How to handle uncertainty in future projections?

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http://www.helsinki.fi/science/fem/

My background

- PhD in biometry
- Bayesian inference in fisheries science
- Dynamic models
  - Alternative model structures
  - Lots of uncertain parameters
  - Interest in latent variables: the true stock size has never been observed
- Role in the FEM group
  - Supervising the use of statistical methods

Purpose and outline of the talk

- Food for thought
  - Basic principles illustrated with simple examples
- Three parts
  - Part I: There is no uncertainty
  - Part II: Correlation is good for you
  - Part III: Weight the average

Part I: There is no uncertainty

- Uncertainty does not physically exist
- Uncertainty exists in mind
- Uncertainty only exists in the context of a person
  - Subjective object by definition

- Uncertainty of a ”collective mind”
  - Scientific community
  - Panel of experts

Uncertainty about the future

- When future becomes observed, it is not the future anymore
- We can only have beliefs about the future
  - The belief can be well documented,
  - consistently updated and
  - scientifically sound
  - But it is still a (scientific) belief
    - Varies between scientists

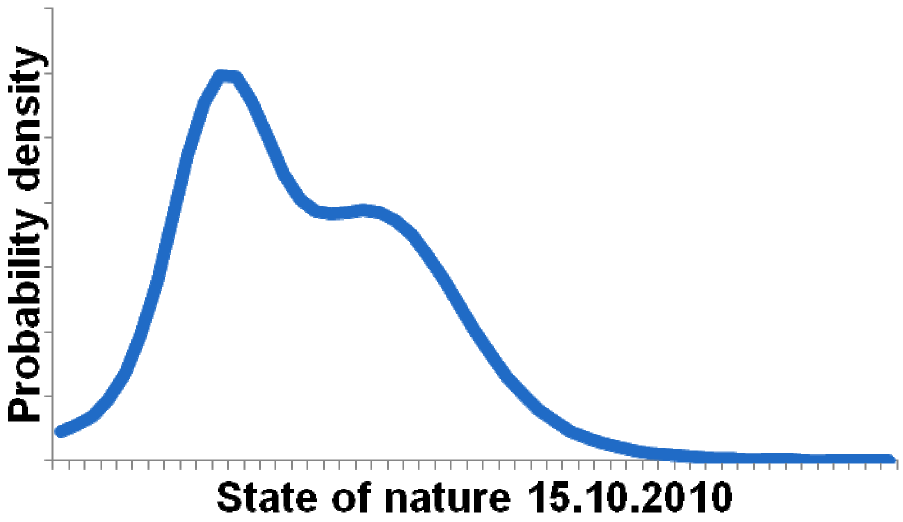
Is my uncertainty more correct than yours?

- Uncertainty is what it is: everyone is right
- Being wise afterwards: a reality check?
  - Predict the future
  - Observe what really happened
  - Compare and learn : ”calibration”
- Some statements of uncertainty fit to observations better than others
  - How to take this into account?

Sources of uncertainty: Why I am uncertain?

- Unpredictable natural variability
  - Can be reduced by better modeling
- Uncertainty about causalities
  - Alternative models
- Uncertainty about model parameters
  - More data -> less uncertainty
- Uncertainty about implementation of management actions
  - How will governments, industry and consumers react?

How to handle uncertainty systematically?

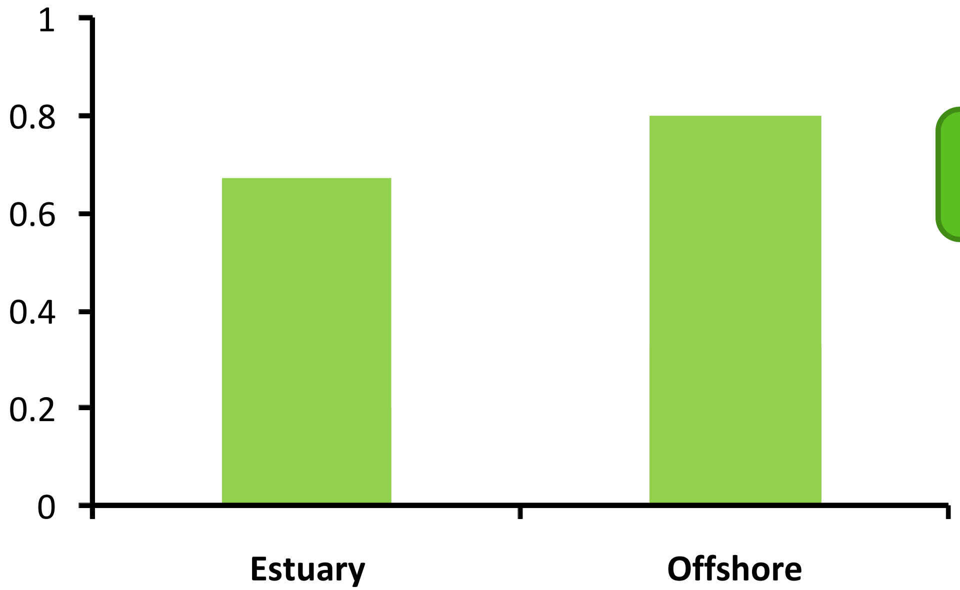


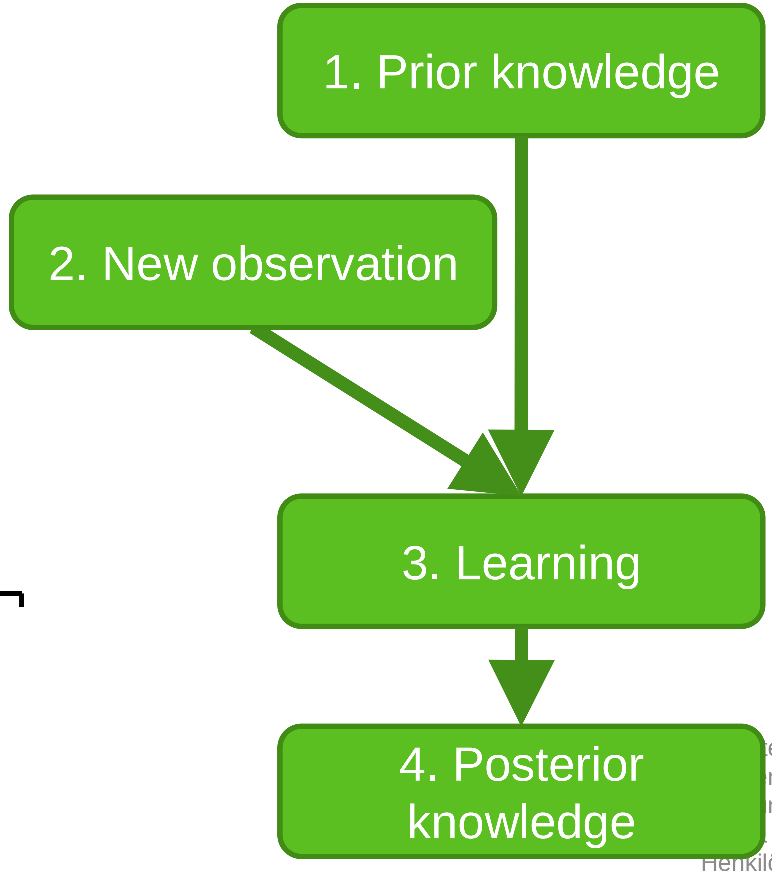
- Probability: measure of uncertainty
- Interpretation of probability:
  - Relative frequency
  - Or degree of belief?
- RF is not defined for unique events
  - 15.10. 2010 can not be repeated

Handling uncertainty : statistical inference

- Classical (frequentist) statistics
  - Uncertainty about potential data sets under a fixed hypothesis: long run relative frequencies
  - Assumes a repeatable experiment to define the concept of probability
- Bayesian statistics
  - Uncertainty about hypotheses given a fixed set of data
  - Probability : personal degree of belief
  - Data consists of facts, everything else is a matter of believing
  - Mathematical logic for handling beliefs
    - Transparent and consistent framework

Learning from experience : location of a fish school





The Bayes' rule: "Artificial intelligence"

h : hypothesis
x : observed data

Likelihood: interpretation of observed data

Prior: initial knowledge

$$P(h \mid x) = \frac{P(x \mid h) P(h)}{P(x)}$$

Posterior: updated knowledge

Normalizing constant: predictive probability of data

Learning: use posterior as prior for the next case

Part I : Summary I

- Everyone is right about their own uncertainty/beliefs
- Best we can do:
  - Systematic approach to our own uncertainty
  - Honest account of uncertainty
  - Emphasize clear communication of uncertainty
- But some people's beliefs are more consistent with data than others : higher ”expertise”

