Proposed design for the ATLSS fire submodel.

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The purpose of the ATLSS fire submodel is to provide annual estimates of the spatial distribution of the areas burned in the Florida Everglades. The term “submodel” is applied because the model is intended to be used to provide input into the ATLSS vegetation succession model. A simple method for incorporating fires into the vegetation succession model would be to use map layers representing fire distributions for each year. Yearly map layers of fire distribution based on observations would be an ideal basis for investigating historical patterns of vegetation change. The capacity to input map layers of fire distribution has already been incorporated into the vegetation succession model. However, the available data are incomplete, lacking information for some regions and time periods and therefore having limited usefulness as input to the vegetation succession model. In addition, historical data do not, by themselves, provide a solution to estimating future fire distributions nor dealing with how these distributions might be affected by alternative management scenarios. For these reasons we feel that a modeling approach is appropriate. The data that are available can be leveraged to parameterize the submodel, which can be used to estimate the annual area burned across the entire landscape. In addition, a modeling approach allows future fire conditions to be estimated and the effects incorporated into Everglades restoration planning.

The design of the fire submodel has been guided by a number of conflicting concerns. On the one hand, we want a mechanistic model that can estimate the spatial distribution of areas burned based on influential environmental factors such as fire history, the distribution of vegetation and patterns of hydrology. We feel that this approach is both appropriate and necessary to capture spatial heterogeneity and provide reliable estimates of future fire distribution. One the other hand we are constrained by the available data and the spatial extent of the Everglades ecosystem. The available data upon which we base our model are of two types. There are data sets, such as the output of the South Florida Water Management Model (SFWMM) and the Florida GAP map, that provide information about spatial variability in the Everglades and are used as inputs into many (if not all) of the ATLSS models. Use of these data is important because it forms a link between all the ATLSS models, providing them with a common environment. In some cases, such as the SFWMM, the use is necessary since hydrology is a dominant factor in the Everglades, and output from this model is the accepted standard for estimating spatial and temporal patterns of hydrology in SF. The second type of data includes empirical data reported in the literature or recorded by government agencies. These data form the basis for estimating parameter values in our model. However, these data are applicable only to portions of the Everglades and may not be wholly compatible with each other. This limits the empirical justification for incorporating detailed representations of natural patterns and indicates the development of a simpler model would be appropriate.

The vegetation succession model covers most of the natural areas of SF, including the water conservation areas, the Everglades National Park and Big Cypress National Preserve (Figure 1). The fire submodel we present here is designed to be coincident in space with the vegetation succession model. Modeling over this entire area presents significant computational challenges, but is necessary to capture the dynamics of this interconnected system and to provide an assessment tool in which relationships between subregions can be evaluated.

Both natural and anthropogenic fires occur in the Everglades, and both have important effects on vegetation(Main & Barry 2003, Lockwood, Ross *et al.* 2003). The goal of the ATLSS fire submodel is to estimate the occurrence, location and severity of naturally occurring fires. Anthropogenic fires, including managed burns, arson and accidental fires, result from different processes and may have different effects on the ecosystem, suggesting that these types of fires should be modeled separately. At this time we feel that it is best to focus on modeling natural fires and incorporate anthropogenic fires and their effects at a later stage of model development.

We divide natural fires into hot and cool fires. Hot fires are those that result in the death of trees and/or the burning of soils and peat material. These fires reset the successional process to “early” vegetation types. Cool fires are those that do not kill trees or burn soils. These fires burn only above-ground portions of plants and arrest succession at different stages of development depending on fire frequency. A fire model should be able to provide an estimate of the spatial distribution of both hot and cool fires. Wetzel’s reports to the ATLSS project(Wetzel 2001, Wetzel 2002) provide details on how the vegetation succession model utilizes the outputs of the submodel.

We take the approach that landscape-scale fire patterns can be estimated by modeling fire spread as a collection of local stochastic processes. In our approach, the landscape is divided into a number of smaller, spatially distinct units of equal size and shape. It is between these smaller units that the process of fire spread is simulated. In principle, the subdivision can take a number of different forms. However, it is convenient to match the subdivisions with those used in the vegetation succession model. Therefore, each unit within the fire model represents a 500x500 meter plot. At this resolution approximately 73,000 plots are required to cover the ATLSS study area.

