RANDOM SET MODELING OF FOREST FIRES

Jeff Picka

UNBF

Two central questions in forest fire modeling

1. How can the inherent unpredictability of a fire be modeled?

2. How can the fit of a forest fire prediction model be assessed?

Motivating questions

1. If a forest fire model makes a single prediction for any one fire,
   is it one of the many predictions that could be made
   or an average of all predictions consistent with observed conditions?

2. If a model makes a single prediction of a known fire,
   when is that prediction only trivially different from what was observed?

A strategy for answering these questions

- Use stochastic models for the fires
  to generate estimated probability maps and distributions.

- Use statistical inference to identify differences between model predictions and reality.

- Use models which are useful
  in specific prediction problems,
  but which may be wrong in other respects.

Why use stochastic models?

To model variability arising from:

- Errors in measurement
  of boundary and initial conditions
- Sensitivity of combustion processes to changes
  in initial and boundary conditions
- Inability to construct a deterministic model
  which produces a unique prediction
  based on observed initial and boundary conditions

Some definitions

Fire sequence the sequence of burn regions over time in a single fire

Stochastic model a collection of stochastic processes whose realizations are fire sequences

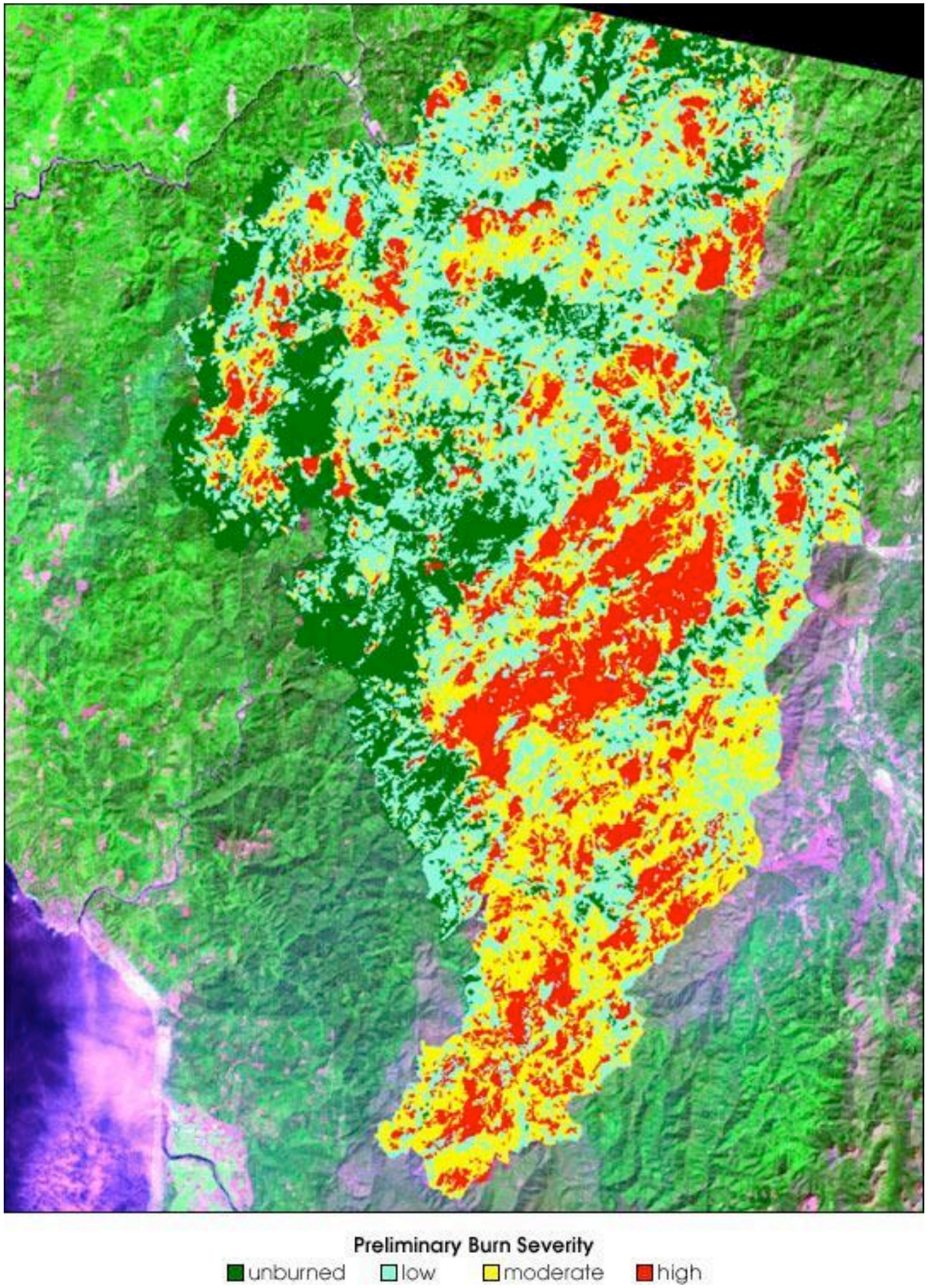
Parameters numbers which index the processes within the stochastic model