Part I : Summary II

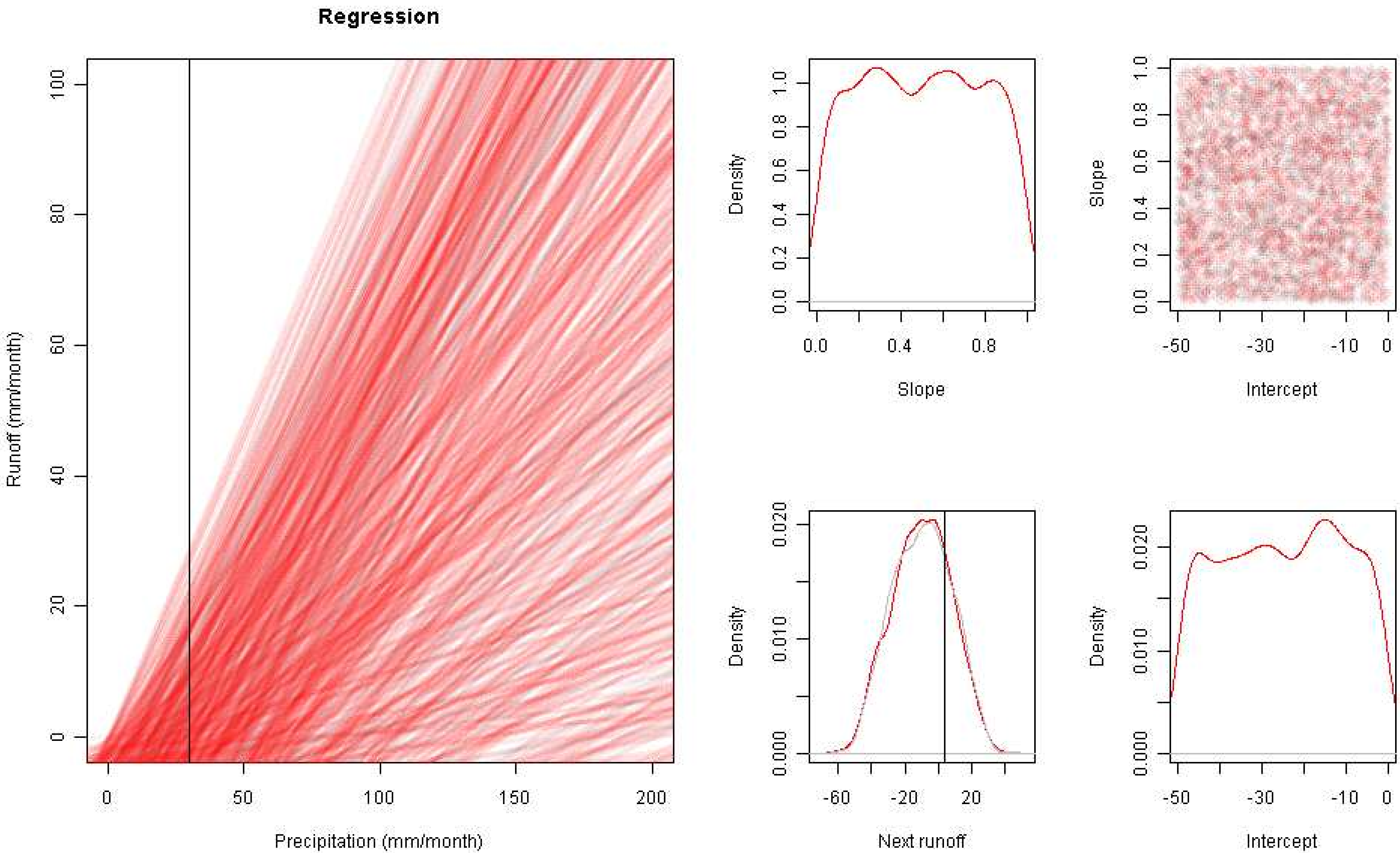
- Classical statistics :
  - No direct statements of uncertainty about past and future states of nature, no parameter/structural uncertainty
- Bayesian statistics:
  - Consistent framework for handling beliefs
  - Probability as measure of uncertainty
  - Baye’s rule for learning from data

Part II: Correlation is good for you

- ”Correlation of parameter estimates is a problem, as it indicates that the parameters are difficult to identify”
- On the other hand:
  - Higher correlation = more information
  - Less correlation = less information
- Example from linear regression

