Predicting severe wildfire years in the Florida Everglades

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Wildfires result in important ecological benefits to many ecosystems, but have costs associated with fire fighting and property loss. Accurate, timely forecasts of the severity of upcoming wildfire seasons could facilitate wildfire management, limiting the most destructive aspects of fires, while preserving their ecological benefits. We demonstrate an approach where time series models are used to predict the severity of the wildfire season in Everglades National Park in southern Florida 3 months and 1 year beforehand. Model predictions contained all obserations within a 90% credible interval and also anticipated severe wildfire seasons. These models may be used to implement more ecologically sound wildfire management.

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Wildfires are a natural, recurring, and necessary component of ecological communities worldwide, and many ecosystems are unable to persist without periodic fires (Whelan 1995). Decades of fire suppression and altered fire regimes have had substantial ecological consequences for these ecosystems, including increased fuel loads (Agee 2002). At the same time, there are more wildland–urban interfaces as new development often abuts wilderness areas. These anthropogenic changes have increased both the risk of wildfires and the economic costs of their suppression, making wildfire management an important economic and ecological challenge.

An optimal approach to wildfire management should minimize the economic costs while recognizing the important ecological roles of fire. Such ecologically-based management would be facilitated by accurate and timely forecasts that give land managers adequate lead time to take proactive and ecologically sound management actions before severe wildfire seasons began. Potential management actions might include setting prescribed fires in the preceding fire season to reduce the continuity of fuels, the creation of limited protective buffers around at-risk structures abutting wildlands, and the efficient and timely allocation of firefighting resources, such as moving resources from low-risk to high-risk areas.

Recent approaches to wildfire forecasting have relied on climatic indices such as the El Niño–Southern Oscillation (ENSO) (Harrison and Meindl 2001; Chu *et al.* 2002; Kitzberger 2002) because of its relationship to global rainfall patterns (Ropelewski and Halpert 1987). We build on this approach by introducing a time series statistical model that confers two important advantages. First, time series models can account for wildfire activity in preceding years. This could be particularly important when wildfires burn a large portion of the landscape, making wildfires less likely the following year, regardless of ENSO conditions, because less fuel will be available for new wildfires. This is likely to be common in relatively small, regional landscapes, where proactive management efforts are most easily and effectively applied, such as Florida's Everglades National Park (ENP), as opposed to larger regions such as the entire US Southeast. Second, our time series model accommodates changes in the relationship between predictor variables and wildfire severity as conditions evolve over time. This is an important consideration as both climate changes and wildfire management alter the observed relationship between wildfire predictors and wildfire occurrence.

We explore the potential for time series models to predict the area burned in ENP during the spring wildfire season (April and May), 3 months and 1 year ahead of time. Three-month predictions would allow for the creation of buffers to protect structures or other sensitive areas, including cultural sites, from wildfires, while one-year predictions would allow for prescribed fires during the previous natural fire season, thus maximizing ecological benefits by mimicking natural lightning fires (Herndon *et al.* 1991; Platt *et al.* 2002). Our goal is to demonstrate the potential to forecast the severity of an upcoming wildfire season and, therefore, the potential effectiveness of a proactive management approach.

Everglades fire ecology

Fire is critical to Everglades ecosystems, where frequent wildfires result from the interaction of ecosystem characteristics, hydrology, and climate (Beckage *et al.* in press). Extensive sawgrass (*Cladium jamaicense*) marshes require periodic fires for rejuvenation (Wade *et al.* 1980) and produce sufficient biomass to fuel wildfires in two to three wet seasons (Gunderson and Snyder 1994). Fire-adapted subtropical pine (*Pinus elliottii* var *densa*) savannas require frequent fire to prevent displacement by native and invasive woody species (DeCoster *et al.* 1999; Platt 1999;

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Figure 1. *Ingraham fire (1989) in Everglades pine savannas, west of Long Pine Key, during the transition period from dry to wet season. Transition fires are important for the maintenance of savannas and associated indigenous herbaceous plant species in the diverse ground cover by removing litter and top-killing woody subtropical species.*

Figure 1).

The Everglades has a seasonal subtropical climate (Sarmiento and Monasterio 1975). Frequent, lightning-ignited wildfires occur during the spring wildfire season in April and May, the transition from winter dry to summer wet season, when water levels are at their lowest (Beckage *et al.* 2003). Wildfires during the transition period burn 70% of the annual area burned, and are the most difficult and costly to control. For example, the Ingraham Fire, one of the largest recorded lightning-initiated fires east of the Mississippi River, burned over 40 000 ha beginning in May 1989 and cost $850 000 (over $1.2 million in 2001 dollars) to manage and contain (Nate Benson, pers comm).