Fitted stochastic model a fire-sequence-generating process whose parameters are chosen to match the data

Realization a single fire sequence simulated by a fitted stochastic model

Statistic any number calculated from a burn region or a fire sequence (not necessarily an average)

Biscuit Fire of 2002, Oregon USA



(Credit: Image courtesy Keith Lannom, Remote Sensing Applications Center, USDA Forest Service via sciencedaily.com)

Using a fitted stochastic model

The goal: to predict loss of product over the next 12 hours.

1. Generate many independent realizations from the fitted model
   based on the burn area now and boundary conditions.

2. For each realization, calculate losses
   based on are region burned over next 12 hours.

3. Present the losses as a histogram
   and summarize them using fitted densities and statistics.

4. Extreme realizations could be studied
   to see if they have any unusual features.

The goal: to determine which parts of a forest will burn.

1. Generate many independent realizations from the fitted model based on the burn area now and boundary conditions.

2. At each point, estimate the burn probability with the fraction of realizations which cover that point.

3. Create a contour map based on the estimated burn probabilities.

Fires as multiscale physical processes

- Macroscale [> 1 km^2]: large forest fires
- Mesoscale [10-100 m^2]: initial stages of fires, test burns
- Microscale [1mm-10m]: individual combusting objects

Properties of a ‘good’ multiscale model

- Microscale elements interact in simple ways.
- Macroscale behaviour is largely independent of the details of microscale behaviour.
- Macroscale behaviour can be summarized by a small number of known and observable variables.
- The macroscale variables are essentially deterministic and any variation in their values can be explained by measurement error.
- Some form of mathematical model exists that completely summarizes all important interactions among the macroscale variables.

Examples of 'good' multiscale models

- the ideal gas model
- Navier-Stokes models for laminar fluid flow and heat conduction in Newtonian fluids

Canadian Forest Service

Forest fires .vs. ‘good’ multiscale models

- Microscale events are too difficult to model on account of the complexities of convection and the extreme interdependence among combustion events

- Macroscale variables are defined over too small an area to annihilate the variability arising from microscale events

- There is no clearly established set of macroscopic variables which reduce the description of the fire to a small collection of numbers, and there is no established mathematical model to relate those variables.

Constituents of an ideal stochastic model

- A method for generating fire sequences that are consistent with the initial and boundary conditions.
- A probability density which assigns to each fire sequence a measure of how likely that sequence is to occur, given the conditions.

Obstacles to ideal modeling

- Any model will produce only approximations of real fire sequences, and there is no simple theory to provide these approximations.

- The probability density for fire sequences is unlikely to be uniform, and there is no theory to suggest what it should be.

A more realistic goal

Do not initially attempt to produce fire sequences
that are as close to real fires as possible,
but instead seek to produce fire sequences
so that statistics generated from them
have the right distributions for solving prediction problems.

As models are found that can predict well in specific cases,
these can be improved so that the paths become more realistic.