Bayesian linear regression: predicting surface runoff using precipitation

- Priors
  - Intercept : between -50 and 0
  - Slope: betweem 0 and 1
- Add one data point at a time
- Show predictions with and without correlation of parameters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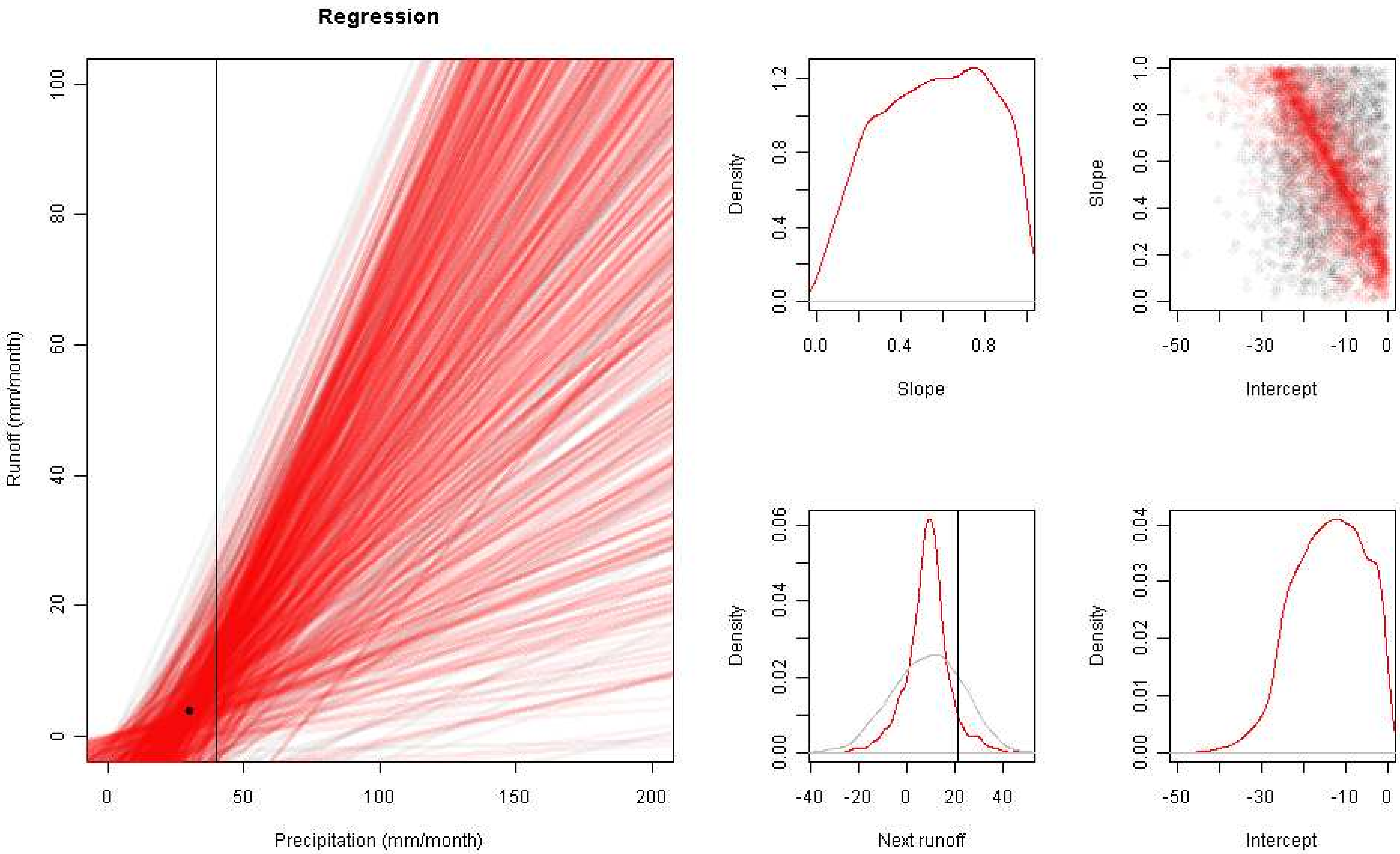
Runoff (mm/month)
Precipitation (mm/month)
Density
Slope
Intercept
Next runoff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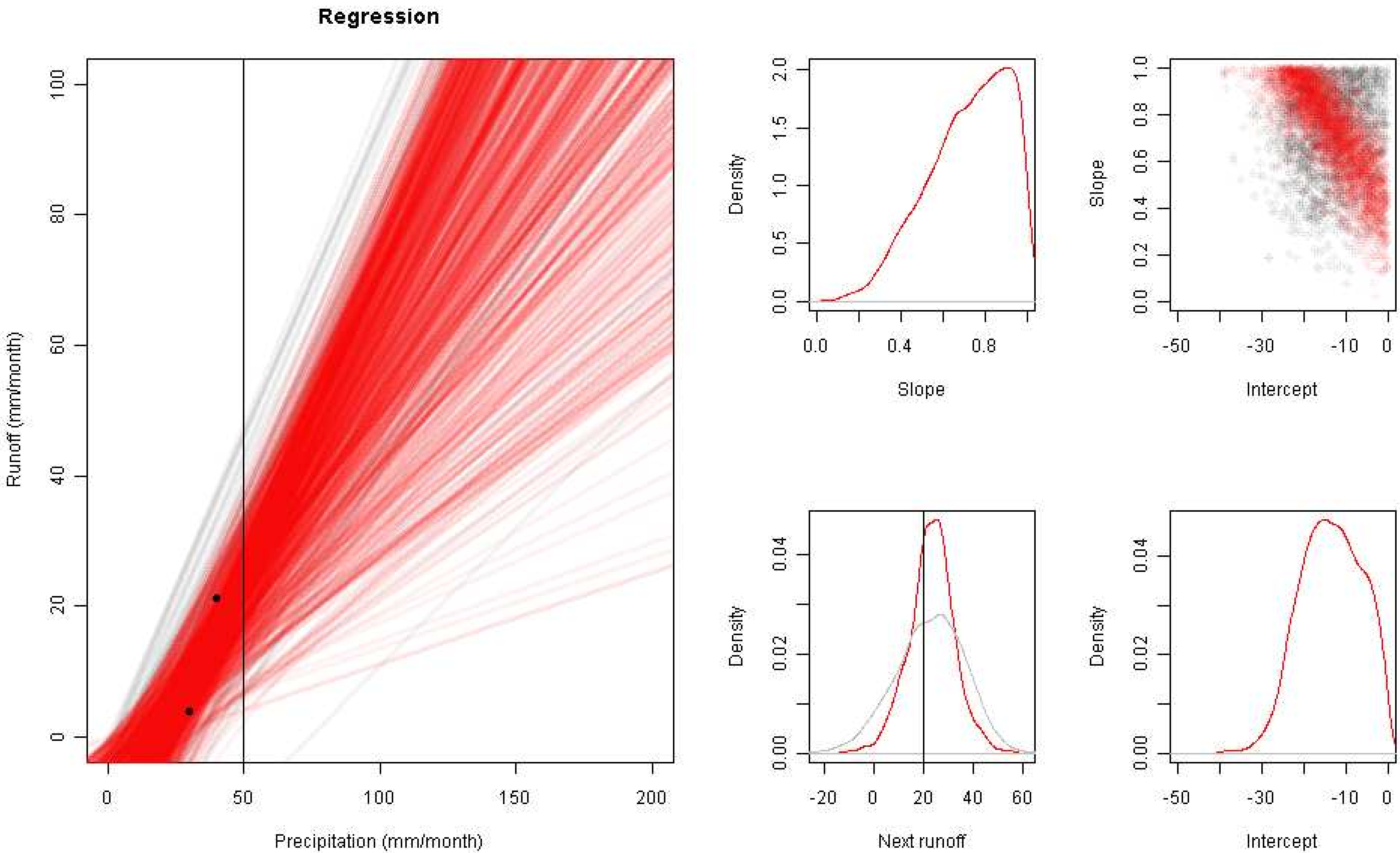
Intercept



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Density
Slope
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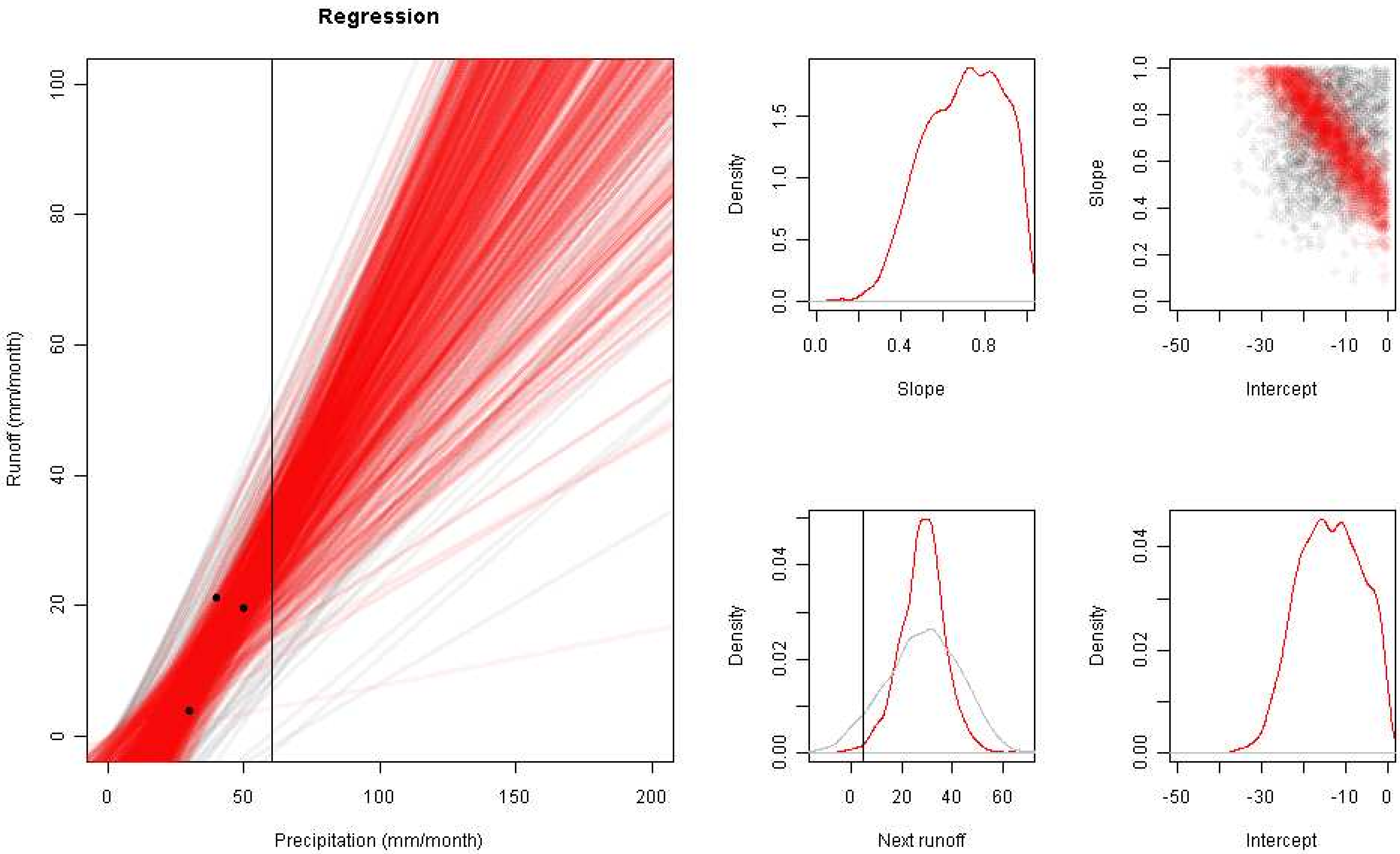
Next runoff



