Post-fire recovery in the Cape Floristic Region of South Africa

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Abstract

This document describes the supplementary data associated with the manuscript *Climatic controls on ecosystem resilience: post-fire regeneration in the Cape Floristic Region of South Africa* (Wilson, Latimer, and Silander).

1 Posterior Summaries

The data include several geotif files mapping summaries of the posterior distributions of recovery parameters, including:

γ increase in NDVI from the initial post-fire value (α) to the asymptotic value (in NDVI units)

λ: recovery rate (unitless) indicating more rapid recovery with smaller values

A Amplitude of seasonality (unitless)

$ages$ Estimated post-fire recovery time (years) calculated as the time until the predicted curve approaches $\gamma+\alpha$ Here we define $ages$ to be when the exponential component of the model equals $\gamma-0.005$. So solving $\gamma_i\left(1-e^{-\frac{age_{i,t}}{\lambda_i}}\right)=\gamma-0.005$ for age, we have

$$ages_i = \lambda_i \times log\left(200 \times \gamma_i\right) \tag{1}$$

frt Fire return intervals (years) estimated using survival model approach described below.

All parameters include the 2.5%, 50% (median), and 97.5% of the posterior distributions as separate geotif files. Thus they can be used to identify the median and 95% credible intervals for each pixel. These are labeled, for example, as $ages_Q2.5$ which indicates the 2.5 percentile of the estimated recovery time (in years).

The frt layers are slightly different in that they represent the time (years) to the indicated fire probability. For example, the $frt_Q50.tif$ indicates the years until the fire risk is estimated to be 50% in that location

(following the weibull survival model described below). $frt_scale.tif$ is the estimated weibull scale parameter, which can be used to draw 'random' fire intervals for each location according to the fitted fire return interval model described below.

1.1 Transformed areas

Much of the habitat in the Fynbos biome of the Cape Floristic Region has been transformed from its 'natural' state to other uses such as agriculture. The dataset includes predictions into these areas (though limited to the fynbos biome) and thus represent the 'potential' post-fire recovery parameters *as if those areas will still under natural vegetation.* Another layer $transformed.tif$ which has the percentage of each cell that has been 'transformed' from its natural state, is available to mask out those areas if desired.

2 On the estimation of fire return times from satellite-derived post-fire ecosystem recovery

2.1 Background

Fire risk is sensitive to biomass/fuel accumulation rate, which is controlled in large part by climate and soil. We modeled observed fire return times along a satellite-derived post-fire biomass recovery gradient to make estimates of fire return distributions.

2.2 Input Data

1. Climate and satellite-derived post-fire ecosystem recovery trajectories at 500m spatial resolution that represent the rate and magnitude of post-fire recovery. This is referred to as "post-fire recovery time."
2. Burned area polygons from CapeNature and MODIS that have reasonably complete coverage from 1980-2010 (see De Klerk, Wilson, and Steenkamp 2012; Wilson et al. 2010; Van Wilgen et al. 2010). The fire data were gridded to the same 500m grid as the post-fire recovery trajectories and consist of the dates of any fires that burned each pixel. These data are referred to as "fire return times."

2.3 Methods

A survival model was necessary to account for the incomplete (censored) observations. For example, the fire data cover the period 1980-2010, so the only way we'd observe a 30 year interval is if it burned in 1980 and again in 2010, for a 29 year interval it would have to burn in 1981 and 2010, or 1980 and 2009, etc. So the observed intervals will have a bias towards shorter intervals fires.

A survival model was fit using the survreg function in R's Survival package to the data (including the censored observations) in the following manner (where *surv* is an object that indicates survival times and interval type, *rt* is the median posterior recovery time for that pixel, and weights are interval-type specific weights explained below:

```
survreg(surv~rt,dist="weibull",weights=weights)
```

2.4 Assumptions

Any pixel with at least one observed fire will have two censored observations (from before beginning of record to the first fire, and then from the last fire to the end of the record) in addition to any observed intervals between two observed fires. In this dataset, the number of censored observations quickly overwhelms the observed intervals, extending the expected fire return times to unreasonably long intervals (greater than 100 years in some cases). These were dealt with in two ways:

1. The date of initial monitoring of fires in each reserve was not recorded, so it is unknown when to begin counting the censored intervals prior to the first observed fire. However, after a fire is recorded for a location, it is less likely that future fires will be missed. Since the probability of missing fires is much higher in the early part of the record, only the censored observations from the last fire to the end of the record were included. It is possible to model the timing of the prior fire (e.g. Wilson et al. 2010), but this was beyond the scope of this analysis.
2. After discarding the intervals at the beginning of the record, there were still nearly four times as many censored observations as complete observations. To prevent these from continuing to overwhelm the observed intervals, the censored observations were given a weight of 0.25, while the complete observations were weighted at 0.75 (leading to approximately equal influence of observed and censored intervals in the model fitting).

