Simulating the occurrence of hot pixels along the Amazon forest fringe

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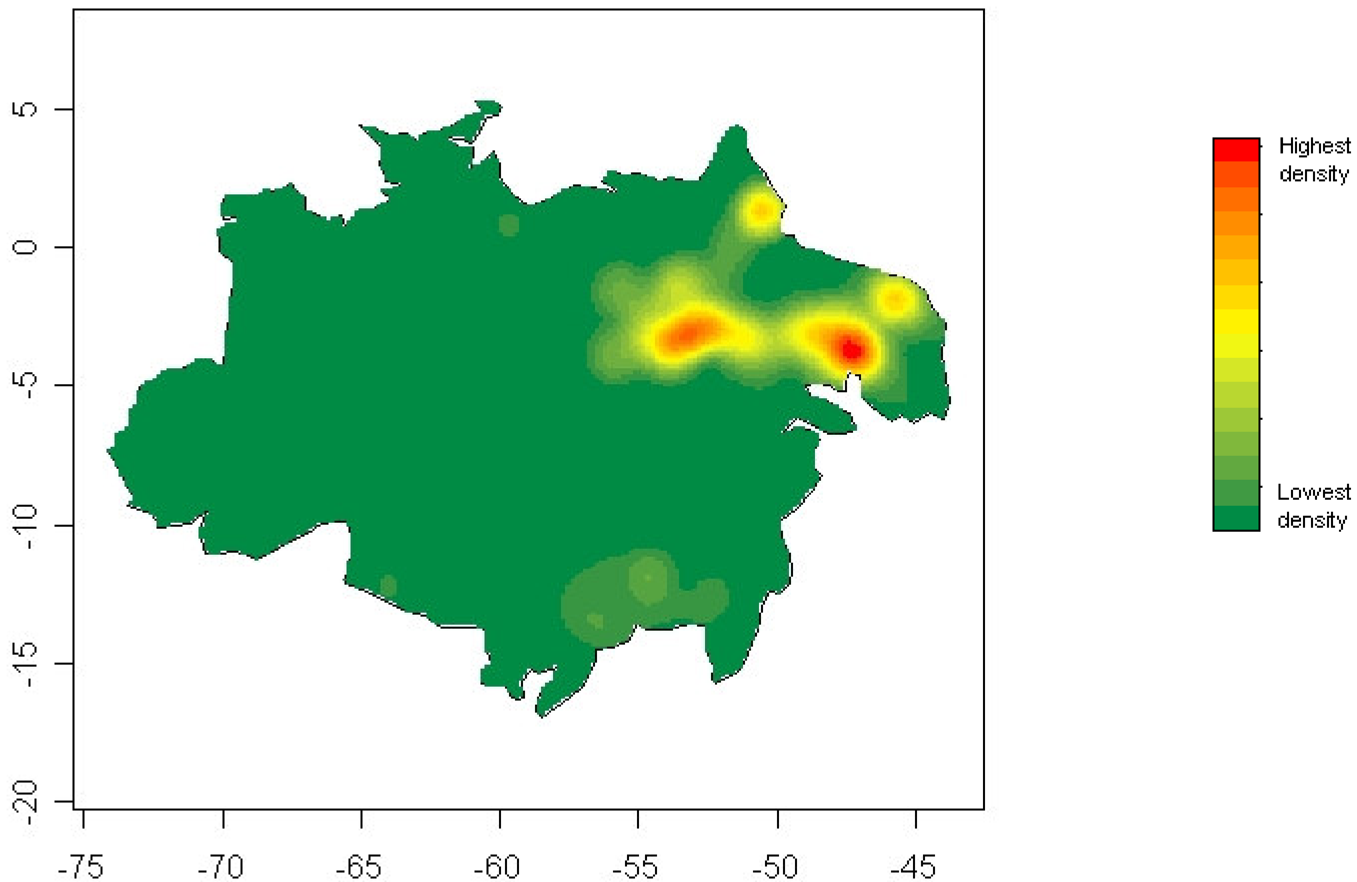
Motivation

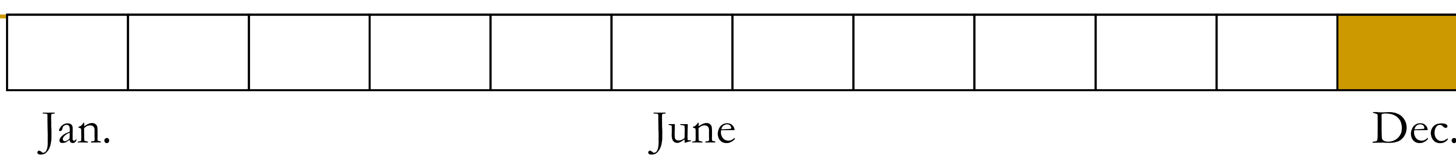
Why study fire models?

- Forest Fires are a major contribution to global warming. (FEARNSIDE, 2002);
- Reduce forest ability to retain water, exacerbating flooding, erosion and seasonal water shortages. As a consequence, it increases forest flammability (Cochrane et al., 2003); and
- Lead the Forest remnants to a cycle of self-destruction (Nepstad et al., 1998)
- Aerosols released by forest fires disrupt normal hydrological processes and reduce rainfall;
- Affects human health;

Hot pixels distribution over space-time



Kernel Density Estimate, 2003



How can we model this dynamical phenomenon?

