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Ecological Modelling

A stochastic fire spread model for north Patagonia based on fire occurrence maps

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ABSTRACT

Understanding fire spread in different ecosystems is of fundamental importance for conservation, management and anticipating the effects of environmental changes. Tailoring existing fire spread models to particular landscapes is challenging because it demands a substantial data collection effort. Here we develop an objective way to fit simple stochastic fire spread models based on readily available data from documented fire events (i.e. approximate ignition point, preexisting vegetation, final perimeter, topography, and average wind direction). We use a simulation-based approach founded on Approximate Bayesian Computation, which allows for a thorough exploration of parameter space as well as the quantification of uncertainty around best estimates. As illustration, we use data from nine fire events that occurred during dry years in northern Patagonia, Argentina. We found that fire spreads readily in shrublands, while forests tend to act as firebreaks. Topography has a strong effect not only because fire moves easily upslope but also because it modulates wind direction. Finally, aspect affects fire spread mainly in forests, probably due to its effects on fuel moisture. Simulating fire spread sampling parameters from the approximated joint posterior distribution resulted in individual fires roughly similar to the ones used for model fitting. Furthermore, the fitted model was able to produce simulated fire-size distributions in good agreement with the historical record for dry years in Nahuel Huapi National Park, Patagonia. The approach presented here can be used in places where standard fuel models have not yet been developed.

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1. Introduction

Wildfire is a global contagious spatial process with important ecosystem and societal effects as well as biosphere feedbacks. Rapid shifts in fire regimes, amplified by global environmental change, call for an assessment and understanding of the suite of processes that govern fire spread across different ecosystems (Bowman et al., 2009; Stephens et al., 2013). Despite the fact that fire is governed by common biophysical processes, its occurrence and spread in particular landscapes are usually hard to predict. This is because fire spread is controlled by complex system-specific interactions of fuel quantity and quality modified by environmental heterogeneity, climate, weather and the occurrence of both natural and anthropogenic ignitions (McKenzie et al., 2011; Stephens et al., 2013).

There have been numerous studies about the physics that rule fire spread (Rothermel, 1972; Albini, 1976; Van Wagner, 1977), and a lineage of fire modeling tools based on these mechanisms starting with BEHAVE in the late seventies (see Andrews, 2014 for a review). More recently, complex mechanistic models of fire propagation such as FARSITE and PROMETHEUS have been developed and adopted by governmental agencies (e.g. Finney, 1998; Tymstra et al., 2010). These models require detailed information such as hourly or daily weather data (temperature, humidity, wind speed and direction) as well as estimates of the load and spatial arrangement of different fuel classes (Tymstra et al., 2010). Other software such as FlamMap (Finney, 2006) are based on these mechanistic models but require few GIS layers to run but still need assigning each pixel to one of several possible "fuel model" categories as well as determining canopy height and crown bulk density. Furthermore the user has to set fixed fire spread times.

Relatively simpler fire-spread models are used in Landscape Fire Succession Models where the goal is to understand the relationship between vegetation dynamics and the fire regime and to predict the consequences of climate and land use changes (reviewed in Keane et al., 2004 and Cary et al., 2006). These models vary in whether simulated fire size is pre-determined or an emergent property of fire spread probabilities (e.g. Baker, 1993; Yassemi et al., 2008). In any case, some sort of ad hoc procedure is required to obtain fires

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similar in size, shape and the type of vegetation burned, to those occurring in the target ecosystem or cases. An objective and general methodology to calibrate fire spread probabilities is needed. Here we develop an objective way to estimate parameters of a simple stochastic fire spread model based on readily available data from documented fire events (i.e. ignition point, preexisting vegetation, final perimeter, topography, and average wind direction).

Stochastic models where fire propagate from cell to cell of a raster map according to some probability have been used extensively to study fire size distributions and landscape memory as emergent properties of both the contagion process (the spread probability) and the shape of the curve describing how fire susceptibility in a cell changes with time since the last fire (e.g. Zinck and Grimm, 2009; Kitzberger et al., 2012). Recently, Kennedy and McKenzie (Kennedy and McKenzie, 2010; McKenzie and Kennedy, 2012) fitted a stochastic fire spread model to fire-scar data from semi-arid mountain systems in Washington State, USA. Their model included a single parameter for fire propagation representing bottom-up controls such as fuel types, topography and so on, and a parameter for mean fire size aimed at capturing top-down (climatic) controls on the fire regime. A third parameter controlled the probability of trees getting scarred during fire events. The work we present here extends their approach by explicitly including the effect of several covariates on fire-spread probability. Another difference is that we do not impose an effective upper limit to the size of simulated fires. We only considered fires that occurred during dry years, when fire-spread is maximal and with minimum differences in top-down controls on fire size. Finally, we use a simulation-based approach founded on Approximate Bayesian Computation, which allows for a thorough exploration of parameter space as well as the quantification of uncertainty around best estimates (Beaumont, 2010; Hartig et al., 2011).

Our study area is located in northern Patagonia where the vegetation has been strongly influenced by both natural and anthropogenic fires (Veblen et al., 1999, 2003; Gowda et al., 2012). Biotic and abiotic variables strongly influence the occurrence of fires across northern Patagonian landscapes but their effects on fire spread have not been yet modeled nor formally quantified. Our goal here is twofold; we want to develop ways to fit stochastic fire-spread models to available fire map data, and we aim at increasing our understanding of the determinants of fire regimes in northern Patagonian forests so that we can eventually build appropriate Landscape Fire Succession Models for this area.