Regression
Runoff (mm/month)
Precipitation (mm/month)
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-30
-10
0
Density
Next runoff
0.00
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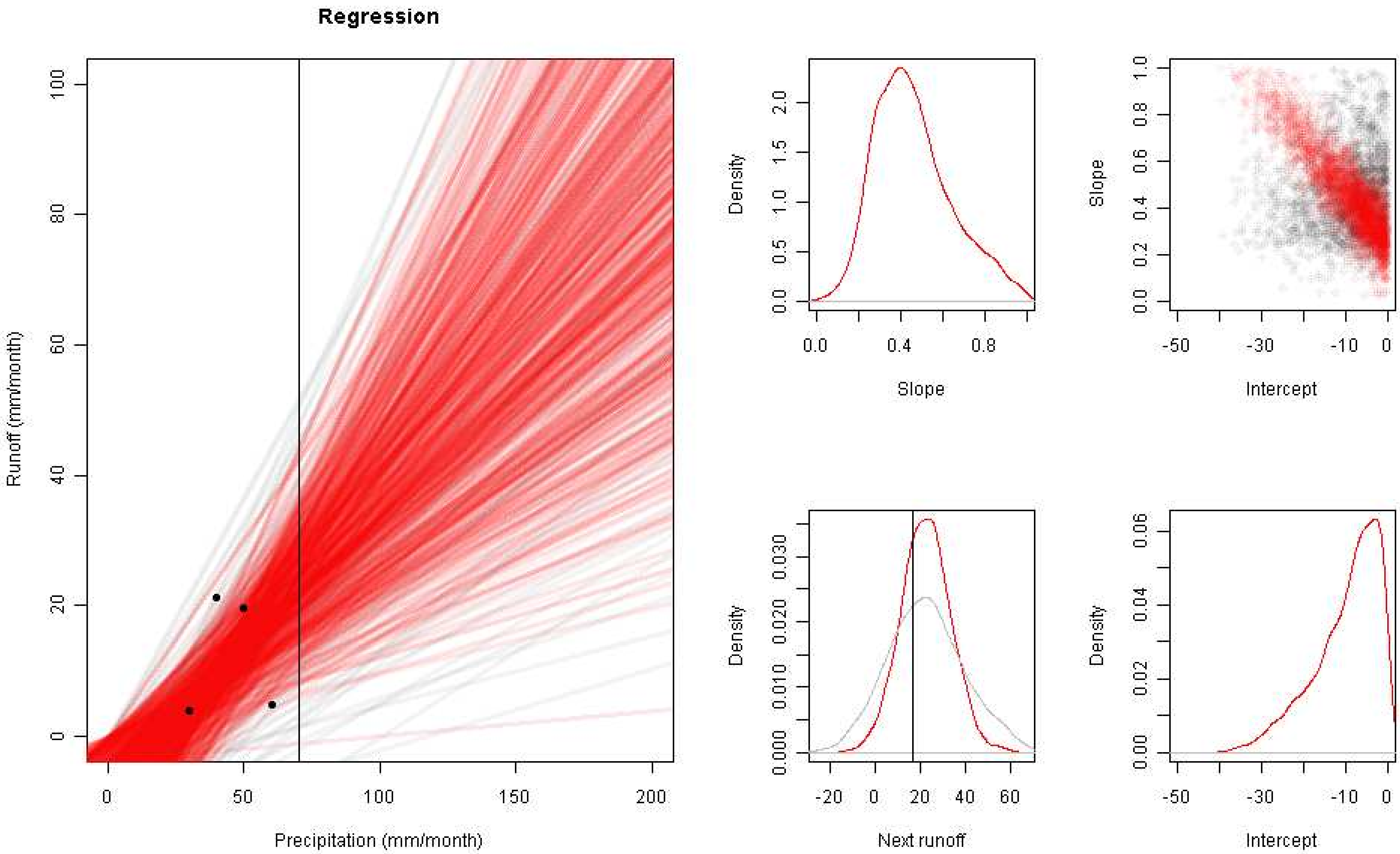
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Density
Slope
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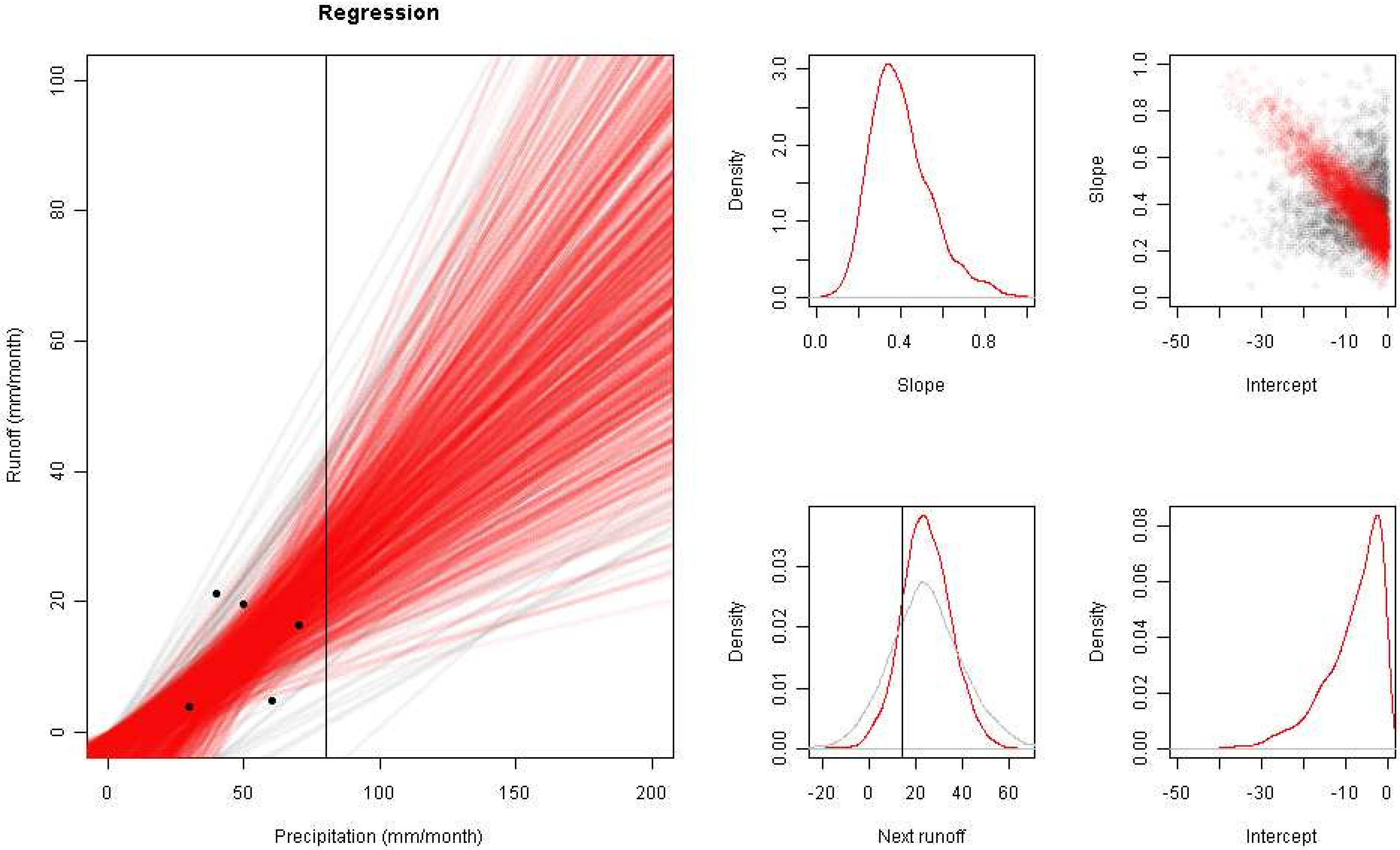
Next runoff