1. Spatial Modeling:

   anthropogenic and biophysical variables → Spatial Probability

2. Space-time Modeling:

   climatic variable – VPD (vapor pressure deficit) →

   Space-time Probability

3. Combining the two → A space-time probability map
4. Using this map to simulate hot pixels.

Only hot pixels within < 5 km from the forests were analyzed

Methodological steps

- Designing and calibrating the model
  - 2003 data.
- Validating the model
  - Data from 2002, 2004 and 2005.
- Conclusions.

Designing and calibrating the model

1. Spatial Probability

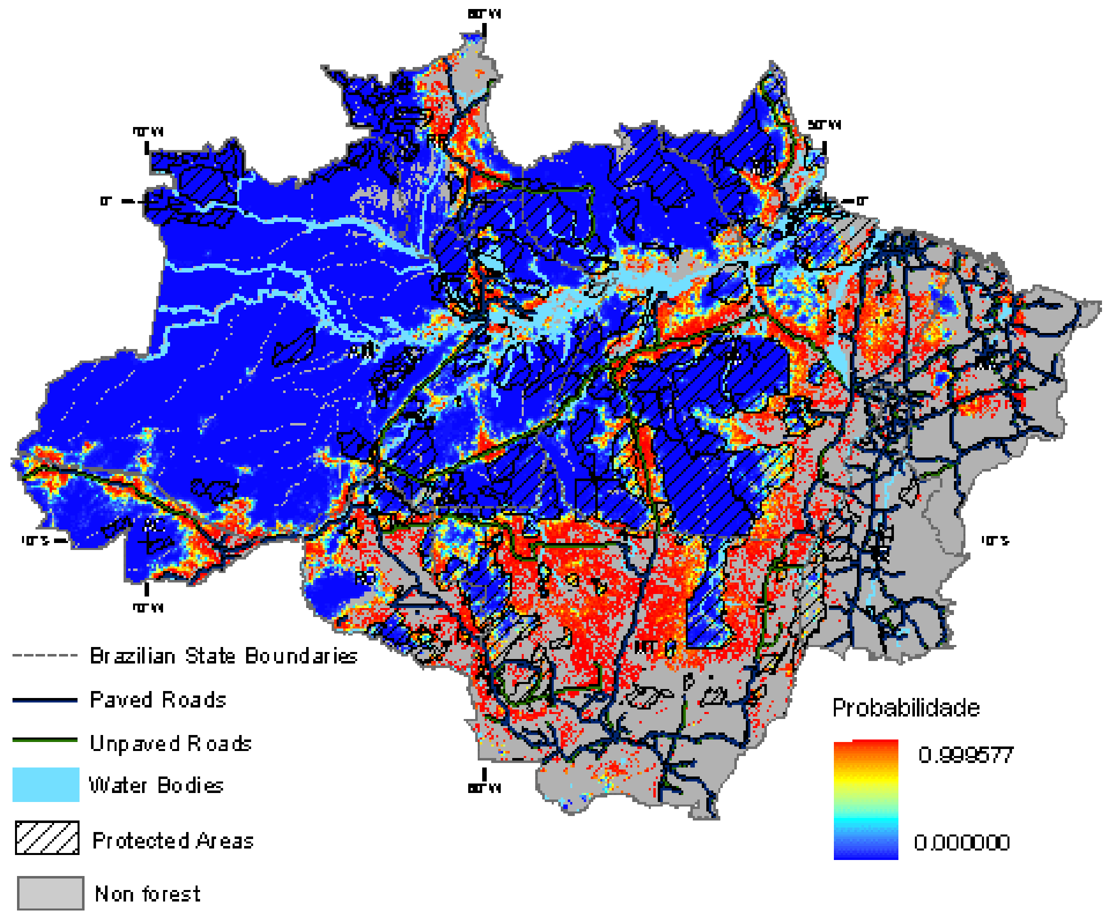
- Method: Weights of Evidence.
- Selected variables:
  - Distance to deforested area or to “cerrado”;
  - Distance to all roads;
  - Distance to the main roads;
  - Distance to the towns;
  - Altitude;
  - Protected areas (indigenous reserves, parks, etc.)
- Annual map

Weights of Evidence

- Based on the Bayes Theorem;
- Computes the probability of fire given the presence of each one of the variables.
- It uses the log(odds), called as W^+, of these probabilities on a logistic regression, which gives the spatial probability map.

$$P(hot\_pixel \mid protected\_areas \cap dist\_roads \cap N) = \frac{e^{\sum_{i=1}^{n} W^+}}{1 + e^{\sum_{i=1}^{n} W^+}}$$

Probability map output from Weights of Evidence Analysis for 2003



2. Space-time probability

- Method: Logistic regression.
- Variable:
  - VPD – monthly average of the vapor pressure deficit;
- Monthly maps

VPD is the difference (**deficit**) between the amount of **moisture** in the air and how much moisture the air can hold when it is **saturated**. **VPD** calculation is an improvement over relative humidity (RH) measurement alone, because **VPD** takes into account the effect of temperature on the water holding capacity of the air. (Preng and Ling)