The Everglades spring wildfire season is sensitive to the El Niño–Southern Oscillation (Beckage *et al.* in press) because of ENSO's influence on winter rainfall in the southeastern US (Ropelewski and Halpert 1986). Winter precipitation is increased during the El Niño phase of ENSO and decreased during the La Niña phase, influencing the severity of the winter drought and the spring wildfire season. ENSO indices during the winter dry season may therefore indicate the severity of the upcoming spring wildfire season. A more detailed discussion of ENSO effects on fire regimes in ENP can be found in Beckage *et al.* (in press).

Statistical model

We modeled the area burned by wildfires in Everglades National Park during the spring wildfire season using a time series model that considers the area burned in previous years and the Southern Oscillation Index (SOI) of ENSO conditions to predict the area burned in the current year. The areas burned by wildfires in the years 1948–2001 were obtained from ENP fire records. We used the SOI from 3 or more months (January or earlier) prior to the midpoint of the spring wildfire season as a predictor variable in the 3-month predictions. This allowed us to compute various summary values of SOI indices – eg January SOI, mean December–January SOI, mean November–January SOI, etc. The 3-month model used area burned in previous wildfire seasons and the SOI covariate to predict the area burned in the upcoming wildfire season, while the 1-year model used only the area burned in previous wildfire seasons.

Area burned in previous years might be a useful predictor of area burned in the current fire season for two reasons. First, the 2–3 years following large fires might see reduced fires as fuel recovers. Also, climatic conditions that positively or negatively influenced wildfire conditions might tend to last a number of years, resulting in similar areas burned (either large or small) in adjacent years. These mechanisms could lead to a combination of positive and negative relationships between area burned in the current year compared to past years.

We modeled area burned with an autoregressive moving average (ARMA) form of a dynamic linear model time series (Box and Jenkins 1976; West and Harrison 1999). In the ARMA model, the area burned in previous time steps predicts area burned in the current time step through autoregressive (AR) coefficients. These describe the effect of previous area burned on area burned in the current time step, and moving average (MA) coefficients describe the effect of previous Gaussian error terms (ie, a_{t-1} to a_{t-q}, below, that represent the difference between predicted and observed area burned in previous time steps) on the current prediction. The ARMA model is given by:

$$z_t = X\beta_t + \varphi_t^1 y_{t-1} + \ldots + \varphi_t^p y_{t-p} + a_t + \theta_t^1 a_{t-1} + \ldots \theta_t^q a_{t-q}$$

where z_t is the predicted mean of the log-transformed time series (log[area burned + 0.5]) at year t, and y_{t-1} is the observed area burned (log transformed) at year t-1. X is the design matrix for covariates, and β_t is a vector of estimated coefficients associated with the covariates. The indexing by time indicates that the β_t parameters are dynamic and can change value over time as conditions evolve. φ_t^1 to φ_t^p are the autoregressive (AR) coefficients described above. The time subscript indicates that these parameters can also change value over time. θ_t^1 to θ_t^q are the moving average (MA) coefficients that are also indexed by time, and p and q are the order of the autoregressive and moving average processes, respectively. The order describes the number of previous time steps (years) that are used to predict the current area burned.

The dynamic formulation of the ARMA model (eg indexing of model parameters by time) allowed for model parameters to evolve over time as conditions change, rather than being restricted to a single best estimate across the entire time series (West and Harrison 1999). This is an important and desirable characteristic, as the model can adjust to changing circumstances, such as the institution of vigorous proactive management of wildfires, and can therefore continue to provide useful predictions of upcoming wildfire severity, given changing fire management policy and actions. The model parameters (β_t, φ_t^1, φ_t^2, θ_t^1, θ_t^2) were allowed to evolve through time according to:

$$\beta_t \sim \text{Normal}\,(\beta_{t-1}, W_1) \quad \varphi_t^1 \sim \text{Normal}\,(\varphi_{t-1}^1, W_2)$$
$$\varphi_t^2 \sim \text{Normal}\,(\varphi_{t-1}^2, W_3) \quad \theta_t^1 \sim \text{Normal}\,(\theta_{t-1}^1, W_4)$$
$$\theta_t^2 \sim \text{Normal}\,(\theta_{t-1}^2, W_5)$$

The W_1-W_5 are variance parameters that describe how quickly model parameters can change through time; larger values mean that parameters can evolve more rapidly. These variance parameters were static; in other words, they were not allowed to evolve through time. Placement of diffuse prior distributions, indicating that we have relatively little prior information on parameter values, completes the model description.