Regression
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Density
Next runoff
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Density
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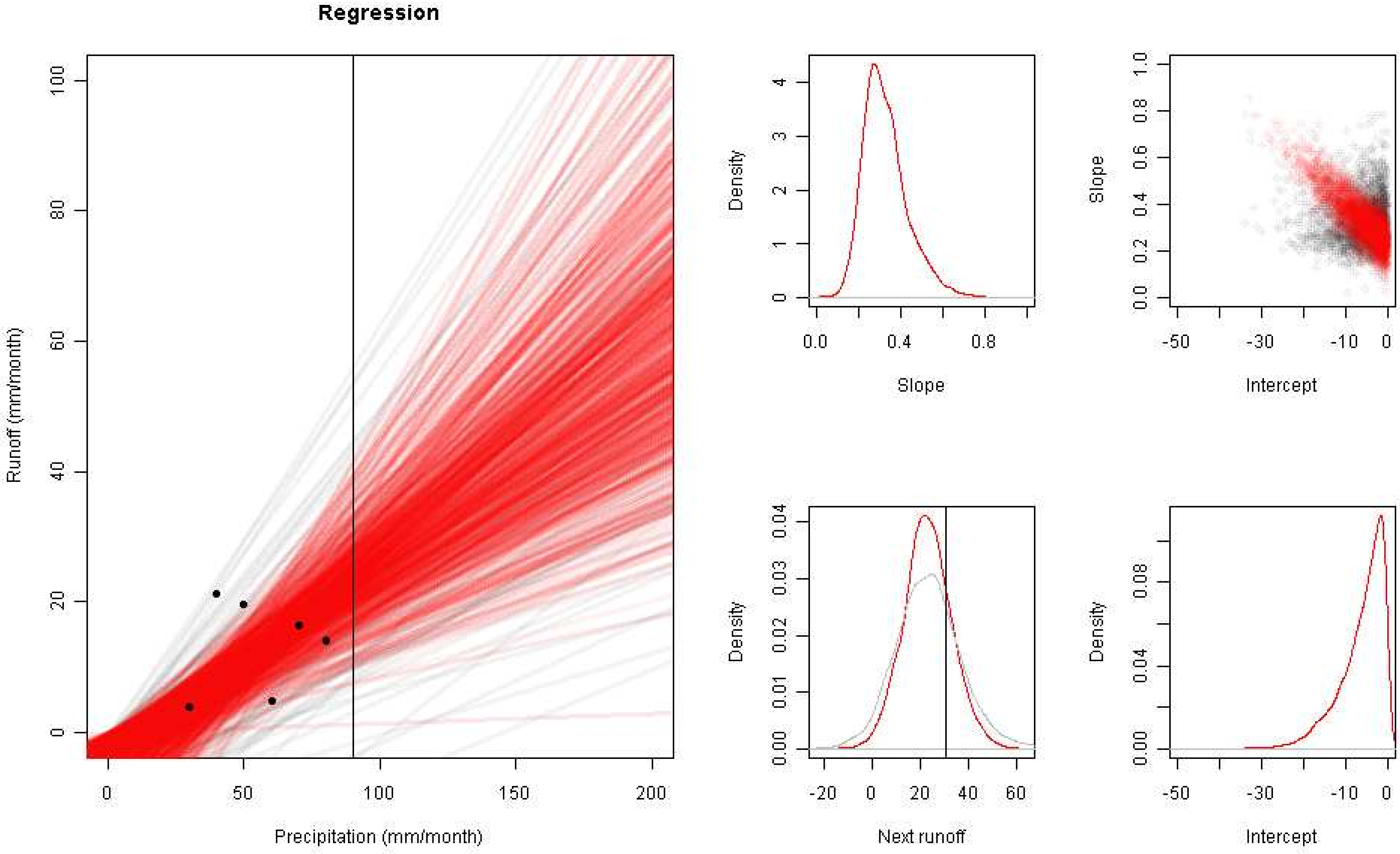
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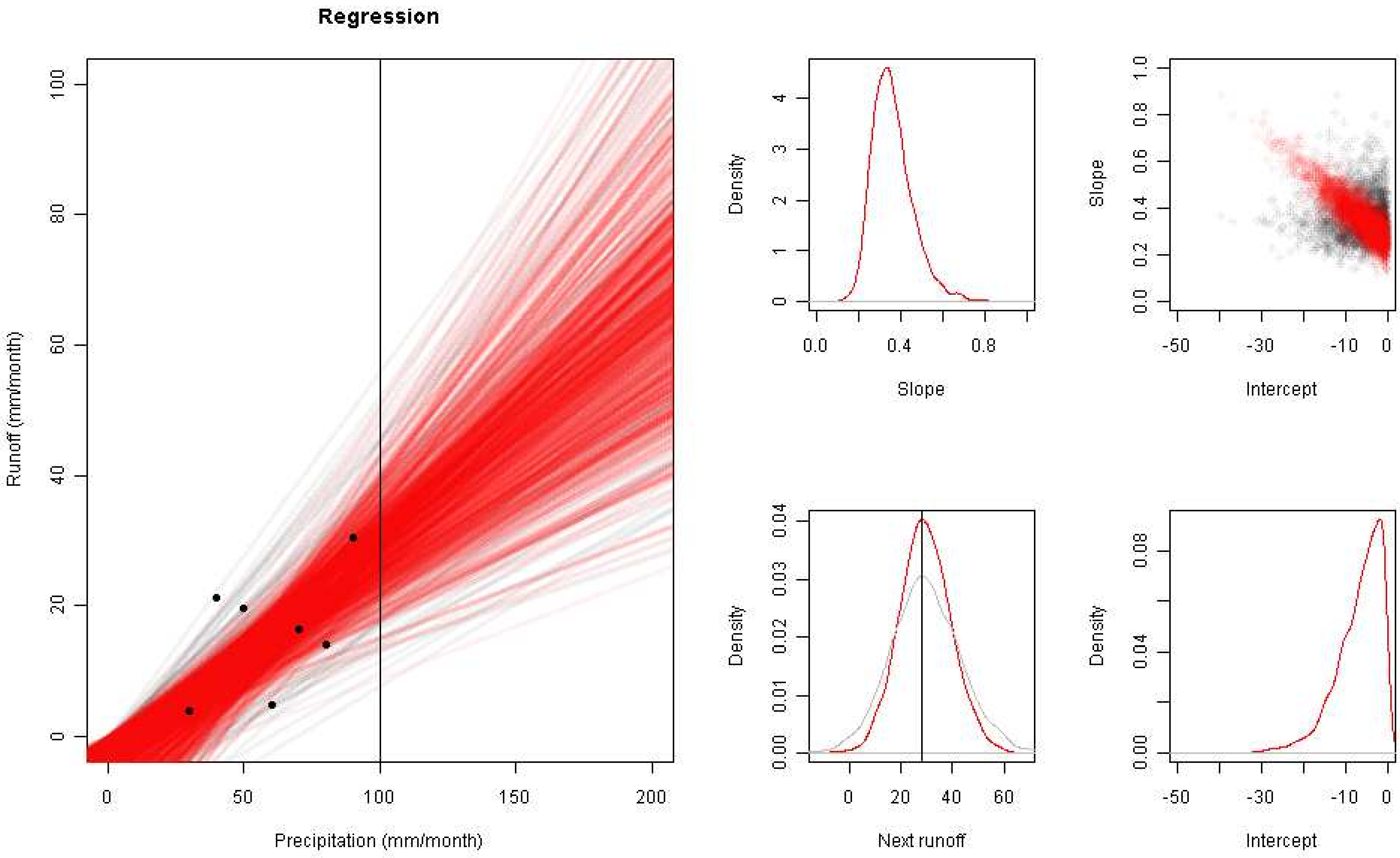
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Runoff (mm/month)
Precipitation (mm/month)
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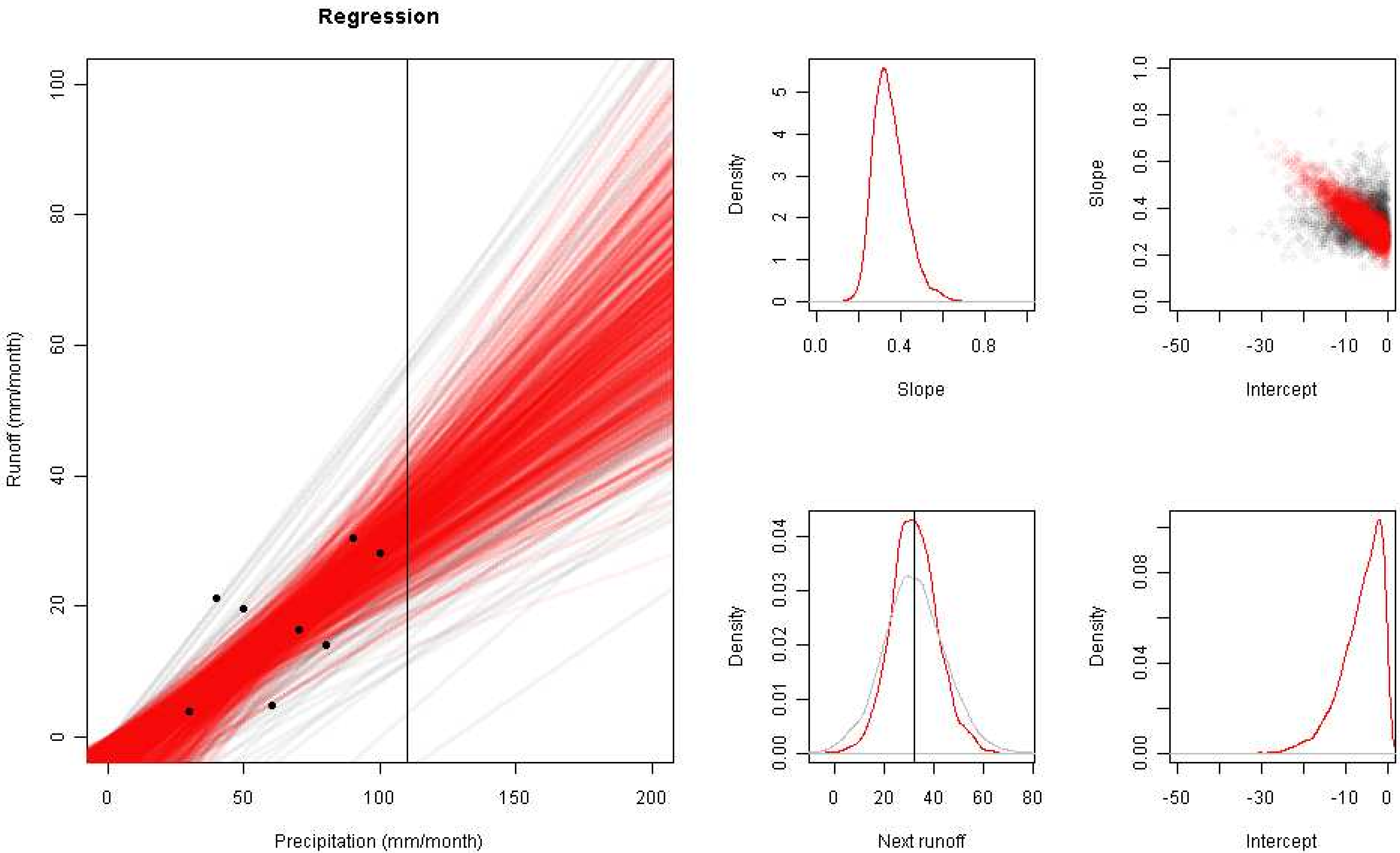
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Density
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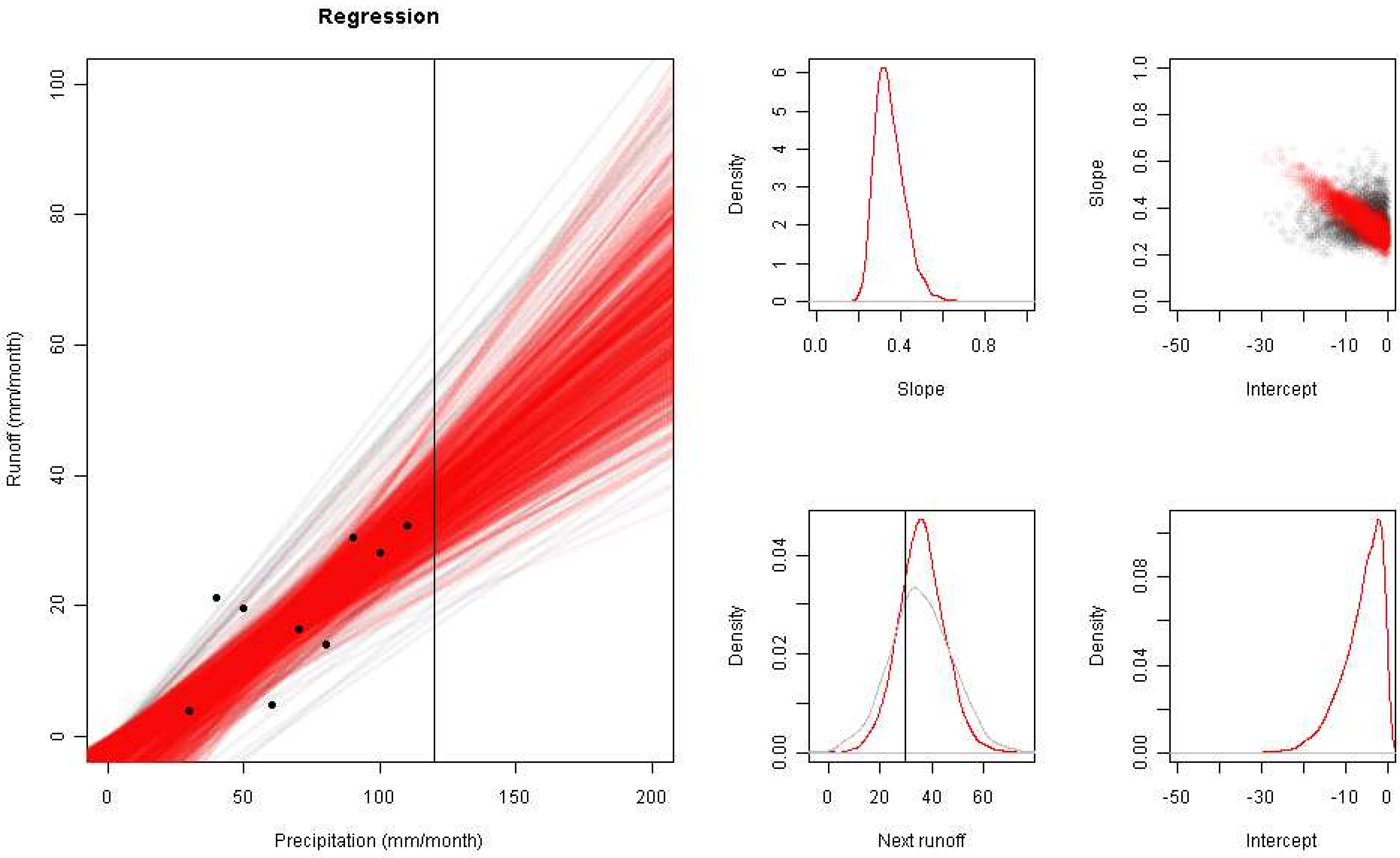