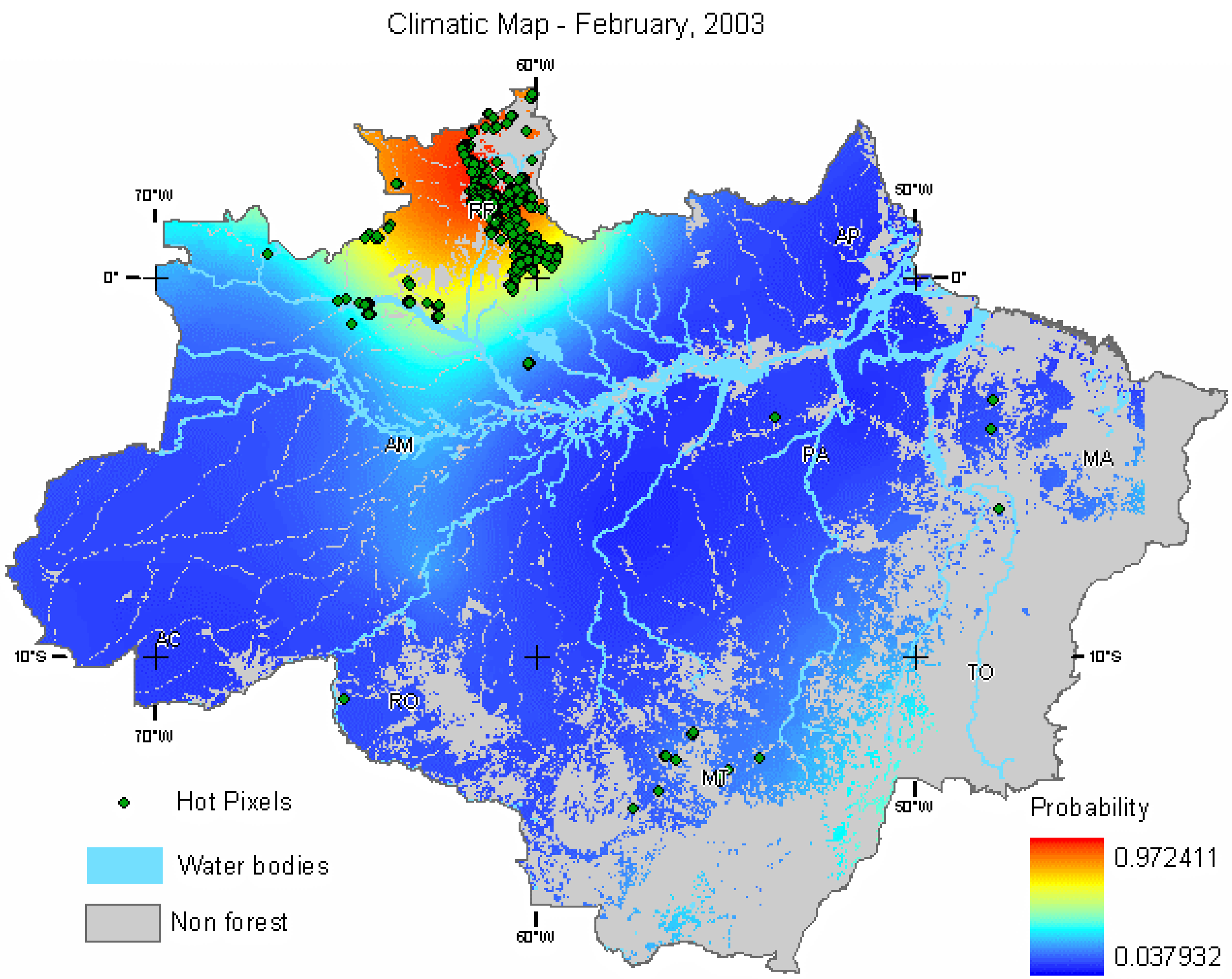
Logistic Regression

1. For each month of 2003, a logistic regression model was developed.
2. Finally, we chose the average of β_0 and β_1 from 2003 monthly models to establish an equation for all months and all years

Why adopt the average coefficients and not one regression for each month?

To build a general model that could fit well over seasonal variation.

Climatic Probability map



3. Combining the two probability maps

Final Probability map

=

α (Spatial Prob.) + (1- α) (Space-time Prob.),

where α is a constant that depends on the month of the year.

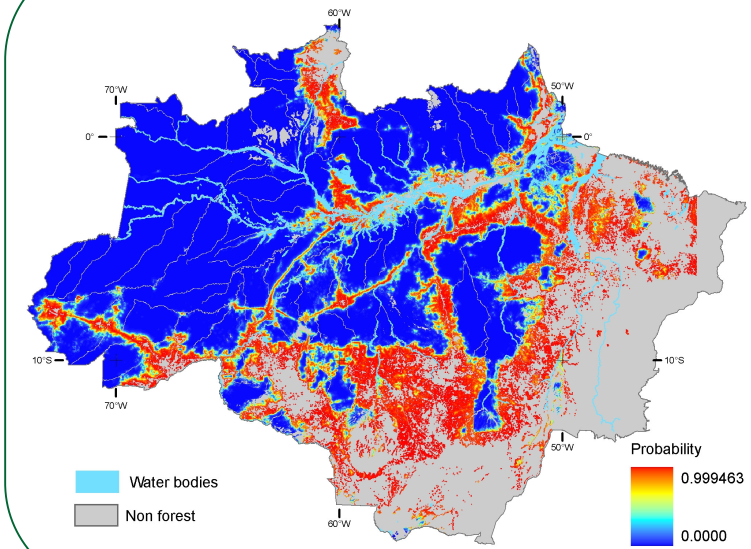
months	α
February and March	0.2
other months	0.4

Given a high VPD value, hot pixels will concentrate in area of higher anthropogenic activity.