2. Methods

2.1. Study area

The study area includes Nahuel Huapi and southern Lanin National Parks, located in the northern Patagonian Andean region, at 40°–41°30′ S latitude (Fig. 1). Terrain is mountainous, with typical U-shaped valleys and steep slopes formed by glacial activity. Soils are derived from volcanic ash deposits overlaying the glacial topography. Average annual precipitation varies between 3000 mm in the western limit to 800 mm in the eastern area, with approximately 60% of the total precipitation falling during the winter season (from May to August). Wind direction is highly constant during the fire season with ca. 78% of days coming from NW (55.4%) or WNW (22.8%; 2010–2013 data Bariloche Airport.) Water deficits are severe in late spring and summer (Paruelo et al., 1998).

In areas with more than 1000 mm of annual rainfall, hillsides and valley bottoms up to the tree line (ca. 1600 m.a.s.l.) are dominated by dense and continuous forests and shrublands. Subalpine forests of the deciduous *Nothofagus pumilio* occur above 1000–1100 m.a.s.l., and the lowland rainforests are dominated

by the evergreen *Nothofagus dombeyi* which forms monospecific, mesic forests or mixed stands with the conifer *Austrocedrus chilensis* at drier sites. Dense, tall shrublands occur at sites that are either edaphically unsuitable for the development of tall forest or as successional communities that develop after burning of tall forest (Veblen et al., 1992). In the wet western district, tall shrublands and dense woodlands of the small deciduous tree *Nothofagus antarctica* occur mainly in valley bottoms where soil drainage is poor. In the central and eastern areas, tall shrublands of *N. antarctica*, the bamboo *Chusquea culeou*, and numerous other small trees and tall shrubs (*Schinus patagonicus*, *Embothrium coccineum*, *Maytenus boaria*, *Diostea juncea*, *Lomatia hirsuta*, and *Berberis* spp.) occur from low to high elevations, and around tall forests. Despite the fact that forest and shrublands can vary in species composition, we consider them as the main types of vegetation in the area, showing very different flammability (Mermoz et al., 2005).

2.2. Fire maps

For model parameterization and testing we compiled mapped fires that matched the following conditions: (1) approximated location of point of ignitions were known, (2) fire occurred during dry years (rainfall between October and December below 0.5 SD the historic mean 1950–2008), and (3) 30 m resolution vegetation maps of the areas affected by fire were available. Only nine recorded fires matched these criteria and were used for parameterization. Elevation, aspect and slope maps were obtained from an ASTER GDEM digital elevation model (30 m resolution, http://gdem.ersdac.jspacesystems.or.jp/). Pre-fire vegetation maps were available from ortho-rectified aerial photos (scale 1:20,000 and 1:60,000) (Mermoz et al., 2005). Fire maps were obtained by comparing pre and post fire Landstat TM images, except for Tristeza 1957, which was mapped from aerial photos (Mermoz et al., 2005).

2.3. Modeling fire spread

Our goal was to model how topography, fuel type and other factors such as wind direction modify fire spread across the landscape. All landscape variables were discretized into raster maps of 30 by 30 m square cells. Once ignited, a landscape cell could propagate fire to each of its 8 neighboring cells. The probability of propagation (p) was determined by a function of fuel type, aspect, relative wind direction and slope of the target cell:

$$p = \frac{0.5}{1 + \exp(-(\beta_0 + I_f + \beta_2 \Psi + \beta_3 \omega + \beta_4 \sigma))} \tag{1.1}$$

where I_f is an indicator variable equal to 1 for cells occupied by forest and 0 otherwise, so that β_0 is then the baseline (untransformed) fire-propagation probability for shrubland cells and β_1 measures the difference between shrubland and forest. If fire is less likely to propagate in forests than in shrublands, then β_1 should be less than zero. Parameters β_2, β_3 and β_4 modify propagation probabilities according to aspect (ψ), wind direction (ω), and slope (σ) respectively. We set the upper limit for this logistic function to 0.5 because larger propagation probabilities produce unrealistic fire patterns (Hargrove et al., 2000).