Regression
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Precipitation (mm/month)
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Next runoff
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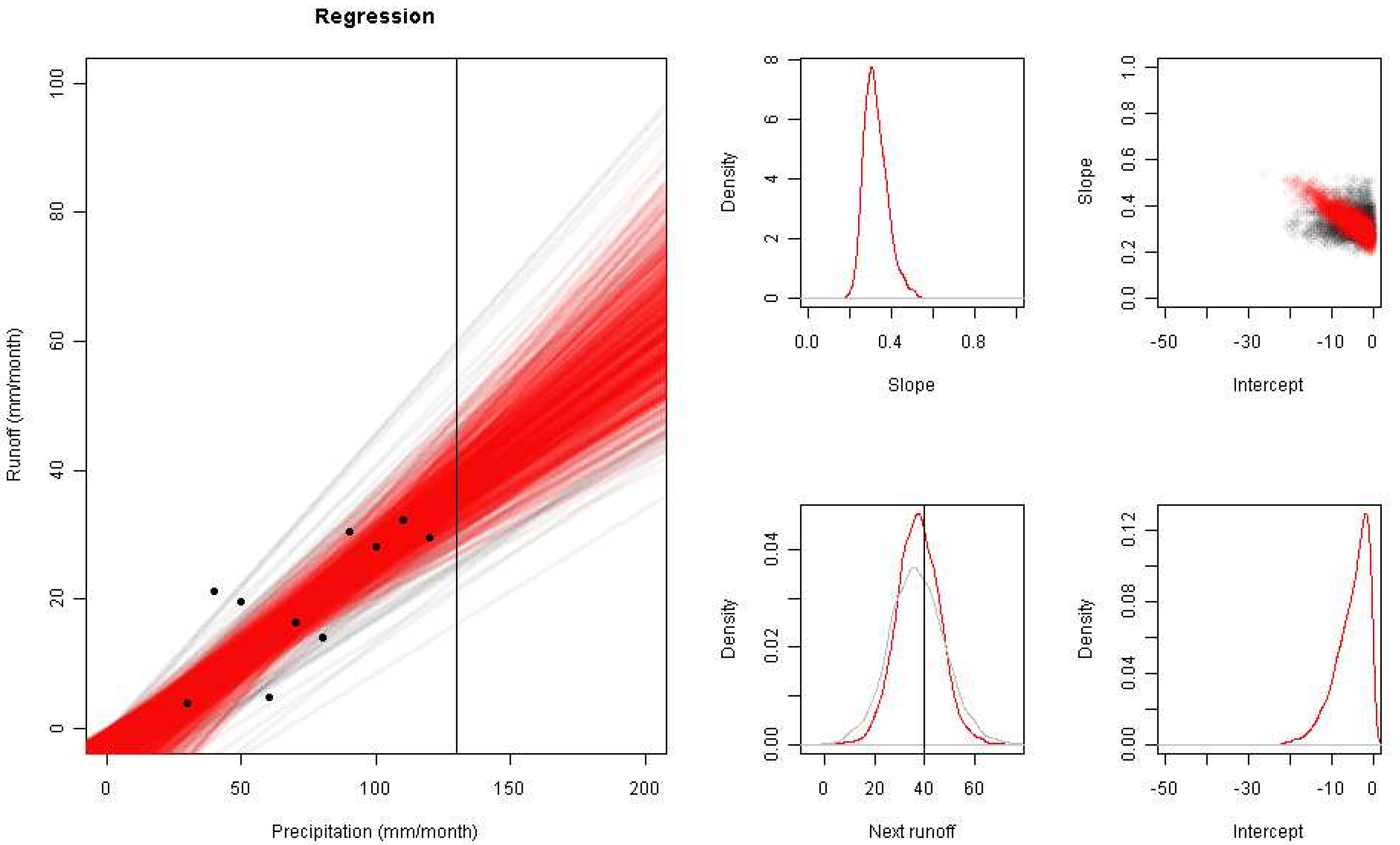
Regression
Runoff (mm/month)
Precipitation (mm/month)
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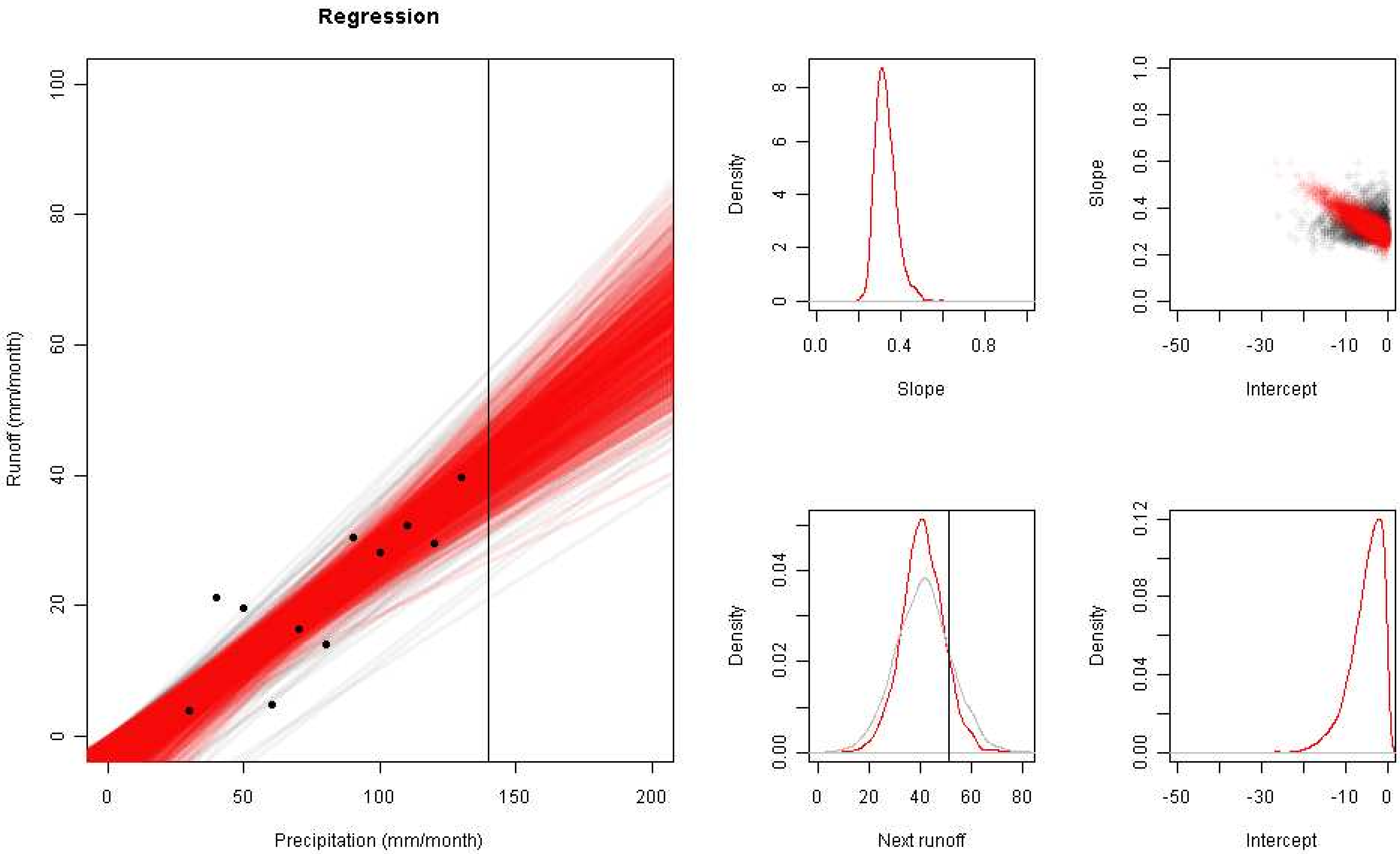