Example: August, 2004

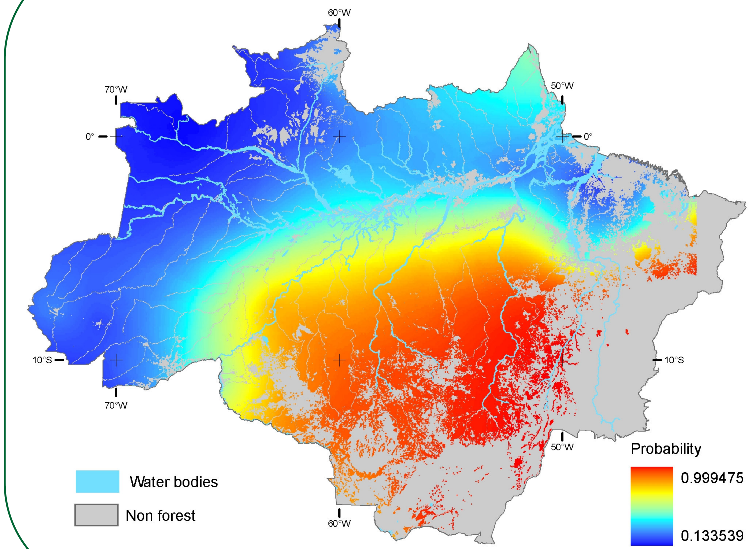
0.4 *

Spatial Probability (1st step) - 2004



+0.6 *

Space-time Probability (2nd step) - August, 2004



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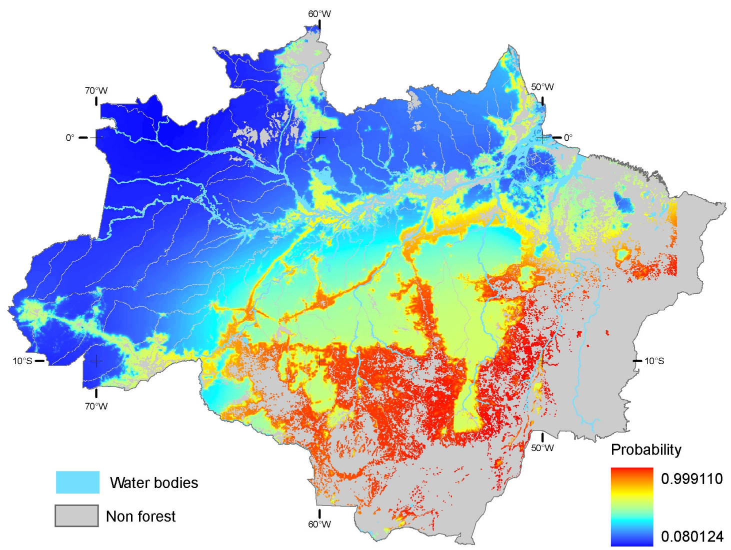
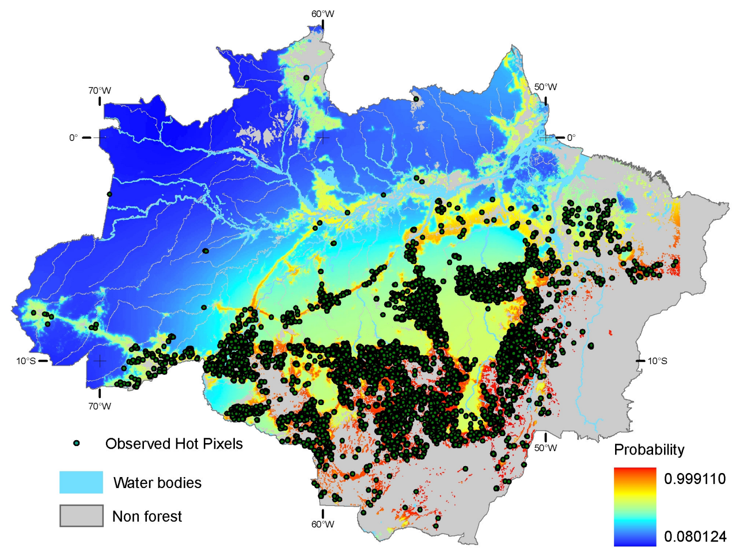
Final Probability (3rd step) - August, 2004



Final Probability (3rd step) and observed hot pixels - August, 2004



4. Simulating the hot pixels

There is a hot pixel if:

$$\{Rand(dist)\} - \gamma < \text{Final Prob} < \{rand(dist)\} + \gamma,$$

where:

- rand(dist) = random number from the "dist" probability;
- γ = constant

Furthermore, x% of the cells are allocated as null cells.

