (t ha -1)	Dead Medium (10 Hour) Biomass (t ha -1)	Dead Coarse (10 Hour) Biomass (t ha -1)	Live Herbaceous Biomass (t ha -1)	Live Woody Biomass (t ha -1)	Surface are: volume Fine Dead (1/cm)	Surface are: volume Live Herb (1/cm)	Surface are: volume Live Woody (1/cm)	Fuel Bed Depth (cm)	Extinction Moisture (%)	Live Fuel Heat Content (Kj/KG)	Dead Fuel Heat Content (Kj/KG)
AFM	3.46	1.68	0.6	3.4	1.96	71	58	48	56	34	20000	20000
DOP	2.32	0.37	0.22	7.76	1.65	71	58	48	118	34	20000	20000
MEM	1.66	0.99	0.01	7.3	4.98	71	58	48	48	34	20000	20000
MMP	17.25	54.39	1.04	19.87	5.12	71	58	48	165	34	20000	20000
MOP	4.58	1.66	0.69	2.95	5.74	71	58	48	88	34	20000	20000
MRM	1.97	0.2	0.03	7.27	0.31	71	58	48	34	34	20000	20000
RM	8.8	1.4	0.17	0.88	4.04	71	58	48	70	34	20000	20000
VW	4	0.65	0.12	5	2.24	71	58	48	91	34	20000	20000
WEM	36.64	11.54	2.22	42.19	10.88	71	58	48	165	34	20000	20000
WRM	24.1	0.1	0	25.73	0.64	71	58	48	122	34	20000	20000
SH4	1.91	2.58	0.45	0	5.72	66	59	52	91	30	18608	18608

SH5	8.07	4.17	0	0	6.5	25	328	52	183	15	18608	18608
SH6	6.5	3.25	0	0	1.4	25	328	52	61	30	18608	18608
SH7	7.85	11.88	4.93	0	7.62	25	328	52	183	15	18608	18608
SH8	4.6	7.62	1.91	0	9.75	25	328	52	91	40	18608	18608
SH9	10.09	5.49	0	3.47	15.69	25	59	49	122	40	18608	18608

Appendix III:

The northern section of the Table Mountain National Park stretches from Table Mountain and Lions Head down to the Hout Bay Valley (see **Fig. 3.1**). This section of the park is the highest; with the pinnacle at Maclear's Beacon measuring 1084 m asl. Table Mountain is scored by many deep gorges, related to natural faults in the rocks that have provided a focal point for runoff, with erosion shaping the steep slopes. The flat 'Table Top' of Table Mountain is a series of plateaus and peaks flanked to the east by Devil's Peak and to the west by Lion's Head. The mountains extend south, with the northern section ending in a steep escarpment down to Orange Kloof, a shallow basin hosting one of the largest forest patches on the peninsula. The western flank extends down the west coast, forming the Twelve Apostles while the eastern flank of the back table extends down into Constantia, with Klassenkop separating Hout Bay in the west from Constantia in the east.

The Northern and Central sections of Table Mountain National Park are separated by Hout Bay valley. Known locally as the Constantiaberg, this section Peninsula Mountain Chain continues to extend southwards, flanked to the west by the urban development of the southern suburbs and the Cape Flats and to the east by Chapmans Peak where the cliffs rise steeply from the sea. This section of the park ends with the relatively flat Steenberg Plateau, which terminates in Kalk Bay Mountain on the east coast. The Central section of Table Mountain National Park is separated from the Southern section by the Noordhoek – Fish Hoek Valley, a natural valley with extensive wetlands that is almost entirely developed into housing. The Southern section of the park is much flatter with a lower elevation mountains range that begins with Elsie's Peak and stretches through Red Hill down to Judas Peak and Paulsberg. These lower elevation peaks form the eastern boundary of the relatively flat Smitswinkel Plain that dominates much of the Cape of Good Hope.