2.5 Results

The observed fire return intervals show an increasing trend with estimated recovery time (Figure 1), but the censored observations show interesting patterns (the pre-fire intervals show the opposite trend, while the post-fire censored intervals show a similar positive trend).

The survival model, fit using only right and observed intervals, identified that recovery time is significantly related to observed fire return time: Call:

```
survreg(formula = with(tfrt, Surv(time = time, event = event)) ~ rt,
data = tfrt, weights = tfrt$weights, dist = "weibull")

              Value Std. Error     z        p
(Intercept)  2.7087    0.01332 203.4 0.00e+00
rt           0.0178    0.00120  14.9 5.16e-50
Log(scale)  -0.8156    0.00955 -85.5 0.00e+00
```

```
Scale= 0.442

Weibull distribution
Loglik(model)= -21897.8   Loglik(intercept only)= -22013.4
Chisq= 231.18 on 1 degrees of freedom, p= 0
Number of Newton-Raphson Iterations: 8
n= 36595
```

So there is a significant and positive relationship between recovery time (rt) and the probability of fire. The intercept (2.7087) and weibull shape parameter (0.442, see help file for survreg for more information) is assumed to be constant across the region in this model. With this fitted model, it is possible to estimate the Weibull distribution of fire return times for each pixel for any recovery time (Figures 2 & 3). The model can also be used to estimate the time to any desired probability of fire (Figure 4).

2.6 Discussion

The scale parameter has been transformed from the model output as follows (m3 is the model object, rt is the recovery time for each pixel):

```
exp(coef(m3)[1]+(rt*coef(m3)[2]))
```

To use the map of estimated scale values ($frt_scale.tif$) to draw random fire intervals for a pixel in R, use the following formula (where scale represents the value from the pixel as encoded in the raster):

```
rweibull(1,scale=scale,shape=1/0.442)
```

The shape parameter must be inverted because of differences in the way the survival package reports weibull parameters and the way the weibull function expects them.

2.7 Caveats

1. This approach ignores the uncertainties in the underlying recovery time estimates (which are quite uncertain in some areas). Instead only the median posterior recovery time is used and is treated as data in the model.
2. This also ignores important covariates (climate, topography, spatial effects, etc.) except to the extent that they are incorporated in the post-fire recovery time.
3. The final values are sensitive to the weights used to downweight the censored observations. However, removing the first interval and downweighting the right censored observations to approximately equal weighting with the observed observations produces reasonable fire return distributions.

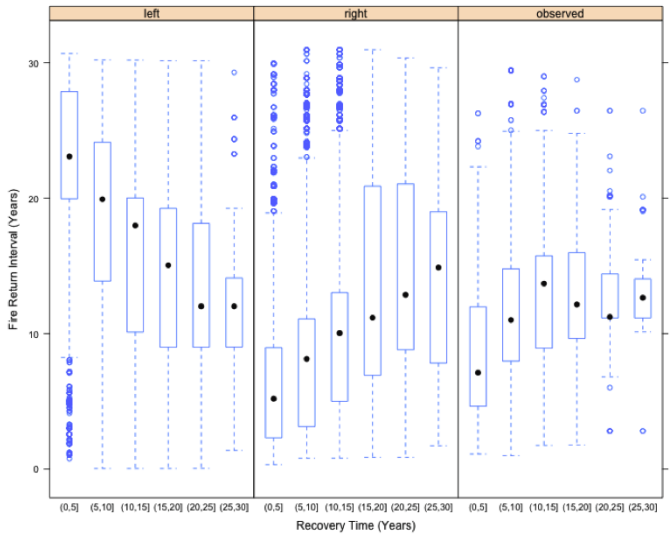

Figure 1: Boxplots of fire return times vs (binned) estimated recovery time. "Left" indicates the length of the intervals from 1980 to the first observed fire, "Right" indicates the length of the intervals from the last observed fire to 2011, and "Observed" indicates the length of observed intervals. Note the increasing trend in both right and observed intervals, but decreasing trend in left intervals