The 500x500 meter plot size imposes a slight bias at the lower end of the distribution of total area burned since the smallest non-zero area burned is 25ha. However, this assumption is not very strong since only about 6% of the fires are smaller than this limit (Wetzel 2002).

Each plot is represented by a stochastic cellular automata (CA). Each plot is in one of three states: unburned, burned by cool fire or burned by hot fire. Transitions between these states are stochastic and depend on local environmental conditions and the presence or absence of fire in a neighborhood of each plot.

Estimation of the spatial distribution of area burned for each year is carried out in three steps. First, the probability of burning, p_b, is computed for each plot in the landscape. Next, the number of lightning strikes and the number of resulting fires is computed. Finally, fires are spread from each burning plot to neighboring plots.

The local fire process is the spread of fire from one plot to neighboring plots. When a plot is burning, each of the neighboring plots has a probability that fire will extend to include them. The process of fire spread is stochastic because each neighboring plot catches fire with a locally determined conditional probability p_b. The conditional probability p_b represents the probability of burning given that a neighboring plot is burning. If a neighboring plot burns, then each of its (unburned) neighbors is checked to determine whether or not the fire spreads farther. This process continues until all neighbors of all burning plots have been checked and no additional plots burn. Currently, we assume that there is no directional bias associated with fire spread. That is, the probability of a neighbor catching fire is determined strictly by the local burn probability for that neighbor and is not affected by the position of the neighbor relative to the burning plot.

The local burn probabilities, p_b, are determined for each plot based on the local environmental conditions, their interactions, and how these conditions change with time. The local environmental conditions we currently propose to include are vegetation type, fire history and hydrologic conditions. The type of vegetation present in a plot determines the maximum and minimum probability of burning. The effects of fire history and hydrology are used to identify a specific probability of burning within the range of probabilities.

The vegetation for each plot is determined by the vegetation succession model. Using the succession model as a source of vegetation information is a natural choice and provides feedback between the vegetation succession model and the fire submodel. The vegetation succession model classifies each plot as containing a single vegetation type. Currently, the vegetation types are based on those used by the Florida GAP project for the FGAP map (Pearlstine, Smith *et al.* 2002). FGAP is used to initialize the spatial distributions of vegetation in the vegetation succession model. FGAP vegetation types follow the United States National Vegetation Classification Scheme (NVCS) (The Nature Conservancy 1997). Using this classification scheme and the FGAP map, each plot is assigned to one of 25 natural vegetation types that occur in the ATLSS study area (Table 1). To simplify the vegetation effects on the fire submodel, we group the 25 FGAP vegetation types into 5 more general groups based on the characteristics of the species that make up each type. All types within a group are assumed to have similar probabilities of burning and are assigned a single group-level maximum and minimum burn probability. The five groups are grasses, pines, hard woods, flooded vegetation and shrubs. The group for each vegetation type is shown in column three of Table 1.

While the range of burn probabilities is determined by the vegetation type, local fire history and hydrologic conditions determine the specific value within the range. We wish to capture two basic relationships between these environmental variables and probability of burning. First, the probability of burning is low in the year following a fire, with probability increasing each subsequent year without fire until the maximum burn probability is reached. Second, wetter conditions tend to decrease the probability of fire while drier conditions tend to increase the probability of fire. We seek an approach that will combine these two relationships.

We propose to represent the relationship between fire history and the probability of burning as a piece-wise linear function similar to the one shown in Figure 2. In this function the probability of burning is at $p_{min,v}$ in the first year following a fire, where $p_{min,v}$ is the minimum probability of burning for vegetation type v. The probability of burning increases yearly until $p_{max,v}$ is reached, which is the maximum probability of burning for vegetation type v. The parameter $T_{R,v}$ represents the time required to return to the maximum burn probability. Values for these parameters depend on the type of fire that occurred previously. If the fire was hot, then the parameters are for the "early" successional type that occupies the site following the fire. If the fire was cool, the pre-fire vegetation persists and the parameters are for this vegetation type. The equation describing the graph in Figure 2 is:

$$p_{fire,v}(t) = \begin{cases} p_{min,v} + [(p_{max,v} - p_{min,v})/(T_{R,v} - 1)] * (t-1) & t \leq T_{R,v} \\ p_{max,v} & t > T_{R,v} \end{cases} \tag{1}$$

where t is the number of years since the fire, which is computed directly from the fire submodel.