Issues with model fitting

Physical Parameters

- parameters which are set by physical arguments
- values are estimated from physical experiments
- generally associated with physical basis of path models

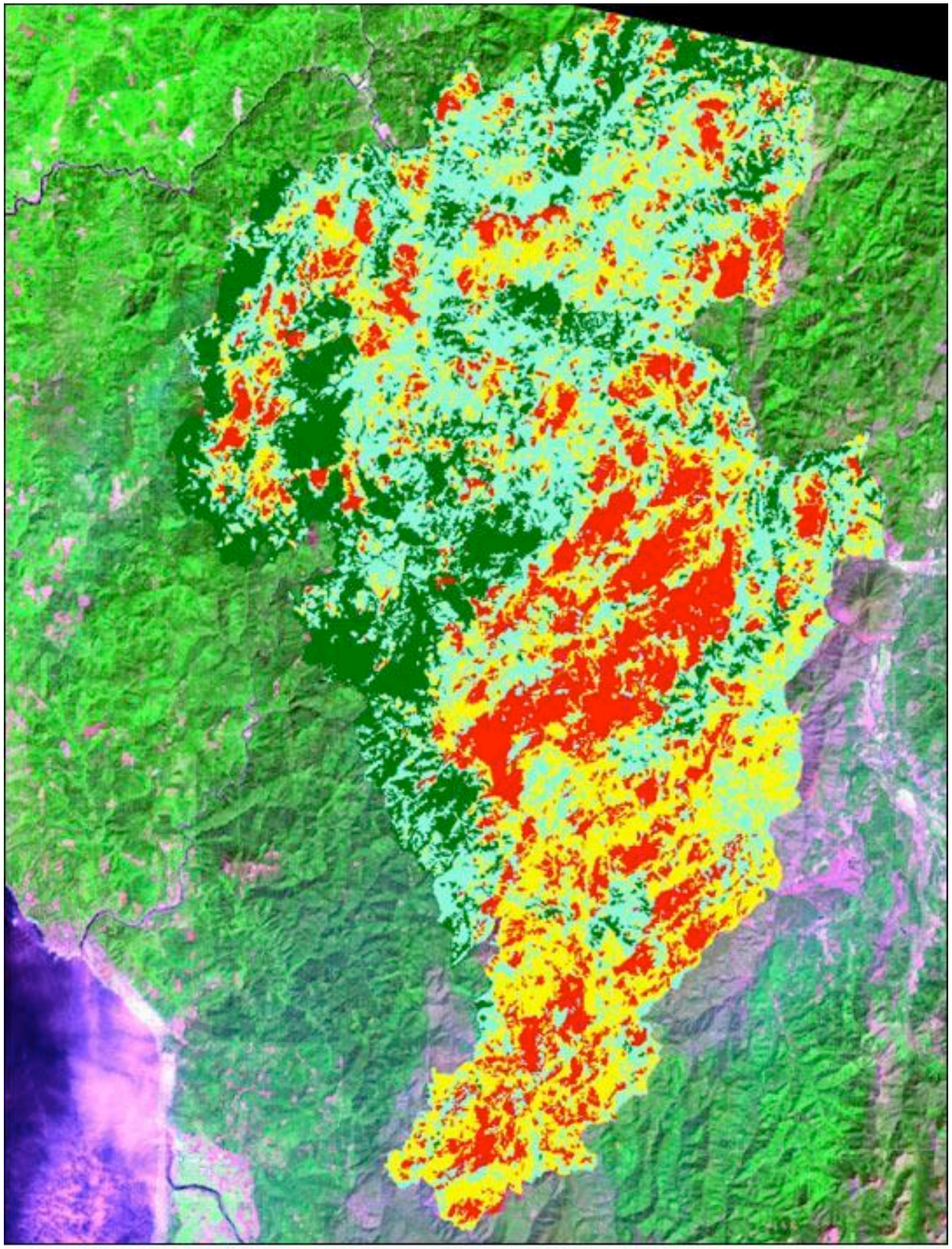
Calibration parameters

- all other parameters
- values are estimated by means of the method of moments
- associated with the distribution of paths
  and with adjustments necessary to make the path models work