We evaluated a number of potential models based on alternate SOI summaries and order of the ARMA process before selecting the "best" model based on a static (non-time varying) ARMA time series model and Akaike's Information Criterion (AIC). AIC is a model selection criterion that selects the "best" or most parsimonious model for the data. The model selection process yielded similar SOI summaries and order of the ARMA process over different time periods (eg 1948–1990, 1948–2001, etc). ARMA models of order $p = 2$ and $q = 2$ were selected for both the 3-month and 1-year models, and mean Nov–Jan SOI was used as an additional covariate in the 3-month model.

The time series models were fit using Bayesian Markov Chain Monte Carlo methods and the winBugs software (Spiegelhalter and Best 1999; Congdon 2001). The Bayesian approach facilitated the computation of unconditional likelihoods by easily accommodating imputation of data values from before the beginning of the ENP fire record. This approach also simplified the calculation of auxiliary quantities, such as the probability of larger wildfires occurring in the current wildfire season compared to the last. We evaluated model fit by computing the mean absolute deviation between the predicted and observed data on the transformed scale.

Results

We were able to accurately model area burned in the spring wildfire season in Everglades National Park. Predicted area burned approximated the observed area burned with the 90% credible intervals containing all observations (Figure 2). Increased SOI index (La Niña conditions) was associated with increased area burned, and decreased SOI index (El Niño conditions) was associated with reduced area burned during the April–May wildfire season from 1960 onward (Figure 3). The relationship between SOI and area burned was reversed for the period 1948–1959.

The probability of a larger area being burned during the transition period in the current year compared to the preceding year was predicted to range from <0.01–0.99 across years, providing a simple but discriminating measure of wildfire risk. The quality of the predictions decreased as the forecast length increased from 3 months to 1 year; the mean absolute deviations between the predicted and observed data increased from 1.40 to 1.45. For example, the 1-year model predicted that 21 000 ha would be burned in 1989, the year of the Ingraham fire, compared to the 51 000 ha actually burned. Although the absolute error was substantial, the predicted area burned was the third largest in 54 years, clearly indicating that the upcoming wildfire season would be severe. The 3-month model predicted that a larger area (32 000 ha) would be burned, providing a further indication that the upcoming wildfire year would be severe. Advance predictions of an upcoming severe wildfire season could have resulted in proactive fire management actions that would have greatly reduced the costs associated with the Ingraham fire.

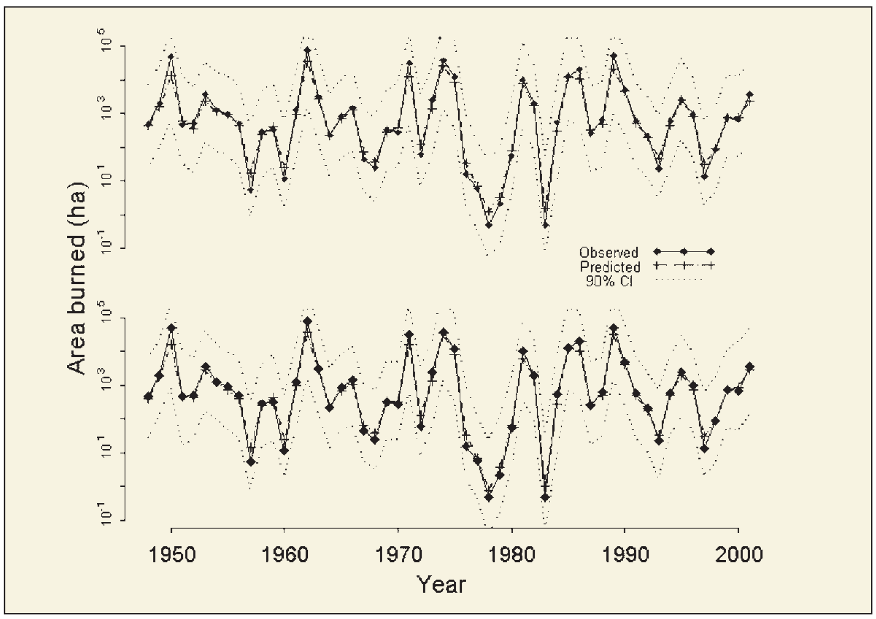

Figure 2. Predicted (median) and observed area burned in the April–May wildfire season in Everglades National Park, 1948–2001. (top) One-year predictions. (bottom) Three-month predictions that included mean November–January SOI as a covariate.