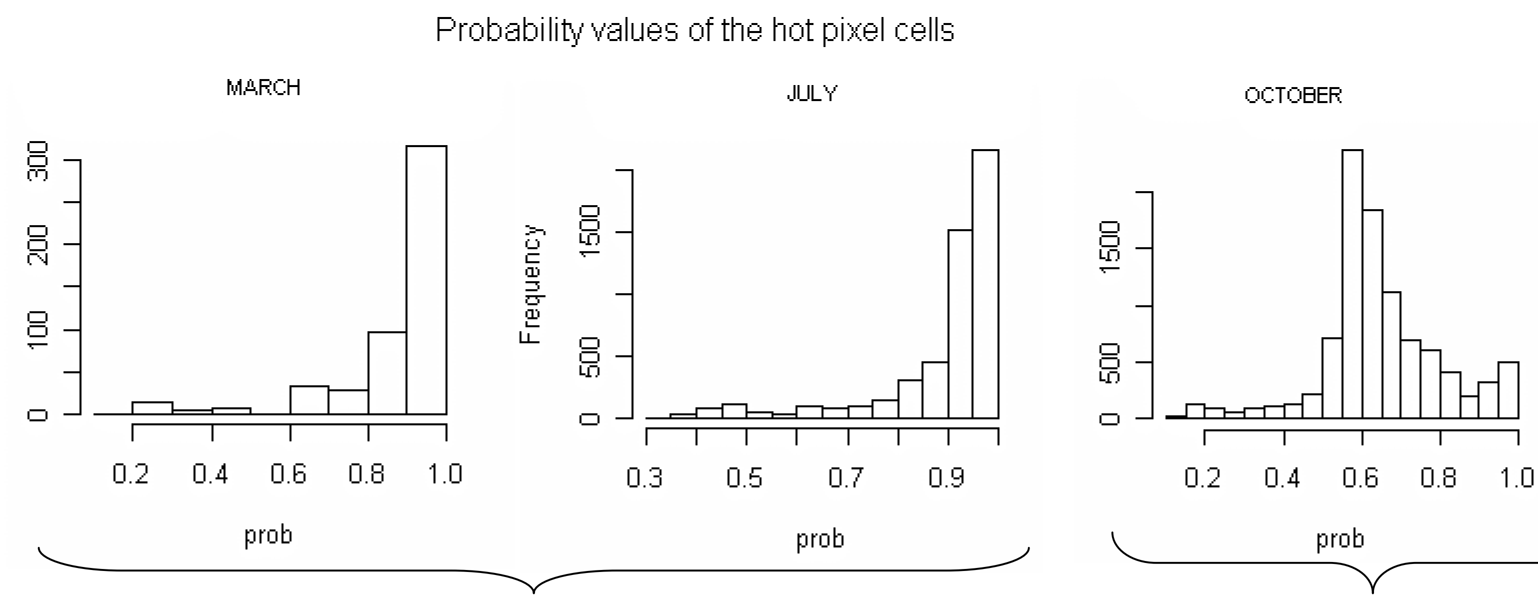
Parameter	February - March	May - September	October - December, January, April
γ	0.05	0.1	0.4
x	90%	85%	90%
dist	Beta(0.985, 0.1) truncada em 0.5	Beta(0.985, 0.1) truncada em 0.5	Weibull(13,0.6)

Control the number of hot pixels

Control the spatial distribution

How did we choose the distribution "dist"?

- Histogram of the probabilities values of the hot pixel cells.



Beta(0.985, 0.1).
truncated in 0.5, to avoid noise on the map

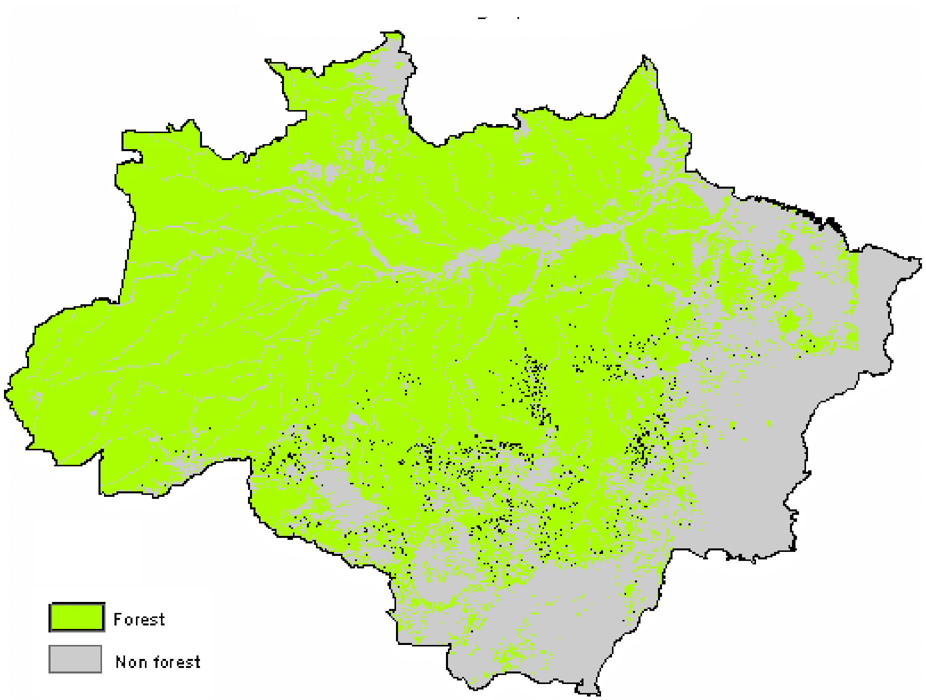
Weibull(13,0.6)

Model OK! Now, we have to test it.