Aspect is known to affect fire occurrence in the study area (Mermoz et al., 2005), probably through its effects on fuel moisture. The driest conditions are on sites facing toward the NW while those facing to the SE are the moistest. Thus, for landscape cells with a slope greater than 5 degrees we computed $\Psi = \cos(\theta - 315°)$, where θ is the untransformed aspect in degrees. This relative aspect takes values of 1 for NW facing sites and −1 for those facing SE. Thus, values of $\beta_2 > 0$ indicate that fire propagate more readily in drier slopes. We did not have access to detailed wind speed and direction during
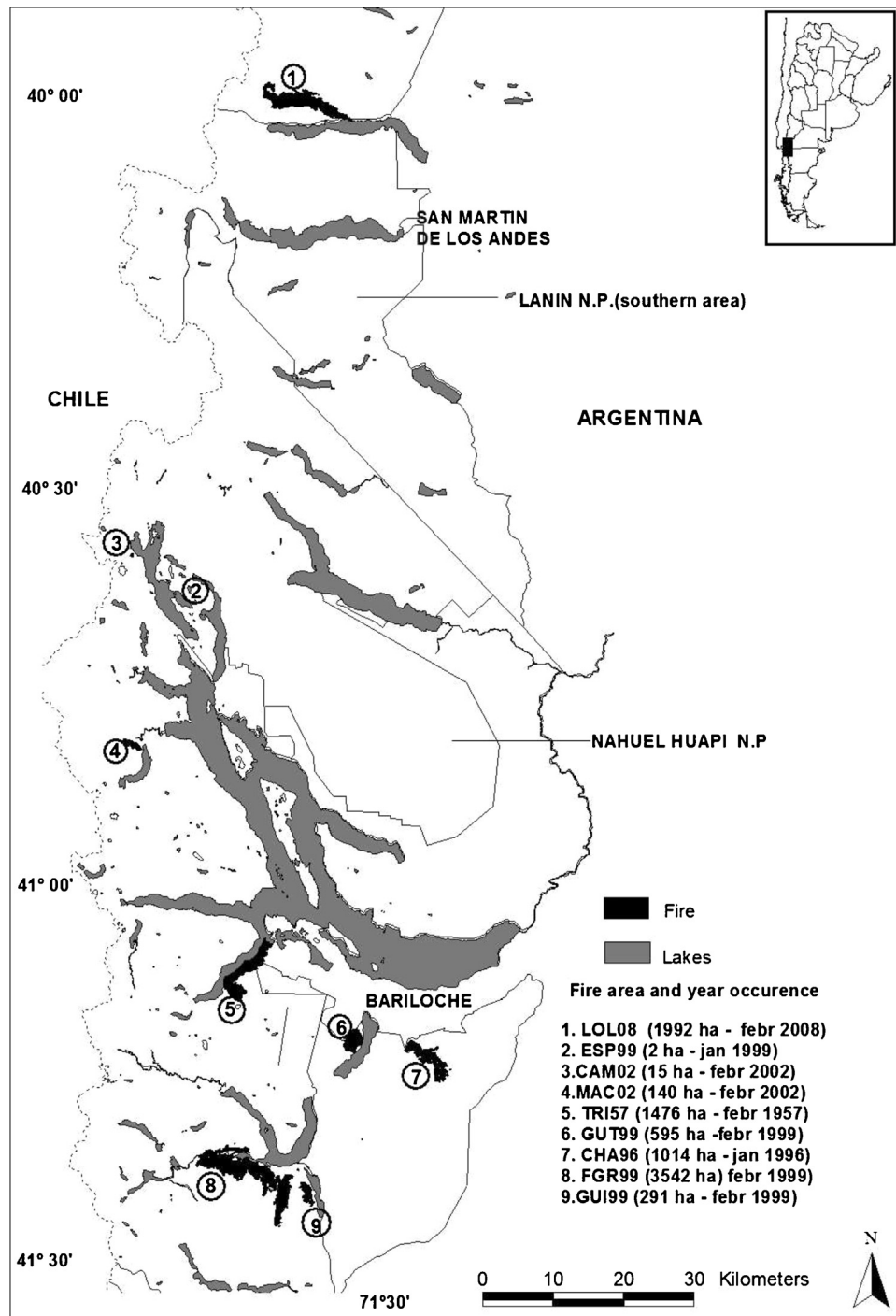
Fig. 1. Map of the study area showing the recorded fire events used for model parameterization and testing. To minimize the potential effects of weather control on fire spread we selected fire events with known ignition point and that occurred during dry years. Acronyms are for the name and year of the fires used for model fitting.

the fire events so we assumed an effectively constant and unknown wind speed. Wind direction for each landscape cell was derived from the average dominant wind direction during the fire season and modified from topography using WindNinja (Forthofer, 2009). For each of the 8 landscape cells neighboring an already ignited cell we calculated $\omega = \cos(\phi_w - \phi_c)$ where ϕ_w is wind direction in the target landscape cell and ϕ_c correspond to the angle between the ignited cell and the neighboring cell. Thus, ω takes values of 1 if the landscape cell is downwind from the ignited cell and −1 if it is upwind from it. Hence increasing probabilities of fire propagation downwind should translate in fitted values of $\beta_3 > 0$. Slope can

also affect fire spread, with fire moving readily upslope and slowing down gradually down slope (Rothermel, 1972; Van Wagner, 1977). Here we decided to ignore any potential effects of down slopes so that σ in Eq. (1.1) above is zero whenever the target landscape cell is at a lower elevation, or when slope is zero, and takes the slope value if the target cell is higher in elevation than the burning cell.