The prediction of the large area burned in 1950 (Figure 2), 3 years into the time series, suggests that reasonable predictions of severe fire seasons can be

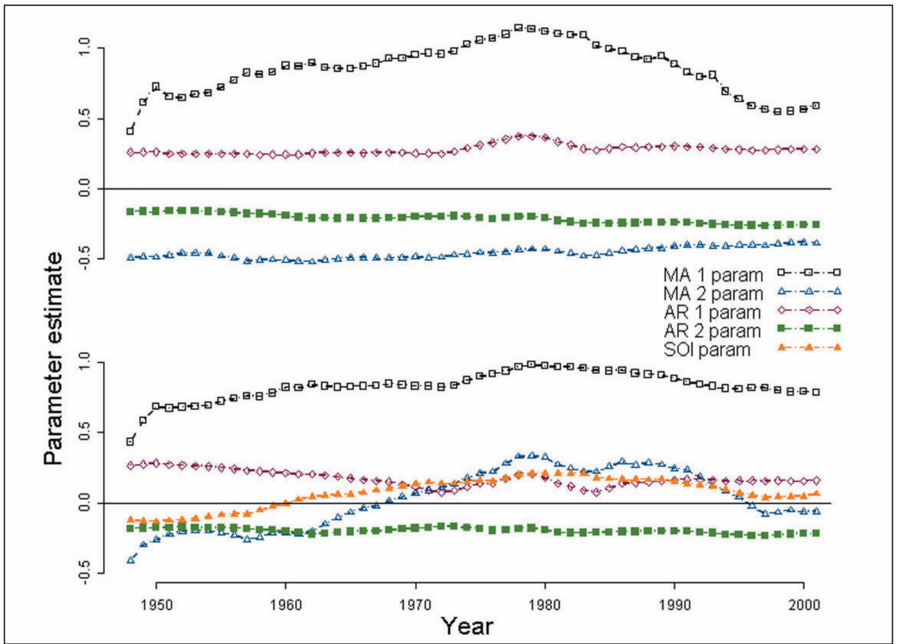

Figure 3. *Evolution of model parameters (median values) through time. (top) One-year predictions. (bottom) Three-month predictions that included mean November–January SOI as a covariate.*

made with relatively short data series once an appropriate model has been selected. This is reflected in the initial rapid evolution of model parameters during the first 3 years (Figure 3). The continued slow migration of model parameters beyond 3 years appears to result from strong correlations between model parameters. This correlation means that we can accurately estimate the combined effect of the model parameters, and therefore make accurate predictions, but our estimates of individual model coefficients require longer time series. For example, the SOI parameter requires 12 years of data before it enters the positive region where it should probably lie, because La Niña conditions are negatively associated with winter rainfall in south Florida (Beckage *et al.* in press). The longer time required for the SOI parameter to reach this range probably results from its strong correlation with the AR φ_t^1 (ρ = -0.83), MA θ_t^1 (ρ = 0.91), and MA θ_t^2 (ρ = 0.94) model parameters. These high correlations may also explain the good performance of the 1-year model, which does not contain the SOI covariate, since the AR and MA model terms can "absorb" the SOI effect. Longer-term variability in model parameters, such as the decline in the SOI parameter in the 1990s (Figure 2), may reflect variability in the ENSO–fire relationships, or may be due to other changes in the hydrology of the Everglades, such as altered water management or increased incidence of tropical storms, producing high water levels that persist into the subsequent dry season (Beckage *et al.* in press).

Discussion

Accurate forecasts of the severity of upcoming wildfire seasons may be possible months in advance. Encouragingly, our model of wildfire severity appears to have only modest data requirements. However, longer data time series, as well as an understanding of the processes that drive wildfire regimes in a particular region, will facilitate the formulation of an appropriate statistical model for systems other than the Everglades. We also caution that our predictions were not true "out of sample" predictions because model selection, parameter estimation, and the modeling process itself used the data that were to be predicted. Large discrepancies between model predictions and data would lead us to further refine our model structure. Nevertheless, our results are encouraging, and land managers in ENP have expressed interest in our forecasts of wildfire severity.