Fitting of calibration parameters

- Very few parameters relative to the amount of information required to describe the fire sequence

- Statistics used to fit the calibration parameters are not very powerful
  (i.e. they cannot clearly distinguish
  between realizations from different models)



Preliminary Burn Severity

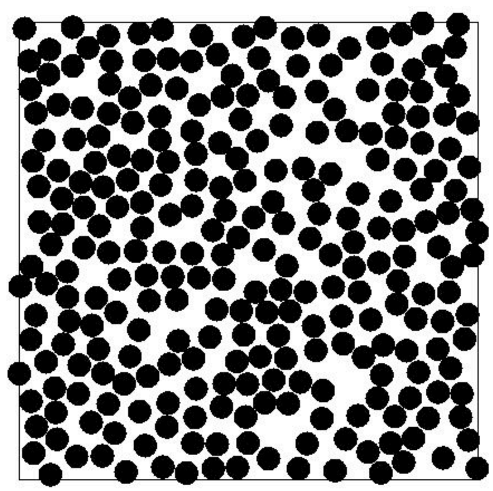
unburned   low   moderate   high

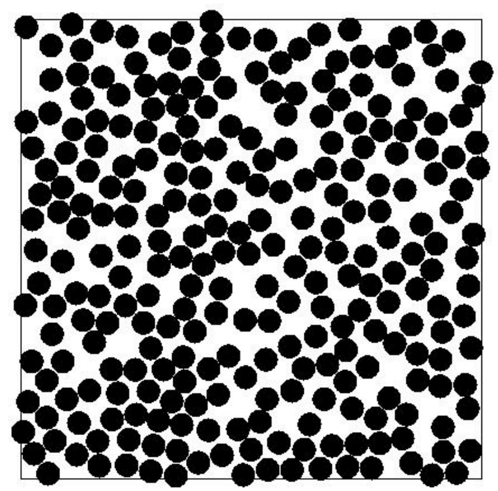
Once the model has been fitted…

- the fitted model may have only a superficial resemblance to nature
- it is necessary to assess the fit of every fitted model by objective means