We propose to represent the relationship between hydrology and the probability of burning using a function similar to the one shown in Figure 3. In this graph the highest probability is given by $p_{fire,v}(t)$, as computed using equation 1 and is associated with short hydroperiods. The probability then follows a smooth decrease as hydroperiod increases. The equation for this relationship is given by :

$$p_{hydro,v}(hp) = p_{min,v} + [p_{fire,v}(t) - p_{min,v}] * [1 - CDF_v(hp)] \tag{2}$$

where $CDF_v(hp)$ is the cumulative distribution function for a normal distribution, $N(\mu_v, \sigma_v^2)$ and hp is the hydroperiod. The parameters for the normal distribution are based on hydroperiod preferences for vegetation type v. Hydroperiod preferences are documented in Wetzel (2001). For each vegetation type, Wetzel (2001) provides a maximum and minimum hydroperiod preference, $hp_{max,v}$ and $hp_{min,v}$ respectively. Currently, we use the center of range defined by $hp_{max,v}$ and

$hp_{min,v}$ for the mean, $\mu_v = (hp_{max,v} + hp_{min,v})/2$, and choose the variance, σ_v^2, such that 95% of the distribution is between $hp_{min,v}$ and $hp_{max,v}$. The purpose of this approach is to be able to vary the mean to reflect a preference on the part of the species in vegetation type v for one or the other end of the specified hydroperiod range.

ATLSS High Resolution Hydrology (HRH), which are based on the output of the SFWMM, will be used as the source of hydrology data. The ATLSS HRH interpolates SFWMM output over a high resolution topography map to create water depths at a 500x500 meter resolution.

Classification of fires in each plot as either hot or cool is based on an empirical relationship reported in Wetzel (2002), page 34. This relationship provides an estimate of the area of hot fires based on the total area burned. How to select plots that are to be classified as having experienced a hot fire is currently unresolved. The plots will be chosen from those that have burned. From there, two approaches suggest themselves. Plots could be selected at random from among the burned plots and classified as having experienced a hot fire. Alternatively, a cluster of plots within each area burned could be classified as having experienced a hot fire. The criteria for selecting a cluster could be as simple as placing it in the approximate center of each burned area, or could be related to local environmental conditions.

An alternative to determining the areas burned by hot fires is to base the estimates on local environmental conditions. Factors such as the identity of local vegetation, time since last burn and hydrology could be used to determine an extra variable p_h, the conditional probability that a plot is burned by a hot fire given that it has burned. The presence of a hot fire also could increase the probability of burning in neighboring cells. In this way the pattern of hot and cool fires in the current year could influence the spatial distribution of area burned.

In addition to changing vegetation, hot fires can also lower local ground surface elevations by burning soils. This results in longer hydroperiod and deeper water which in turn effects succession dynamics. Lowering local ground surface elevations can be easily incorporated into the vegetation succession model by updating the topographic data layer. Based on data reported in Taylor (1981) we propose to reduce local ground surface elevation by 5 cm where hot fires have occurred.

We assume that all natural fires are caused by lightning strikes. To estimate the ignition of fires by lightning, we estimate the number of lightning strikes each year during the natural fire season. The number of lightning strikes is based on two empirical relationships (Beckage, Platt *et al.* 2003), one relating El Niño Southern-Oscillation (ENSO) to annual winter rainfall in SF and the other relating ENSO to annual number of lightning strikes in SF. These two relationships are combined to obtain a single relationship relating annual rainfall to number of lightning strikes. We take this approach because we do not have a climate model, but we do have access to daily rainfall data. Based on this relationship, we can estimate the number of lightning strikes each year. Next, the lightning strikes are distributed randomly across the landscape. Each plot that is struck by lightning has a probability of igniting, p_l. Currently we assume the $p_l = p_b$ for each plot.