Regression
Runoff (mm/month)
Precipitation (mm/month)
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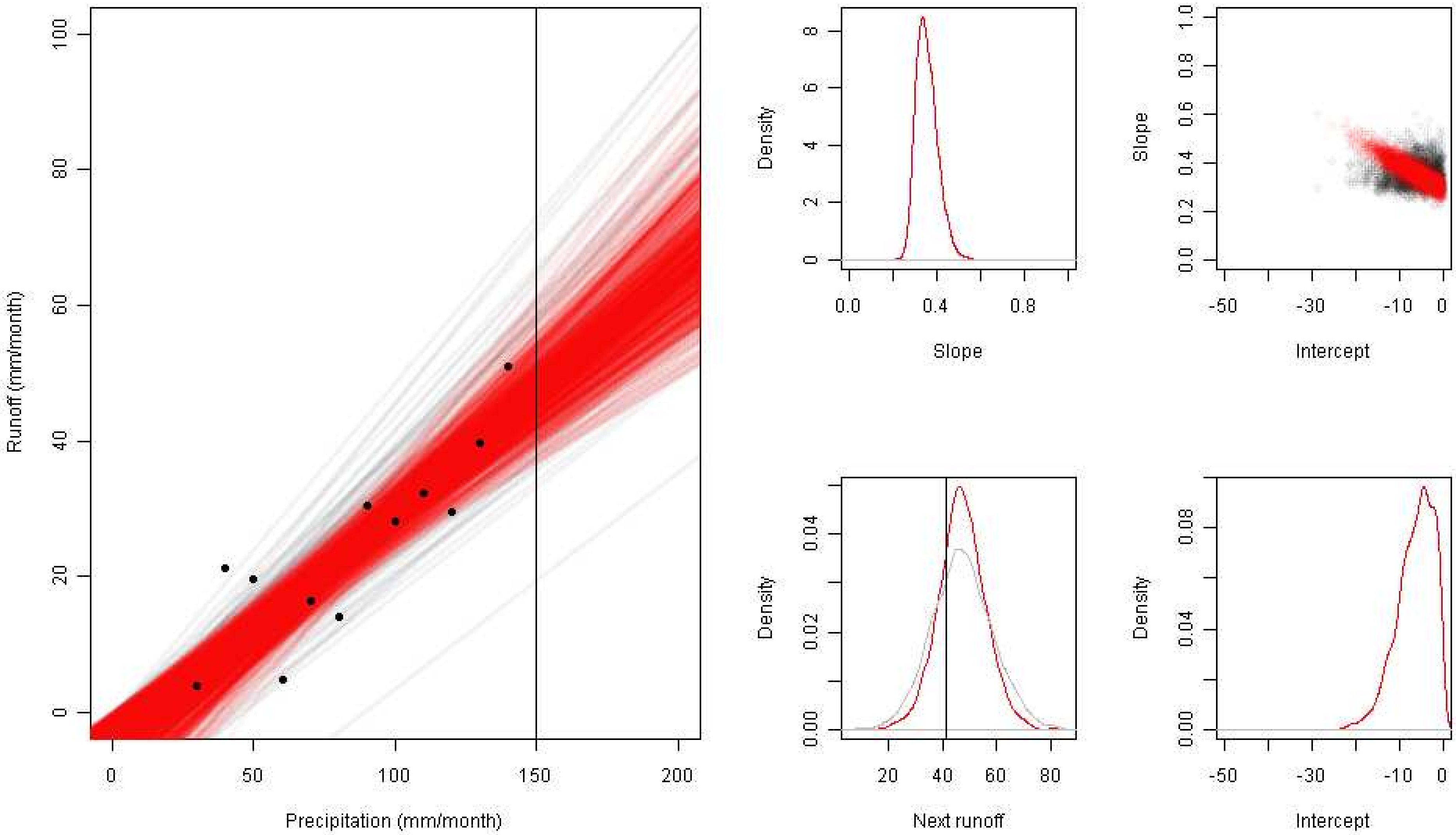
Density
Next runoff
Density
Intercept