A standard method of assessing fit

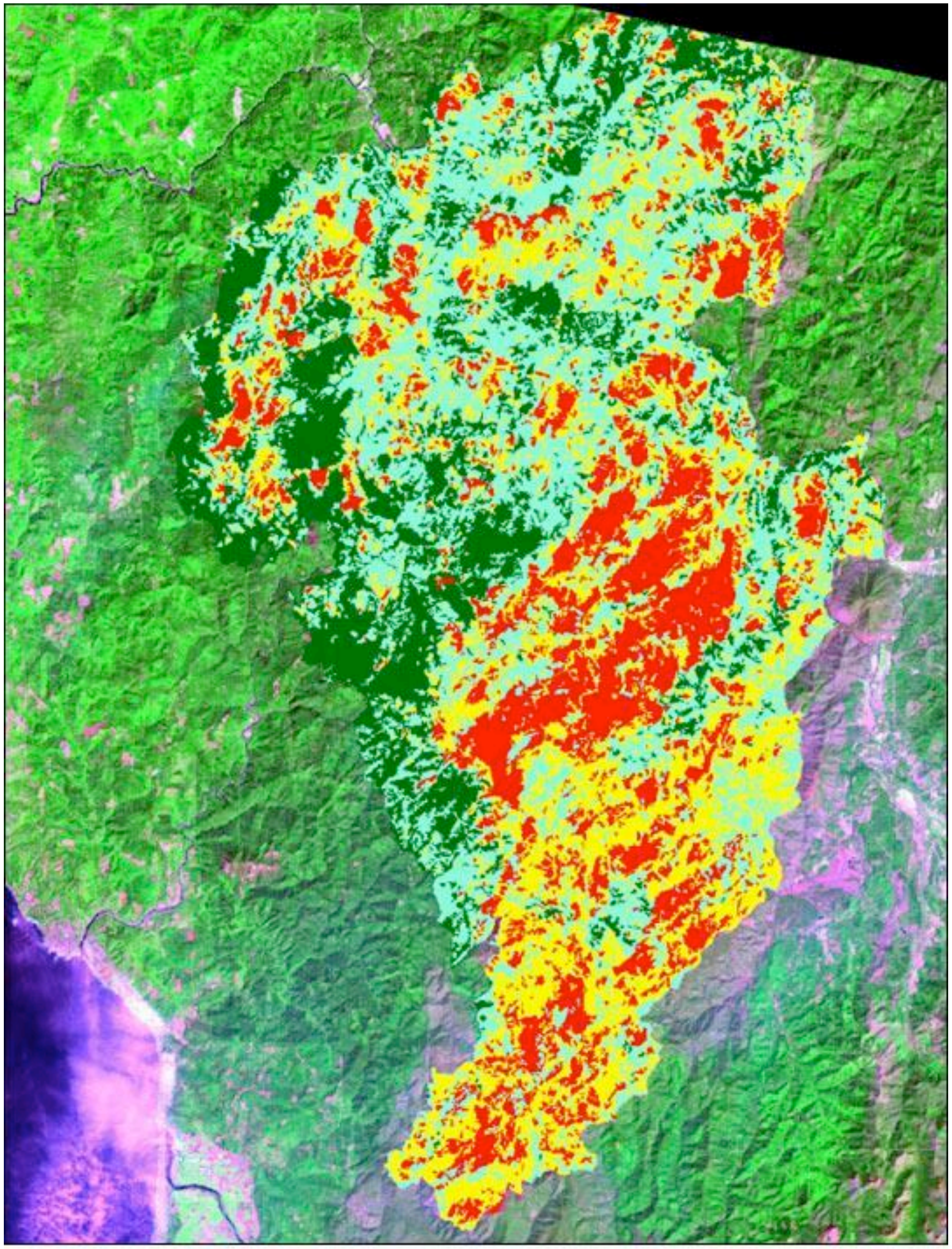
- Ask an expert to see if the prediction looks right.





Problems with expert assessment

- Expert may not be able to be completely objective.
- Expert may not be able to explain the basis of the assessment.
- The human mind may be completely unable to see how the model is failing.



Preliminary Burn Severity

unburned low moderate high

Strongly fitting models

- The joint distribution of any subset of descriptive variables for realizations of the model and the data are identical.
  - No statistical test can distinguish realizations of the model from the data.
  - The model is extremely robust and can be used to predict counterintuitive phenomena.
- Any variance of the variables is so small that it is dwarfed by measurement error.
  - Improved measurement technology guarantees improved predictions.