Beyond any alternative formulations for cell-to-cell fire spread probability and how it relates to landscape covariates, the challenge here is to parameterize a fire spread model given available maps of burned areas and GIS layers. Furthermore, because we lack information on how fire spread evolved in real-time, Eq. (1.1) cannot
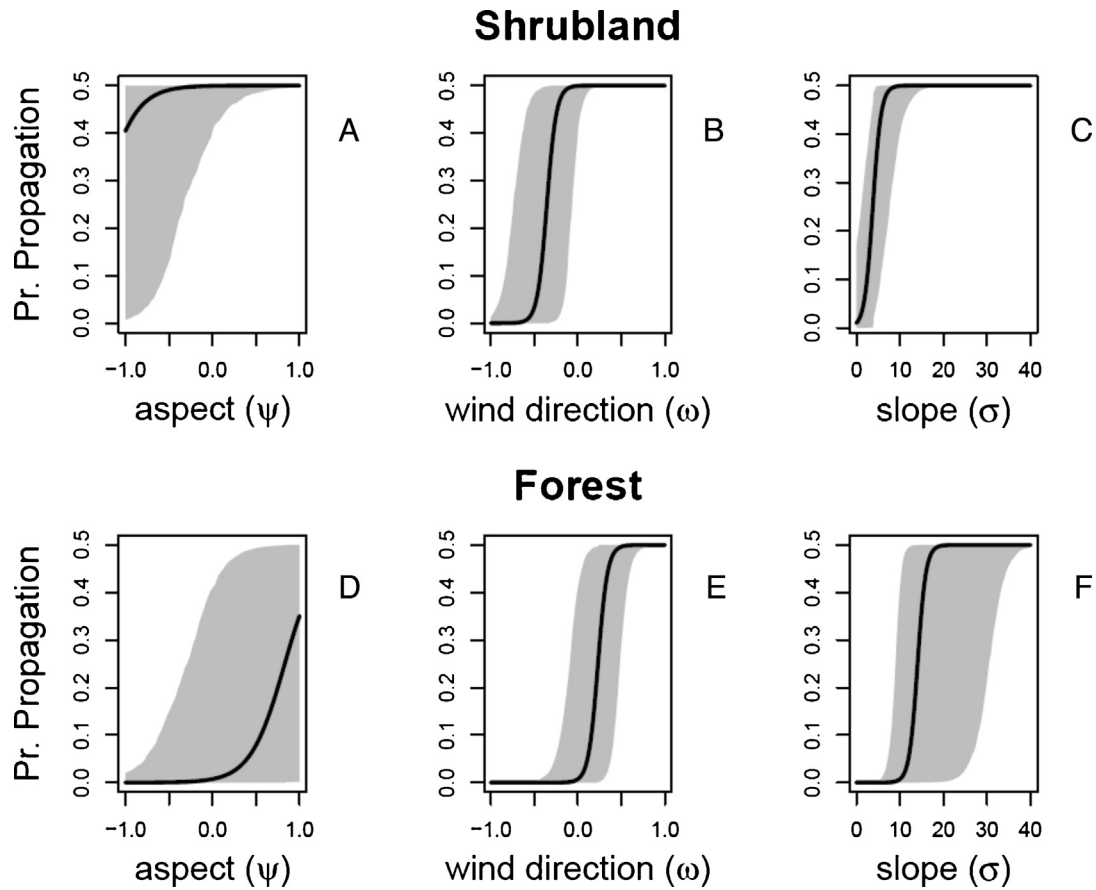
Shrubland

Forest

Fig. 2. Changes in fire propagation probabilities in shrublands (top row) and forests (bottom row) as a function of aspect (ψ), wind direction (ω) and slope (σ). Changes with aspect were calculated based on a slope of 10% and zero wind direction. Changes with wind direction were calculated for neutral aspect ($\psi = 0$) and a slope of 10%. Changes with slope were calculated for aspect and wind direction of zero. Solid lines correspond to values calculated from the best estimates for all parameters and the gray areas contain the 90% credible interval obtained from sampling the model joint posterior and reflect the uncertainty around the expected response.

be evaluated directly. We nevertheless obtained estimates for the βs by simulating fire under different parameter combinations and comparing simulated fires with observed ones in the spirit of an Approximate Bayesian Computation approach (Beaumont, 2010; Hartig et al., 2011). All simulations were run in SELES, a software for spatially explicit landscape event simulations (Fall and Fall, 2001).

2.4. Model parameterization

The main idea behind simulation-based methods for parameter estimation is to replace the calculation of the likelihood of the data given a set of parameter values with a comparison between observed and simulated data. This comparison usually involves computing a distance function δ that measures the degree of discrepancy between simulated and observed data (or more commonly some summary statistics of them (Hartig et al., 2011). We defined a measure that combines the coincidence in space of simulated and observed fires and similarities in burned area for the two main vegetation types. For a particular combination of parameters, the discrepancy (δ) between simulated and observed fires combines all (nine) mapped fires:

$$\delta = \sum_{i=1}^{n} \left(\left| 1 - \frac{A_i \cap A_i^*}{A_{f,i} + A_{s,i}} \right| + \frac{|A_{f,i} - A_{f,i}^*|}{A_{f,i}} + \frac{|A_{s,i} - A_{s,i}^*|}{A_{s,i}} \right)^2 \quad (1.2)$$

where A denotes the set of burned pixels (burned area in number of pixels) and subscripts indicate vegetation type (f for forest and s for shrubland). Subscripts indicate which fire is being considered (i

from 1 to $n = 9$ fires). The superscript (*) indicates values obtained from simulated fires. The first term in Eq. (1.2) measures the degree of overlap between simulated and observed fires, being equal to zero when simulated and observed fires overlap completely and it is equal to 1 if they do not overlap at all. The second and third terms measure differences in total area burned for forest and shrubland respectively, taking values of 0 when the simulated and observed areas are equal and larger than zero when they differ. The discrepancies in burned area can be larger than 1 when the simulated burnt area is more than twice the observed one. Simulated fires were run in maps large enough so that if for some parameter combinations the whole landscape burned, the discrepancies with the observed fire were large.