The parameters $hp_{max,v}$, $hp_{min,v}$ and $T_{R,v}$ are assigned values based on Wetzel (2001). The remaining parameter values, namely $p_{max,v}$ and $p_{min,v}$ for the five vegetation groups will be estimated based on data from the Everglades National Park (ENP) fire records. Currently this data consists of the date and source of ignition and the area burned by each fire. From this data we create distributions of fire sizes and frequencies and use these distributions as the basis for estimating model parameters. The spatial extent of past fires in ENP are currently being digitized by the National Park Service and the US Geological Survey. This data will be available sometime in the spring of 2004 and we will use it to refine our parameter estimations. We assume that the parameters estimated in this way will be applicable throughout the model study area (Figure 1).

The relationship between the model the model parameters ($p_{max,v}$ and $p_{min,v}$) and the predicted area burned and fire frequency are stochastic. This means that traditional methods of parameter estimation, such as maximum likelihood, may not be appropriate. We propose to use a genetic algorithm to explore parameter space to identify values that result in model predictions that best approximate observed distributions.

There are a number of aspects of fires that we have omitted that could be included in later versions of the model. For example, we will need to include anthropogenic fires to address the correlations between these and natural (lighting strike) fires. We could also include a directional bias by modifying local burn probabilities of neighboring plots based on their position relative to a burning plot. The simulation results of Wu *et. al* (1996) as indicate that man made fire breaks, such as airboat trails, are an important factor effecting fire spread. The effect of fire breaks could be included in our model by using a map to reduce the local probability of burning.

The tentative time line calls for an initial version of the fire submodel to be implemented and parameterized by the end of March 2004. The necessary linkages between a fire submodel and the vegetation succession model have already been implemented and tested, so available output from the vegetation succession model should follow soon after completion of the fire submodel.

References

Beckage, B., W. J. Platt, *et al.* (2003). Influence of the El Niño Souther-Oscillation on Fire Regimes in the Florida Everglades. *Ecology*, 1:1–2.

Lockwood, J. L., M. S. Ross, *et al.* (2003). Smoke on the Water: the Interplay of Fire and Water Flow on Everglades Restoration. *Frontiers in Ecology and the Environment*, 1:462–468.

Main, M. B. & M. J. Barry (2003). Influence of Season of Fire on Flowering of Wet Prairie Grasses in South Florida, USA. *Wetlands*, 22:430–434.

Pearlstine, L. S., S. Smith, *et al.* (2002). Assessing State-Wide Biodiversity in the Florida Gap Analysis Project. *Journal of Environmental Management*, 66:127–144.

Taylor, D. L. (1981). Fire History and Fire Recoreds for Everglades National Park, 1948-1979. Technical Report T-619, South Florida Research Center.

The Nature Conservancy (1997). *International Classification of Ecological Communities, Terrestrial Vegetation of the Southeastern United States*. The Nature Conservancy, Chapel Hill, NC.

Wetzel, P. R. (2001). Plant COmmunity Parameter Estimates and Documentation for the Across Trophic Level System Sumulation (ATLSS). Technical report, ATLSS.

Wetzel, P. R. (2002). Nutrient and Fire Disturbance and Model Evalutaion Documentation for the Across Trophic Level System Simulation (ATLSS). Technical report, ATLSS.

Wu, Y., F. H. Sklar, *et al.* (1996). Fire Simulations in the Everglades Landscape using parallel programming. *Ecological Modelling*, 93:113–124.

Type Index	Type Name	Group
2	Tropical Hammock	HardWood
3	Decid/Trop. Swamp Forest	HardWood
4	Xeric/Mesic Live Oak	HardWood
5	Live Oak	HardWood
6	Bay/Gum/Cypress	HardWood
13	S FL Slash Pine Forest	Pine
16	Mesic/Hydric Forest	HardWood
17	Swamp Forest CG	HardWood
18	Cypress Forest CG	HardWood
25	SlashPine Woodland	Pine
28	Brd Lvd/Mixed Evergreeen Shrub	Pine
29	Dry Praire	Grass
30	Gallberry/Palmetto CG	Shrub
37	Decid. Shrub	Shrub
39	Graminoid Dry Prairie EC	Grass
42	Gramminoid March CG	Grass
43	Cladium	Grass
44	Eleocharis	Grass
45	Muhly Grass Marsh	Grass
46	Typha	Grass
52	Sparsely Wooded Wet Prairie CG	Grass
53	Dwarf Cypress Savanna	Grass
56	Forb Emergent Marsh	Flooded
57	Floating Leaved Veg.	Flooded