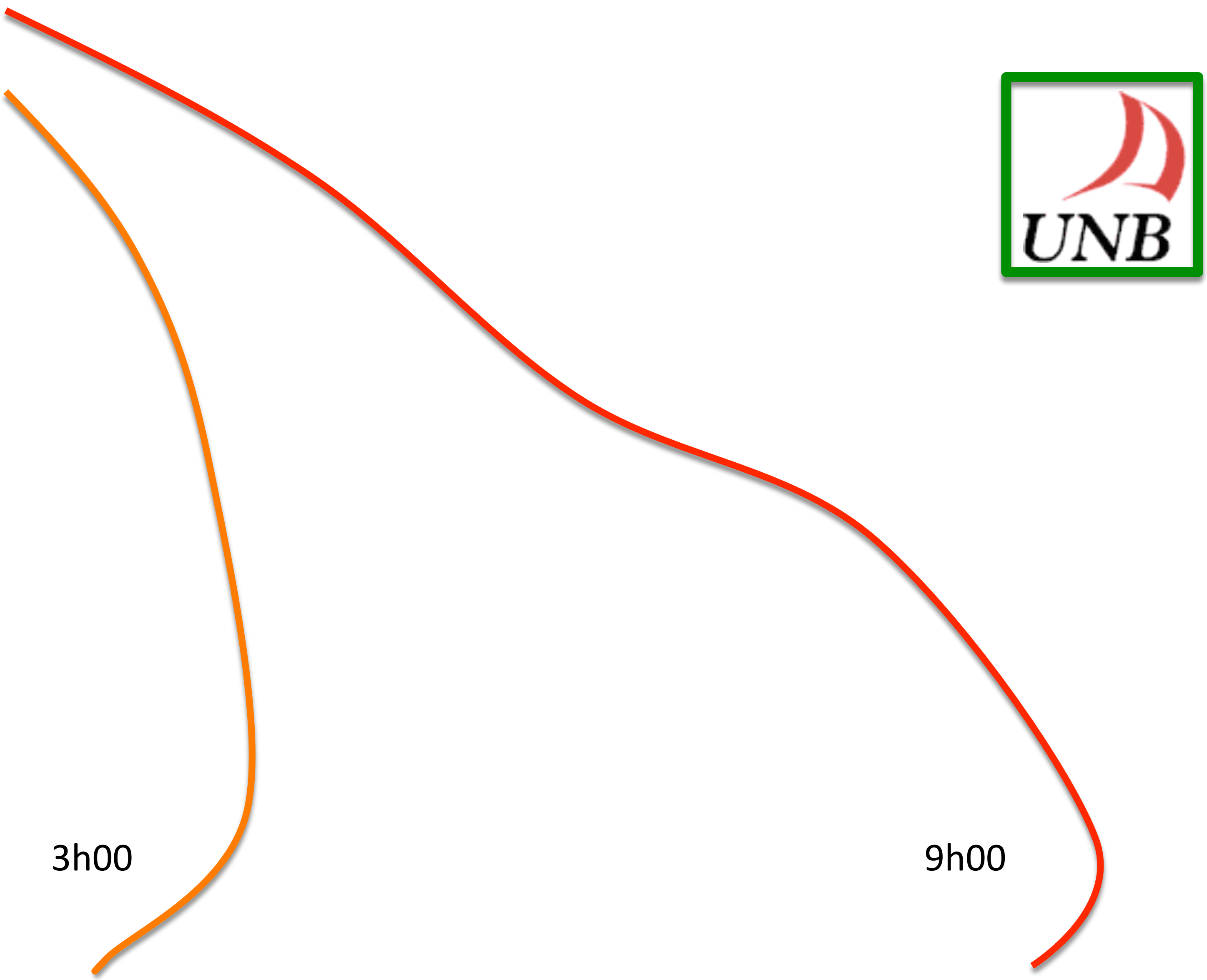
Strategy for model assessment

- restrict attention to prediction of a single aspect of fire evolution
  (e.g. will a village 2 miles NE of here burn tomorrow?)

- find a small set of prediction statistics which provide a comprehensive description of the aspect of interest

- find descriptive statistics which are strongly related to the prediction statistics and which also describe the spatial evolution of the fire in time