Annual predictions of wildfire severity at regional spatial scales such as Everglades National Park could facilitate effective and ecologically sound fire management, enabling simultaneous reduction of the most costly and negative economic effects of wildfires while preserving the necessary and natural role of fire in ecosystem function. We believe that similar time series models might prove useful for modeling wildfires in other ecosystems around the world, because of the similar roles of global ENSO cycles in determining precipitation patterns and wildfire occurrence (Swetnam and Betancourt 1990; Holmgren *et al.* 2001).

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References

Agee JK. 2002. The fallacy of passive management. *Conserv Biol Pract* **3**: 18–25.

Beckage B, Platt WJ, Slocum MG, and Panko B. Influence of the El Niño–Southern Oscillation on fire regimes in the Florida Everglades. *Ecology*. In press.

Box GEP and Jenkins GM. 1976. Time series analysis, forecasting and control. San Francisco: Holden-Day.

Chu PS, Yan WP, and Fujioka F. 2002. Fire–climate relationships and long-lead seasonal wildfire prediction for Hawaii. *Int J Wildland Fire* **11**: 25–31.

Congdon P. 2001. Bayesian statistical modelling. New York: Wiley.

DeCoster J, Platt WJ, and Riley SA. 1999. Pine savannas of Everglades National Park: an endangered ecosystem. In: Jones DT and Gamble BW (Eds). Florida's garden of good and evil. Proceedings of the 1998 Joint Symposium of the Florida Exotic Pest Plant Council and the Florida Native Plant Society. West Palm Beach, FL: South Florida Water Management District. p 81–88.

Gunderson LH and Snyder JR. 1994. Fire patterns in the southern Everglades. In: Davis SM and Ogden JC (Eds). Everglades: the ecosystem and its restoration. Delray Beach, FL: St. Lucie Press. p 291–305.

Harrison M and Meindl CF. 2001. A statistical relationship between El Nino–Southern Oscillation and Florida wildfire occurrence. *Phys Geogr* **22**: 187–203.

Herndon A, Gunderson L, and Stenberg J. 1991. Sawgrass (*Cladium jamaicense*) survival in a regime of fire and flooding. *Wetlands* **11**: 17–27.

Holmgren M, Scheffer M, Ezcurra E, *et al.* 2001. El Niño effects on the dynamics of terrestrial ecosystems. *Trends Ecol Evol* **16**: 89–94.

Kitzberger T. 2002. ENSO as a forewarning tool of regional fire occurrence in northern Patagonia, Argentina. *Int J Wildland Fire* **11**: 33–39.

Platt WJ. 1999. Southeastern pine savannas. In: Anderson RC, Fralish JS, and Baskin J (Eds). The savanna, barren, and rock outcrop communities of North America. Cambridge, UK: Cambridge University Press. p 23–51.

Platt W, Beckage B, Doren B, and Slater H. 2002. Interactions of large-scale disturbances: prior fire regimes and hurricane-induced mortality of savanna pines. *Ecology* **83**: 1566–72.

Ropelewski CF and Halpert MS. 1986. North American precipitation and temperature patterns associated with the El Niño/Southern Oscillation (ENSO). *Mon Weather Rev* **114**: 2352–62.

Ropelewski CF and Halpert MS. 1987. Global and regional scale precipitation patterns associated with El Niño–Southern Oscillation. *Mon Weather Rev* 115: 1606–26.

Sarmiento G and Monasterio M. 1975. A critical consideration of the environmental conditions associated with the occurrence of savanna ecosystems in Tropical America. In: Golley FB and Medina E (Eds). Tropical ecological systems. Ecological Study Series 11. New York: Springer-Verlag. p 223–50.

Spiegelhalter DJ, Thomas A, and Best NG. 1999. WinBUGS Vers 1.2 user manual. Cambridge, UK: MRC Biostatistics Unit.

Swetnam TW and Betancourt JL. 1990. Fire–southern oscillation relations in the southwestern United States. *Science* **249**: 1017–20.

Wade D, Ewel J, and Hostetter R. 1980. Fire in south Florida ecoystems. USDA Forest Service General Technical Report SE-17. Asheville, NC: Southeast Forest Experiment Station.

West M and Harrison J. 1999. Bayesian forecasting and dynamic models. New York: Springer-Verlag.

Whelan RJ. 1995. The ecology of fire. New York: Cambridge University Press.