Once we established a way to measure the discrepancy between simulated and observed data we developed a scheme to explore parameter space. We used a two-stage approach, combining Markov Chain Monte Carlo (MCMC) with Rejection Sampling (see Appendix A1 for details). From the rejection sampling simulation scheme we filtered (selected) the best 1000 parameter combinations and used this set of values to calculate point (best) estimates and uncertainty measures for all parameters. All parameters had non-informative priors (normal with zero mean and variance equal to one hundred).

2.5. Model checking

Once we parameterized the model, we checked whether it was appropriate for recovering two particular aspects of available data.
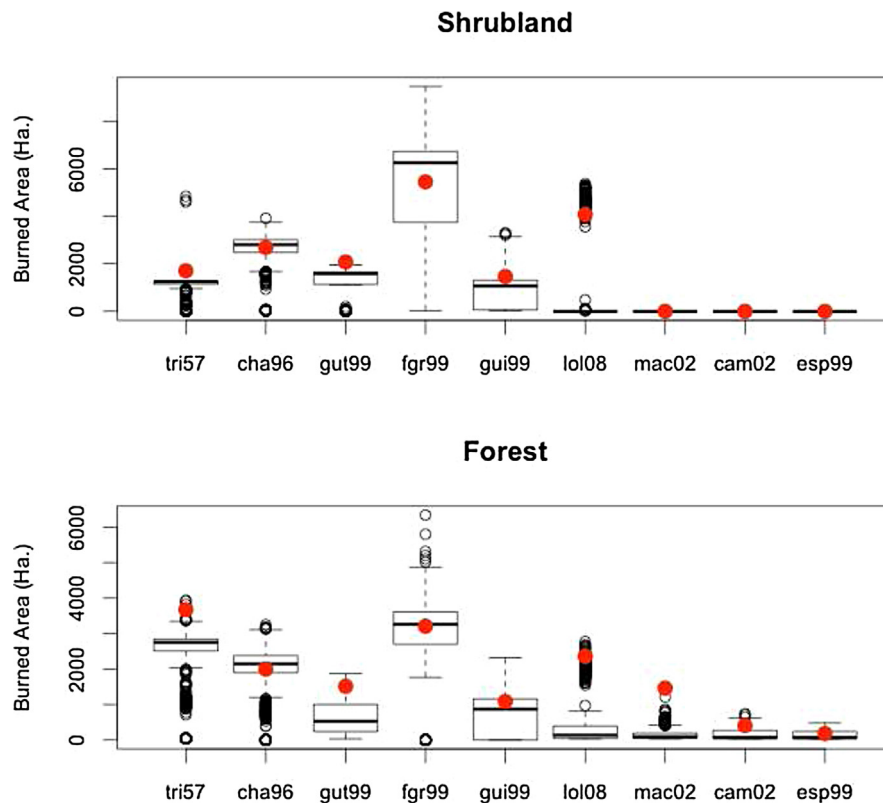
Shrubland

Forest

Fig. 3. Posterior predictive checks showing the distribution of areas of shrubland and forest burned during fire simulations corresponding to known fire events. The red dots show the observed area burnt which in most of the cases fall well within the distribution of simulated fires. Simulated fires were run sampling from the approximate joint posterior of model parameters. Boxes indicate 25th, median, and 75th percentile values, and dots are outliers beyond those values. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

First, we asked if the burned area of forest and shrubland in the observed fires fell within the distribution of burned area from simulated fires. A thousand simulations were performed for each recorded fire to obtain a fire-size distribution. To include full prediction uncertainty we sampled parameters from the approximated joint posterior distribution for every replicate of our simulations. Second, we tested the ability of the fitted model to produce a regional fire-size distribution similar to the sixty-two recorded fires occurring in our study area during dry years between 1950 and 2013. This dataset included the nine fires used to fit the model but also fifty-three recorded fires that were not fully mapped or had an unknown starting location. The observed fire-size distribution was compared using quantile–quantile plots to that of 7000 fires simulated with our fire-spread model and with parameter values sampled from the approximated joint posterior. For this regional comparison, the model was run over a vegetation map of Nahuel Huapi National Park ($\sim$70,0000 ha) re-classified as forest, shrubland, and "not-flammable" areas (lakes, high elevation barren areas). Other environmental variables (elevation, wind direction, aspect) were derived from a model Aster GDEM of 30 m resolution. The probability that a fire started at a particular pixel in the landscape was determined by solving equation 1 excluding the effect of wind direction. Simulated fires were run in batches of seven ignitions at a time to avoid possible overlap among simulated fires.

Thus, we tested whether the fitted model was consistent with the data used to parameterize it in the spirit of a posterior predictive check (Gelman and Hill, 2007), but we also tested whether it was capable of representing the regional fire-size distribution which is an emergent property of the regional fire dynamics which was not used to parameterize the model.

3. Results

After running our simulations, we found that the approximate marginal posterior distributions were well defined around optimal values for all parameters (Fig. A1.1). Estimated parameter values indicate that fires propagate more readily in shrublands than in forests (i.e. $\beta_0 > \beta_1$). Also, fire is more likely to spread in drier NW facing mountain aspects than SW facing ones ($\beta_2 > 0$). Not surprisingly, fires spread predominantly downwind ($\beta_3 > 0$). Since wind direction and aspect have the same range (-1 to 1), wind direction seems to exert a stronger influence on fire spread that aspect. Finally and as expected, fires were more likely to spread upslope ($\beta_4 > 0$).