- use some of the descriptive statistics to fit the calibration parameters to real fires
- calculate the remaining descriptive statistics for a real fire and for many realizations from the model
- carry out a multivariate test to decide if there is evidence that the descriptive statistics from the data are inconsistent with those from the model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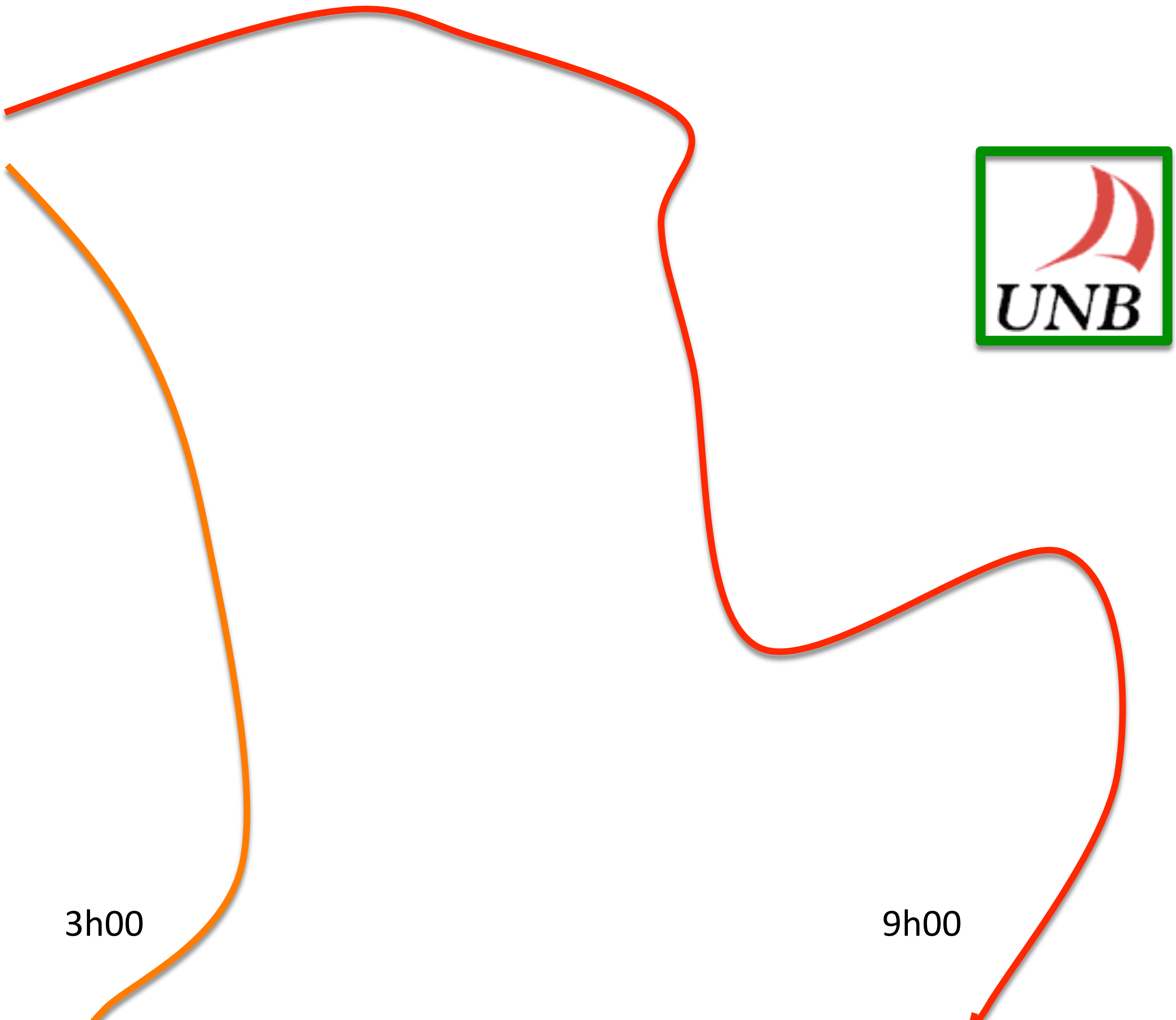
3h00
9h00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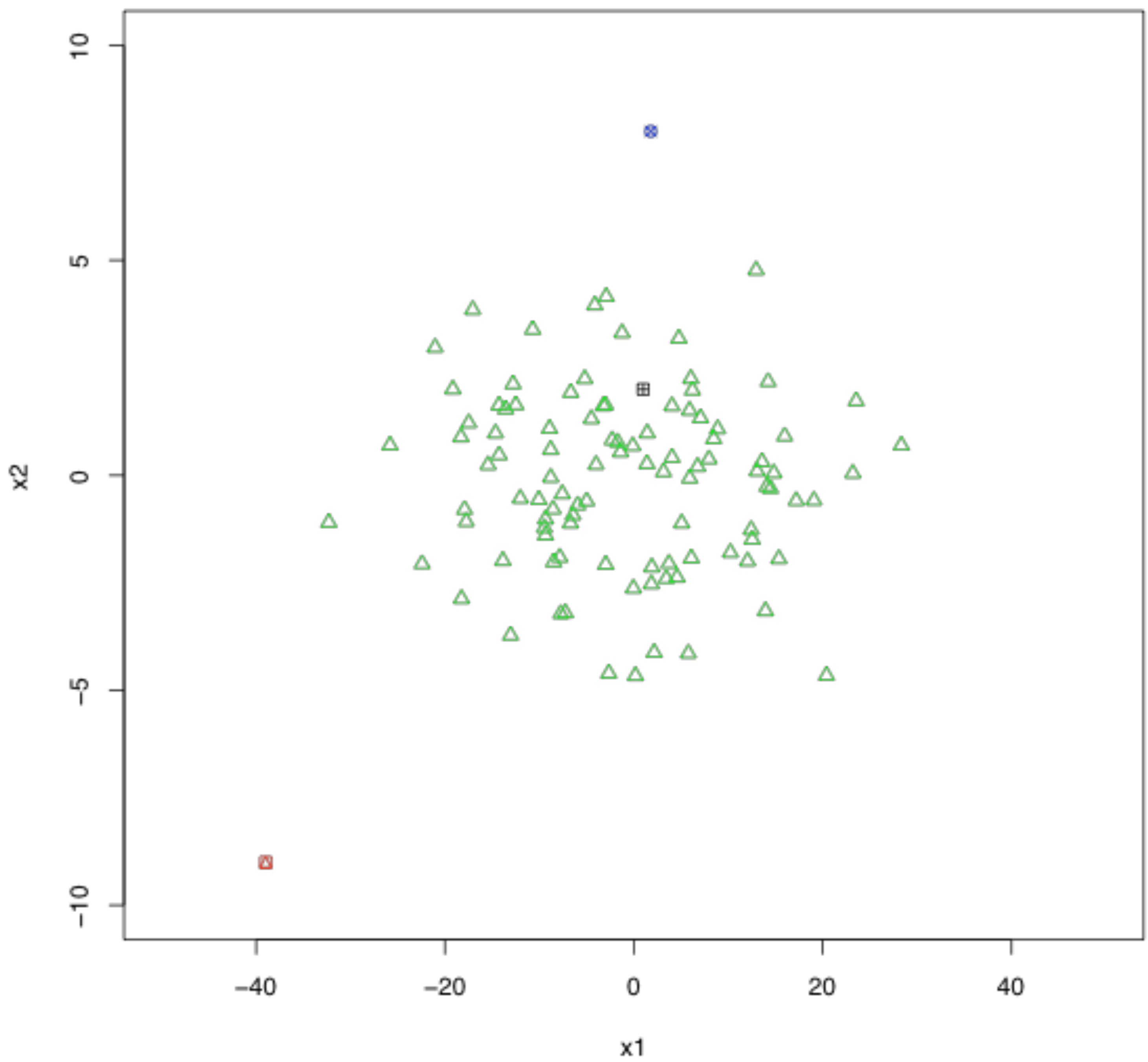

10
5
0
−5
−10
x2
−40
−20
0
20
40
x1

Statistical challenges

1. Identifying a good set of prediction statistics

2. Being able to construct a large library of descriptive statistics which
   - can summarize what an expert can see
   - can summarize what an expert cannot see

3. Using the statistics from the library to find descriptive statistics
   - requires much physical and simulation-based experimentation

4. Once the descriptive statistics have been found, use multivariate methods to determine which statistics indicate problems with the model

How statistical assessment of fit can fail

Type I error

The observed fire is atypical of fires that occur given the observed initial and boundary conditions.

Result: false evidence against a good model.

Type II error

The statistics that are required to clearly show how the model differs from the data have not yet been found.

Result: continued use of a model which is wrong.

A general observation

In many physics- and engineering-based applications of multiscale modeling, stochastic models must be used in order to compensate for our inability to summarize and accurately model macroscale phenomena.

The models that will be used will be inelegant, and will be used (to some degree) as sociologists use linear models in the same circumstances.

The fit of stochastic models will need to be assessed by statistical means and by expert examination, rather than by experts alone.

Assessments of fit will be able to provide extra information about model failure, and so will contribute to the development of more robust models.

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