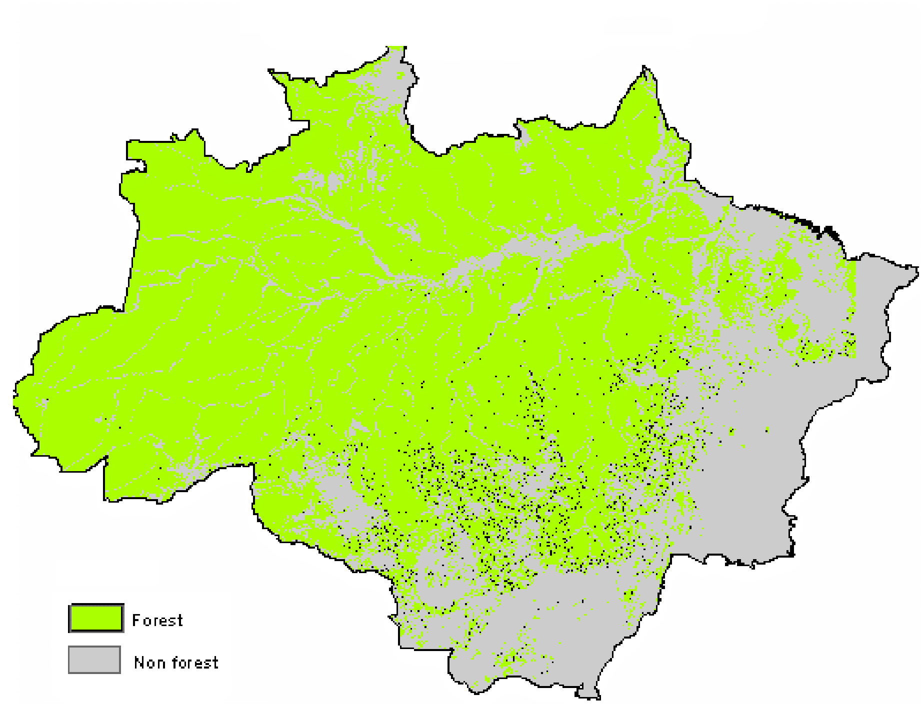
…

Verifying the model fitness

Observed hot pixels – August, 2004



Simulated hot pixels – August, 2004

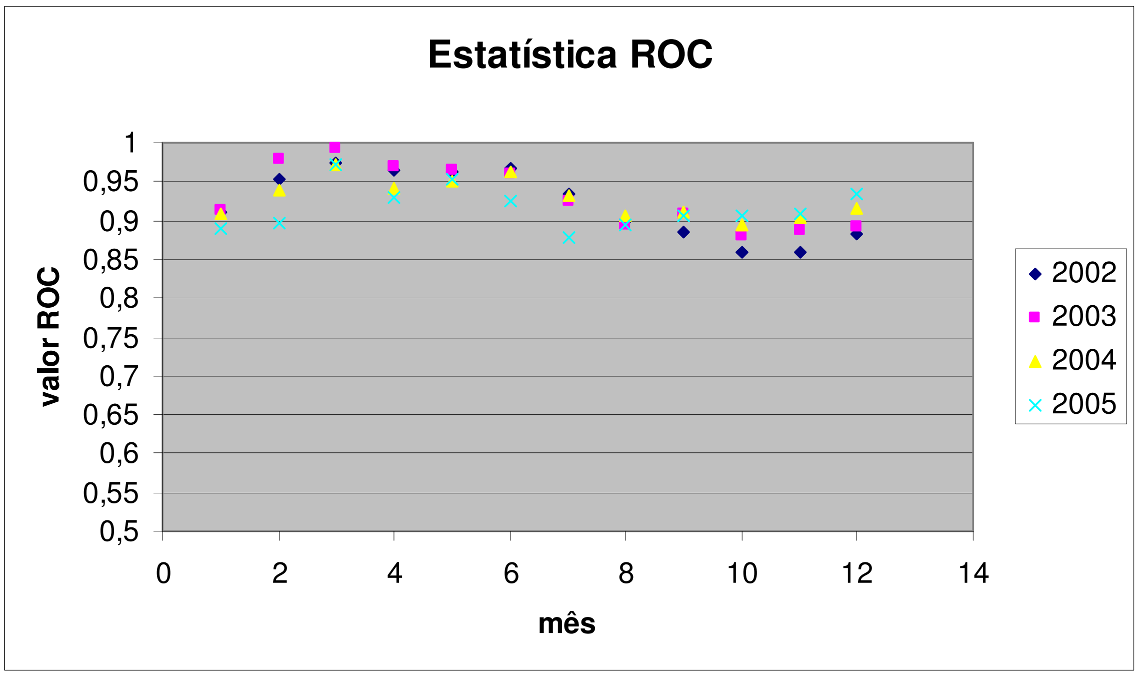


Verifying the fitness of the model

1. ROC statistic;
2. Fuzzy Method;
3. Plot of number of observed hot pixel vs. number of simulated hot pixels.

1. Estatística ROC

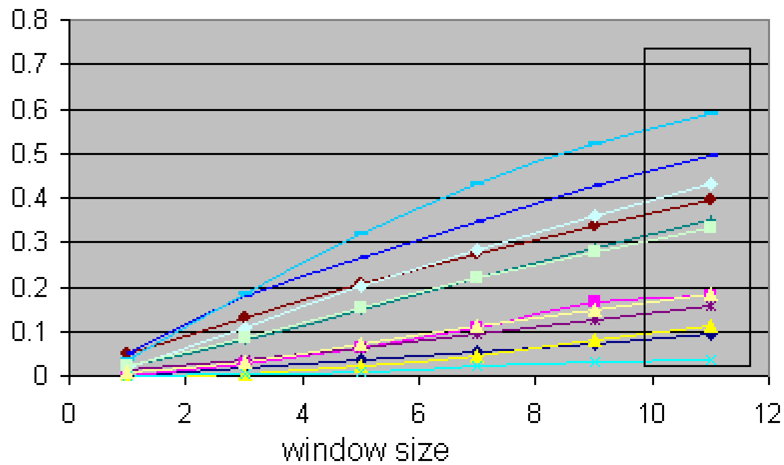