Table 1: **FGAP v6.6 types. The first column contains the indicies use in the FGAP map to identify each vegetation type. The second column contains the type names from the United States National Vegetation Classification System. The third column contains the group to which each vegetation type is assigned. The placement of the Dwarf Cypress Savanna vegetation type into the Grass group was suggested by Paul Wetzel (personal communication).**

Figure 1: The ATLSS modeling region is shown outlined in red. Black lines show the bounderies of various management areas with South Florida such as the ENP and the WCA's.

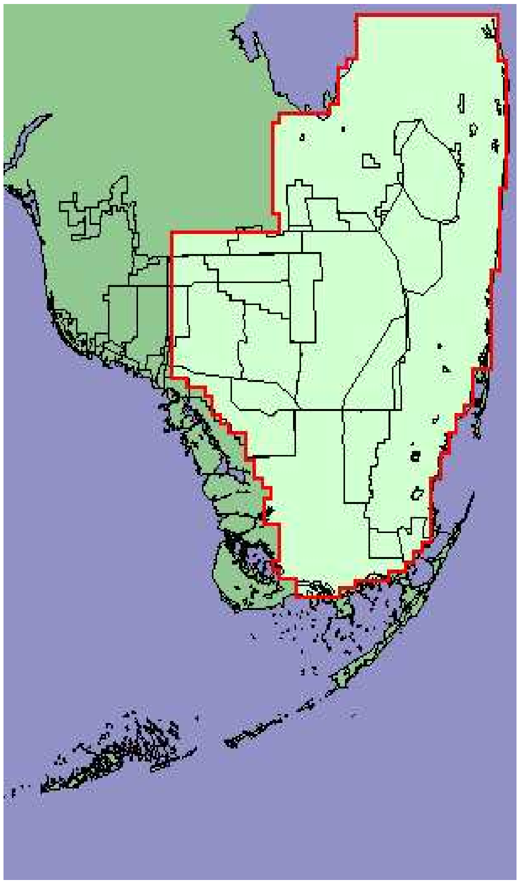

Figure 2: The proposed relationship between time since last fire and probability of burning.

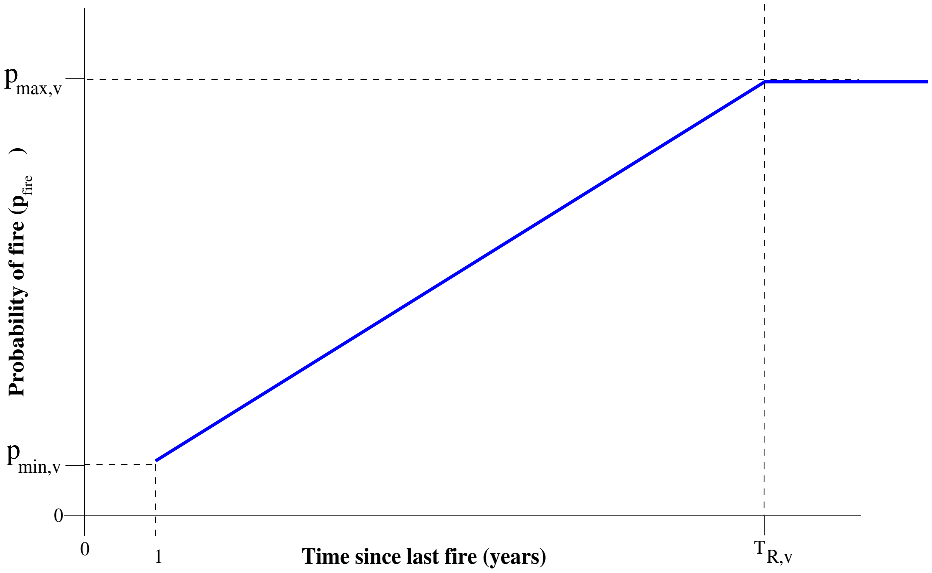

Figure 3: The proposed relationship between hydroperiod (hp) and probability of burning.