Inspection of the approximated joint posterior distribution showed that fuel-related parameters (i.e. β_0 and β_1) were negatively correlated with the three environmental variables (β_2, β_3 and β_4, Table A2.1). There was no correlation between the parameters for forest and shrublands (Pearson's $r = 0.02$), whereas all environmental parameters showed weak positive correlations. The shrubland and slope parameters were negatively correlated; implying that similar fit to data could be obtained increasing the baseline fire spread probability and decreasing the effect of slope (or the other way around). Also, the parameters for shrublands and forests were negatively correlated with the coefficient of wind direction. Thus, the effect of wind direction could be stronger (weaker) if one reduces (increases) the probability of propagation in either vegetation type.

With the fitted model we could assess the influence of environmental variables on fire spread in shrublands and forests (Fig. 2). In general, fire propagation in shrublands was less sensitive to topographic conditions (i.e. slope and aspect) and was reduced
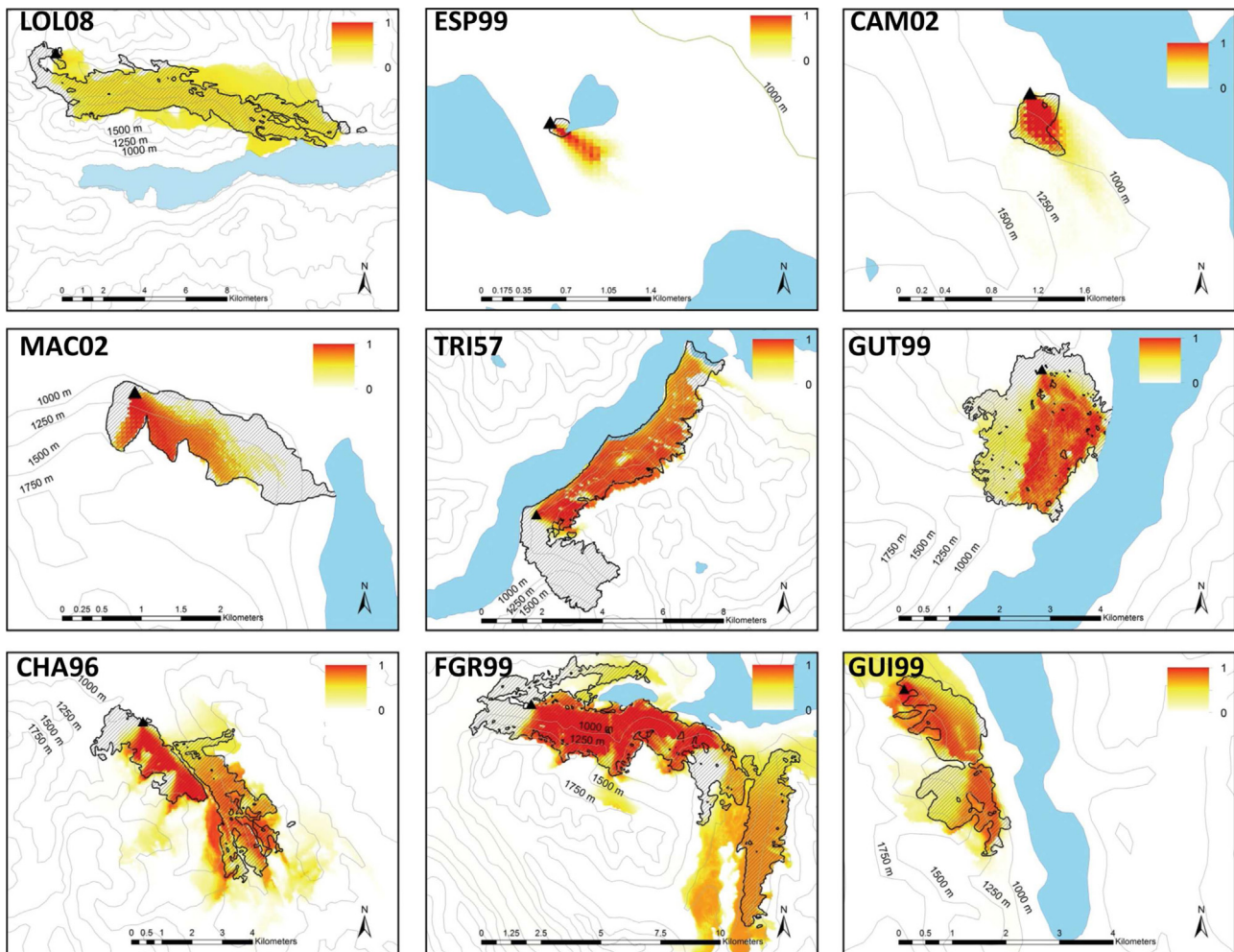
Fig. 4. Recorded fire events and burn probabilities calculated from the fire-spread model. The solid line shows the perimeter of registered fires while the triangle the approximated ignition point. The shades from white to yellow and to red indicate the burn probability after 1000 simulations with parameters sampled from the approximated joint posterior distribution. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

only in cells located strictly against the prevailing wind direction ($\omega < -0.5$; Fig. 2A–C). In contrast, fire propagation in forests was very sensitive to wind direction, becoming very unlikely in cells perpendicular to the prevailing wind direction ($\omega > 0$), on slopes lower than 10%, or in SE-facing slopes (Fig. 2D–F). It is important to note, however, that even though the direction of the effects are clear, the uncertainty around the magnitude of the effects of slope and aspect are quite large (gray areas in Fig. 2).