3 References

De Klerk, Helen, Adam M. Wilson, and Karen Steenkamp. 2012. valuation of Satellite-Derived Burned Area Products for the Fynbos, a Mediterranean Shrubland.nternational Journal of Wildland Fire 21 (1): 367.
`http://dx.doi.org/10.1071/WF11002.`

Van Wilgen, Brian W, Gregory G Forsyth, Helen De Klerk, Sonali Das, Sibusisiwe Khuluse, and Peter Schmitz. 2010. "Fire Management in Mediterranean?climate Shrublands: A Case Study from the Cape Fynbos, South Africa." *Journal of Applied Ecology* 47 (3) (June 1): 63138.
`doi:10.1111/j.1365-2664.2010.01800.x.`

Wilson, Adam M., Andrew M Latimer, John A. Silander, Alan E Gelfand, and Helen de Klerk. 2010. "A Hierarchical Bayesian Model of Wildfire in a Mediterranean Biodiversity Hotspot: Implications of Weather Variability and Global Circulation." *Ecological Modelling* 221 (1): 10612.
`doi:10.1016/j.ecolmodel.2009.09.016.`

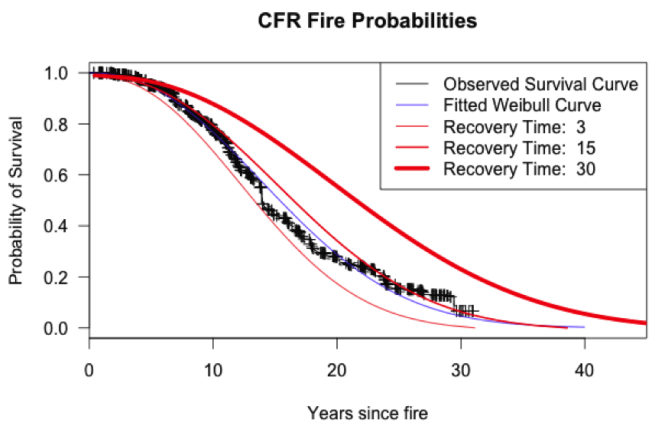

Figure 2: Observed and modeled fire survival probabilities across the CFR as a function of time since fire and post-fire recovery. The "Observed" curve is from survfit() in R with no covariates and represents the overall mean (nonparametric) survival curve. The blue line shows a weibull curve fitted to the observed data using survreg and no covariates. The red lines show the predicted survival curves for three recovery times (3 years, 20 years, and 40 years) estimated using survreg with recovery time as the single covariate. Note that the lines with longer recovery times also have longer expected fire return times.

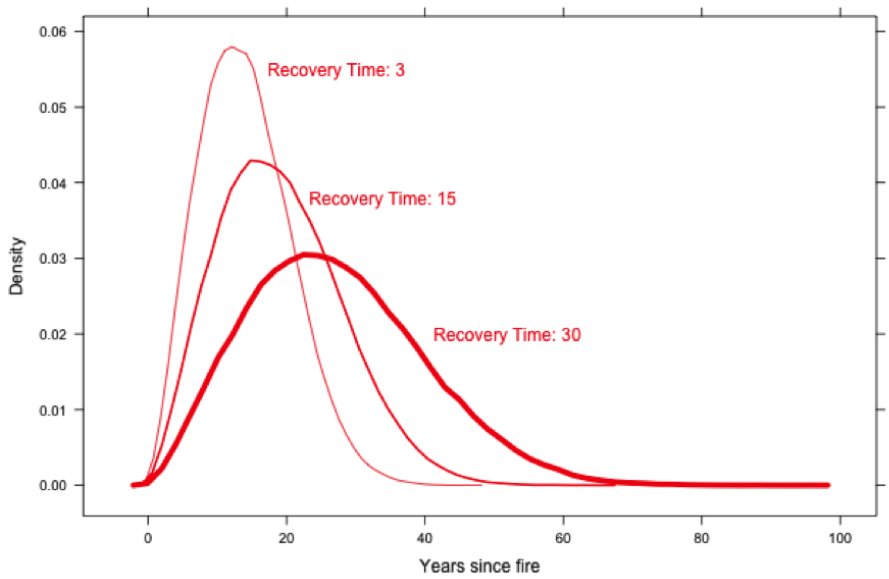

Figure 3: Estimated (Weibull) fire return distributions for three example recovery times (in years). So a pixel with a recovery time of 3 years would be expected to have a distribution of fire return intervals shown with the thin line (mean of 14 years), while an area with a recovery time of 30 years has an expected fire return time of 23 years.