- A ROC value of 1 indicates that there is perfect spatial agreement between the probability map and the observed hot pixels. A ROC value of 0.5 would be expected if there were no spatial agreement.



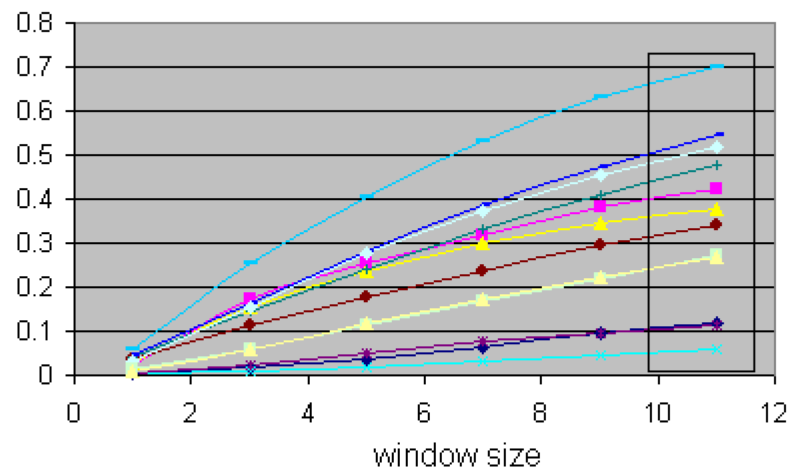
2. Fuzzy similarity

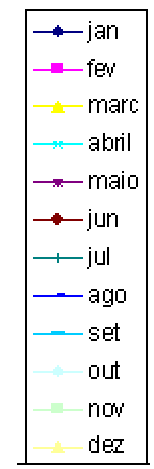
Percentage of right classification considering the different sizes of window