It is also possible to explore how easily fire would propagate or not under different conditions. For example, a site with a slope of 10% and covered with shrubland would get maximum fire propagation probabilities for any value of aspect facing toward the NW ($\psi > 0$) while fires starting in forests facing toward the SE ($\psi < 0$) would not propagate easily (Fig. 2A and D). With neutral aspect ($\psi = 0$) and 10% slope, shrubland fires propagate readily unless they are clearly upwind ($\omega < 0$). On the contrary, the *Nothofagus* forests in our study area would tend to stop fire propagation unless they are downwind ($\omega > 0$, Fig. 2B and E). Finally, for cells located perpendicular to wind direction and on NE or SW aspects, the probability of fire propagation increased rapidly with increasing slope for both shrubland and forest landscape cells but the effect on forests started at about 10% slope and was more variable (Fig. 2C and D).

Replicate simulation runs of fires starting at the reported ignition sites of observed fire events resulted in distributions of burned shrubland and forest that usually contained the observed burned areas of the actual fires (Fig. 3). For some recorded fires, the observed burned areas are extreme compared to model predictions (see shrubland area for LOL and forest area for TRI, LOL, MAC in Fig. 3). The overlap between observed and simulated fires was far from perfect, especially when it comes to burning against wind direction (Fig. 4). Note that these predictive distributions include both variability due to the inherent stochasticity of the fire propagation model and variability due to parameter uncertainty as every replicate run of the simulations was performed with a sample from the (approximated) joint posterior distribution of model parameters.

Simulated regional fire-size distribution for dry years was strikingly similar to that of the recent historical record (Fig. 5). The model tended to under-represent the frequency of fires <1 ha (0 in the log scale). On the contrary, most simulated fires larger than 100 ha (2 in the log 10 scale) are above the one-to-one line in the quantile–quantile plot in Figure 5, meaning that simulated fires had a higher frequency of large and very large fires compared to the observed distribution. This is not surprising given that our model does not explicitly include the effect of fire barriers such as rivers, roads, etc.
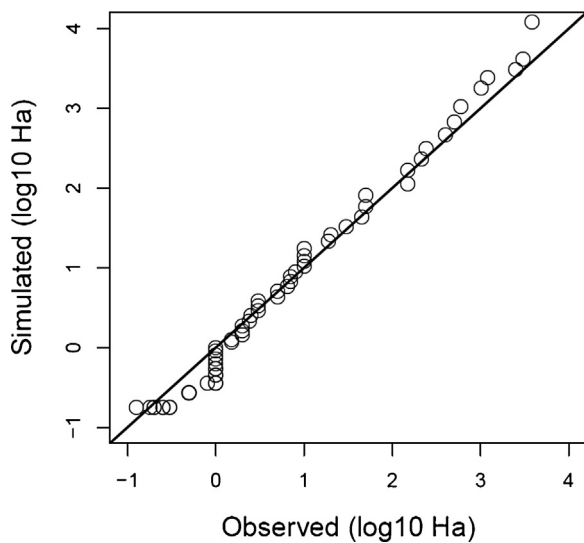
Fig. 5. Quantile–quantlie plot of observed and simulated regional fire-size distributions. Recorded fire events correspond to dry years between 1950 and 2008. Simulated fire-size distributions were similar to observed ones but tended to under-represent fires <1 ha and to over-represent large and very large fires (>1000 ha).

4. Discussion

With only a limited number of mapped fire events we were able to fit a model that relates fire spread probability to fuel type, aspect, wind direction, and slope (Fig. 2). This simple stochastic model produced a reasonably good approximation to key features of the fire regime in our study area even though only nine fires were used for parameterization. Simulating fire spread using parameter combinations sampled from the approximated joint posterior distribution obtained with our MCMC and Rejection Sampling scheme resulted in fire-size distributions that contained the observed values of burned area of shrubland and forest from recorded fires although there is a tendency for simulated fires to be smaller than the observed ones (Fig. 3). Also, the overlap between simulated and observed fires has some systematic errors windward from the point of ignition (Fig. 4). Despite these limitations, the model produced a regional fire-size distribution comparable to that observed for dry years in our study region (Fig. 5).

Our stochastic model is only partially based on the physics of fire spread, but it includes several features that are fundamental for more mechanistic models. For example, rather than using a standard equation for the effect of slope on the *rate* of fire spread, we include slope as one of the covariates affecting fire *spread probability*. Overall, the estimated fire spread parameters are consistent with what is known about fire behavior in general (McKenzie et al., 2011) and the characteristics deduced from previous empirical studies in our region which suggested that *Nothofagus* forests tend to act as fire breaks while shrubands tend to promote fire spread (Mermoz et al., 2005). Thus, *qualitatively*, our study does not add anything new to the understanding of fire dynamics in northern Patagonia, but it is important to note that we now have approximate posteriors for *quantitative* parameters describing fire spread. In a way, it is reassuring that a stochastic model fitted to a few fire maps is able to capture these known facts about fire behavior.