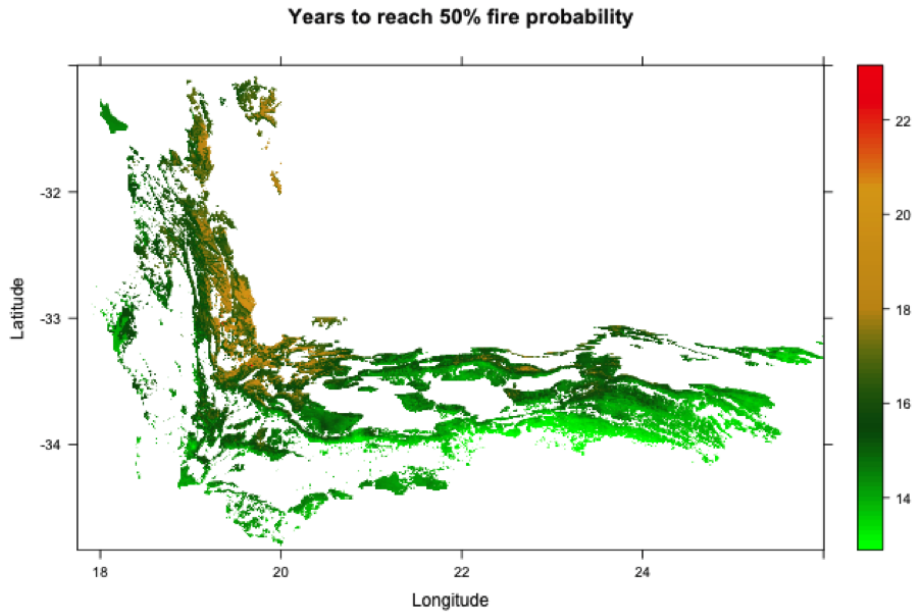

Figure 4: Time for fire probability to reach 50% as a function of post-fire recovery.

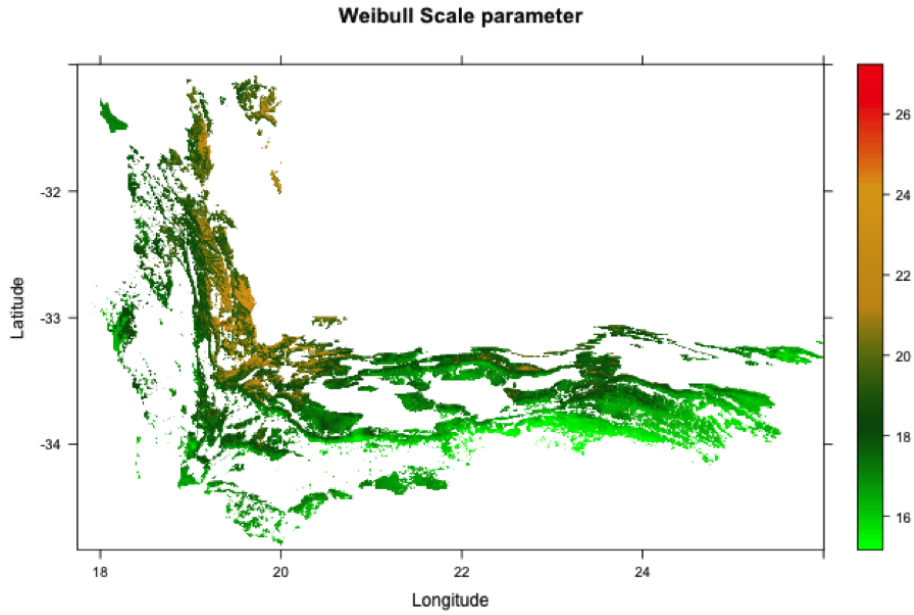

Figure 5: Spatial distribution of the estimated Weibull scale parameter which can be used to estimate fire return time distributions.