2002



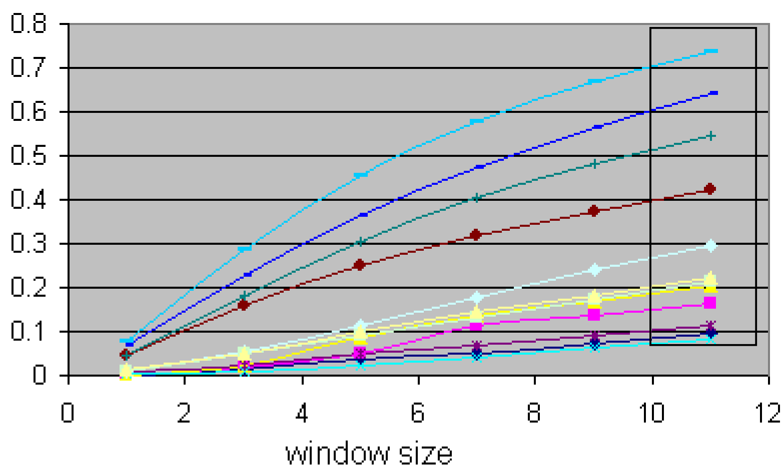
2003



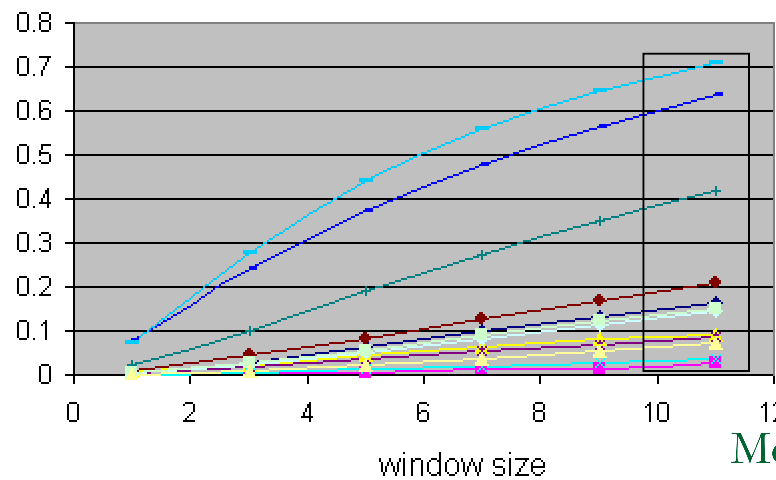


Match of 60~70% within a 10 km x 10 km resolution for the dry months

2004

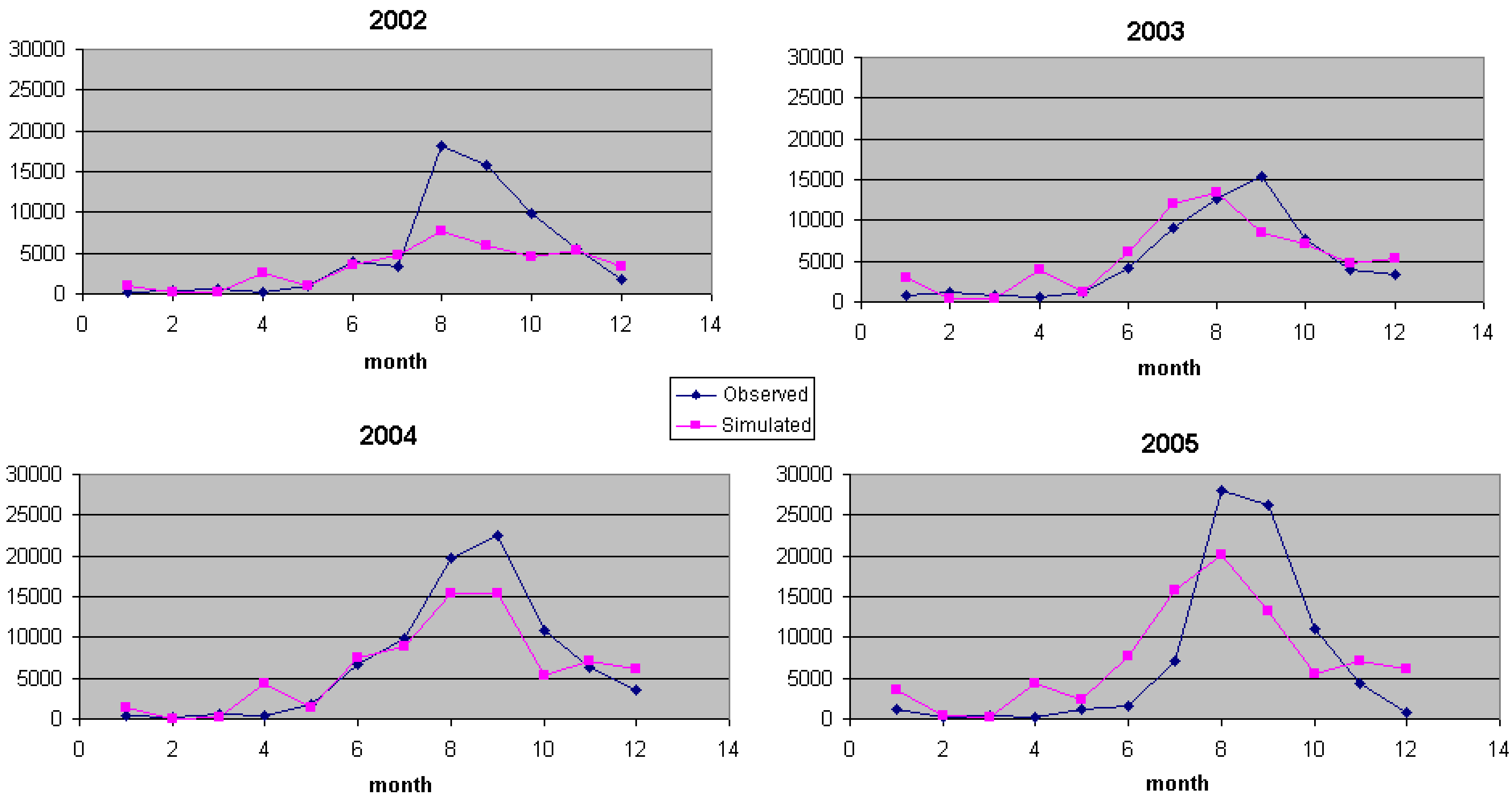


2005



Model fitness

3. Number of Observed and simulated hot pixels



Considering the whole year, the model predicted, in average, 5% more or less than the observed.

Conclusions

- The ROC statistic showed that the probability map used in the simulation is well fitted, so it can be really useful in helping to control the fire in the Amazon forest fringe.
- Anthropogenic variables, such as distance to town centers, protected areas and so on, play a important role when we are talking about fire in the Amazon, where fires are NOT just natural hazards.
- Although the model still has to be improved in the number of pixels per month, the number of simulated hot pixels per year is very close to the real one.
- Next step: include the spread component into the model.

Obrigada/Thank you

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