The match between simulated and observed fires is far from perfect (Figs. 3 and 4), suggesting that there is room to improve both the model and the parameterization. A good option for further model refinement is the incorporation of other vegetation types or conditions. For example, the fire at Lolog (LOL08 in Fig. 4) is rather extreme compared to model predictions. This particular fire started in a *N. dombeyi* forest that was ignited by lightning and burned areas

of both forest and shrubland that were mixed with Chusquea bamboo which had flowered and died a few years before the fire event. The dead bamboo clearly affected fire propagation in this particular event. Another obvious thing to consider is wind speed and direction during fire events (our model includes only dominant wind direction modified by topography). However, these variables can change rapidly and including them would require modeling the rate of fire spread instead of just probabilities of propagation. An inherent limitation of the approach used here is that it does not consider the time it takes for fires to move through the landscape, making difficult (if not impossible) to include changes in conditions during fire events. Thus, even though our model can give some indication of burn probabilities for particular fire events (Fig. 4), it is not really suited as a fire-forecasting tool. Stochastic fire propagation models such as the one we use here have several known limitations besides the lack of a temporal domain as mentioned above. Fire can spread differently than just to the eight neighbors of a lattice, thus there might be inherent limitations for how much these models can represent fire shapes. Also, these models do not take into account fire intensity, which can be crucial for several processes such as plant invasion and succession (e.g. Bowman et al., 2009; McKenzie et al., 2011).

The simulated regional fire-size distribution showed a generally good agreement with the recorded distribution but under-represented fires <1 ha and over-represented large fires (Fig. 5). Some ignitions fail to propagate so that simulated fire size is just one or two pixels (note several dots at the smallest size in Fig. 5). When simulated fires do propagate, they usually burn more that 1 ha. In contrast, real fires about the size of a pixel may go under-reported and others be "rounded up" to one hectare (note several dots at zero in the log 10 plot in Fig. 5). The discrepancy in large fires may be an effect of the relative coarse grain (30 m × 30 m) in our simulations that can blur important (but unmapped) effective natural firebreaks (e.g. small areas of bare soil, rocky ridges, small streams, etc.). In addition, the underestimation may be an artifact of having used a period (1950–2008) with relative low occurrence of larger fire events (except during the 1990s). Only a decade before this period, unusually large fires occurred during the 1943–1944 drought totaling in two years some 48,600 ha burned (Veblen et al., 2008). Also, during the early XXth century some 38,900 ha burned were documented (Willis, 1914). It is important to note also that better discrimination of fuel characteristics together with detailed weather effects are likely to produce a better characterization of the fire regime. In contrast with other stochastic models, the one we used here does not include a stopping rule imposed from a fire-size distribution (that is, we do not impose an "external" maximum fire size in our simulations). At this stage of model development and fitting, we considered only fires occurring during dry years, thus not including the effects of top down controls. Further development of our approach will include rainfall during the fire season as a modifier of fire spread probability.

Our results also have important implications in terms of long-term landscape dynamics and resilience to fire. Shrubland communities in northern Patagonia are in most cases manifestations of early post-fire successional stages given by the resprouting ability of most of its dominant species (Veblen et al., 1992). In the absence of fire, resprouters can eventually lose dominance due to the shading of obligate seed-dispersed trees entering the sites (e.g. *Austrocedrus, Nothofagus*; Kitzberger and Veblen, 1999; Gowda et al., 2012). Therefore, if early succession shrublands are, as suggested by our model, far more flammable than late successional forests (Fig. 2), positive vegetation and fire feedbacks can take place, resulting in self-reinforcing alternative stable states characterized by sharp and stable boundaries between vegetation types. Such landscape dynamics are highly sensitive to increases in ignition frequency and can show irreversible or hysteretic behavior even

after reducing ignition frequencies (Petraitis and Latham, 1999; Kitzberger et al., 2012; Stephens et al., 2013).

Although producing encouraging results, our approach should be taken only as a first step toward efficient simulation-based inferences of fire propagation from available burn maps. Further development of these techniques should explore other ways to sample from the prior distributions and also look for alternative ways to compare simulated fires with observed ones, for example taking into account un-burnt "islands" within the fire perimeter (Zinck and Grimm, 2008). These topics are currently the focus of active research in the Approximate Bayesian Computation literature (e.g. Beaumont, 2010; Hartig et al., 2011). Furthermore, undergoing development of more efficient fire simulation tools will allow us to fit more realistic models, including for example more fuel types, natural firebreaks, and models that consider the effects of recent rainfall events on fire propagation (top down controls). Also, with a more efficient simulation tool it will be possible to treat the fire starting point as another parameter to be estimated, thus allowing the analysis mapped fires with unknown starting points.

In sum, we have shown that readily available information from fires events (burn maps, preexisting fuel types, topography and prevailing wind direction) can be used to parameterize stochastic fire spread models. This approach can be used in places where standard fuel models have not been yet developed, making impossible to apply more sophisticated methods to simulate the spread of fire. For instance remotely sensed data on burned scars from remote areas are getting increasingly available (e.g. Pueyo et al., 2010). We believe that fitting stochastic models to these data using Approximated Bayesian Computation can be useful for quickly improving our quantification of fire propagation in landscapes where no fuel models are available and for developing landscape-level fire spread simulation routines for management purposes and to assess the potential effects of climate and land use change.

Acknowledgements

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecolmodel.2015.01.004.

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