Regression



Runoff (mm/month)
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Precipitation (mm/month)
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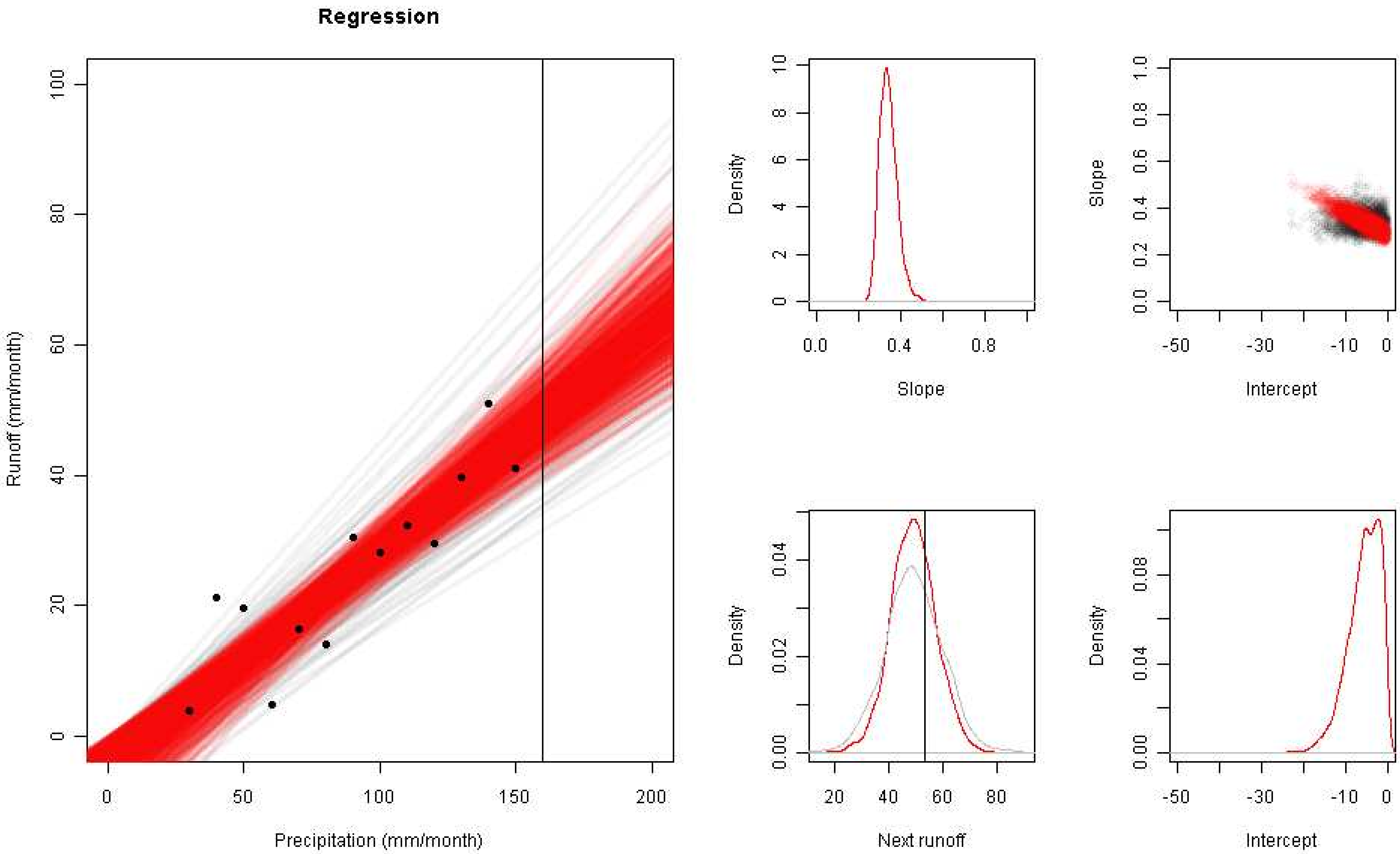
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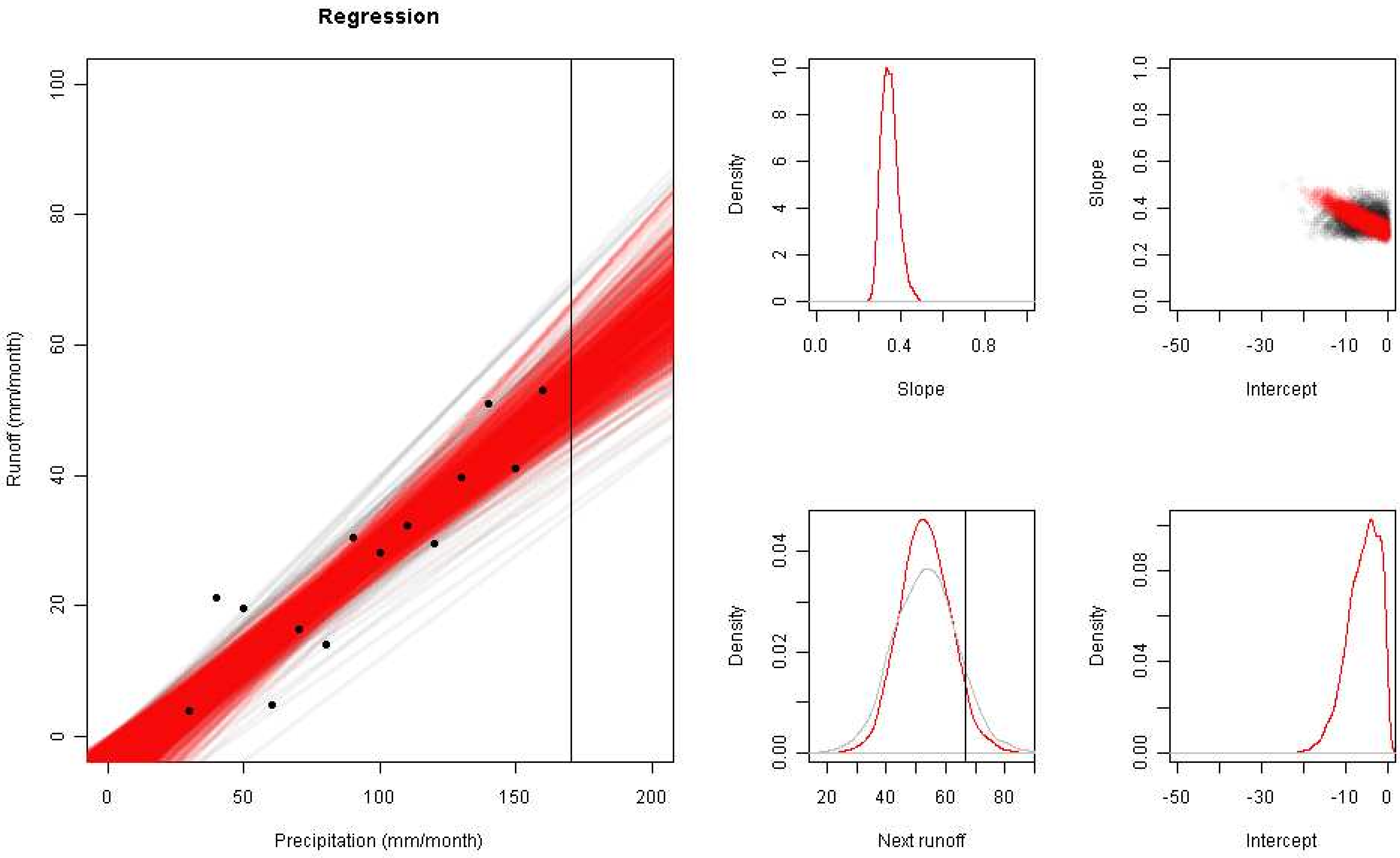
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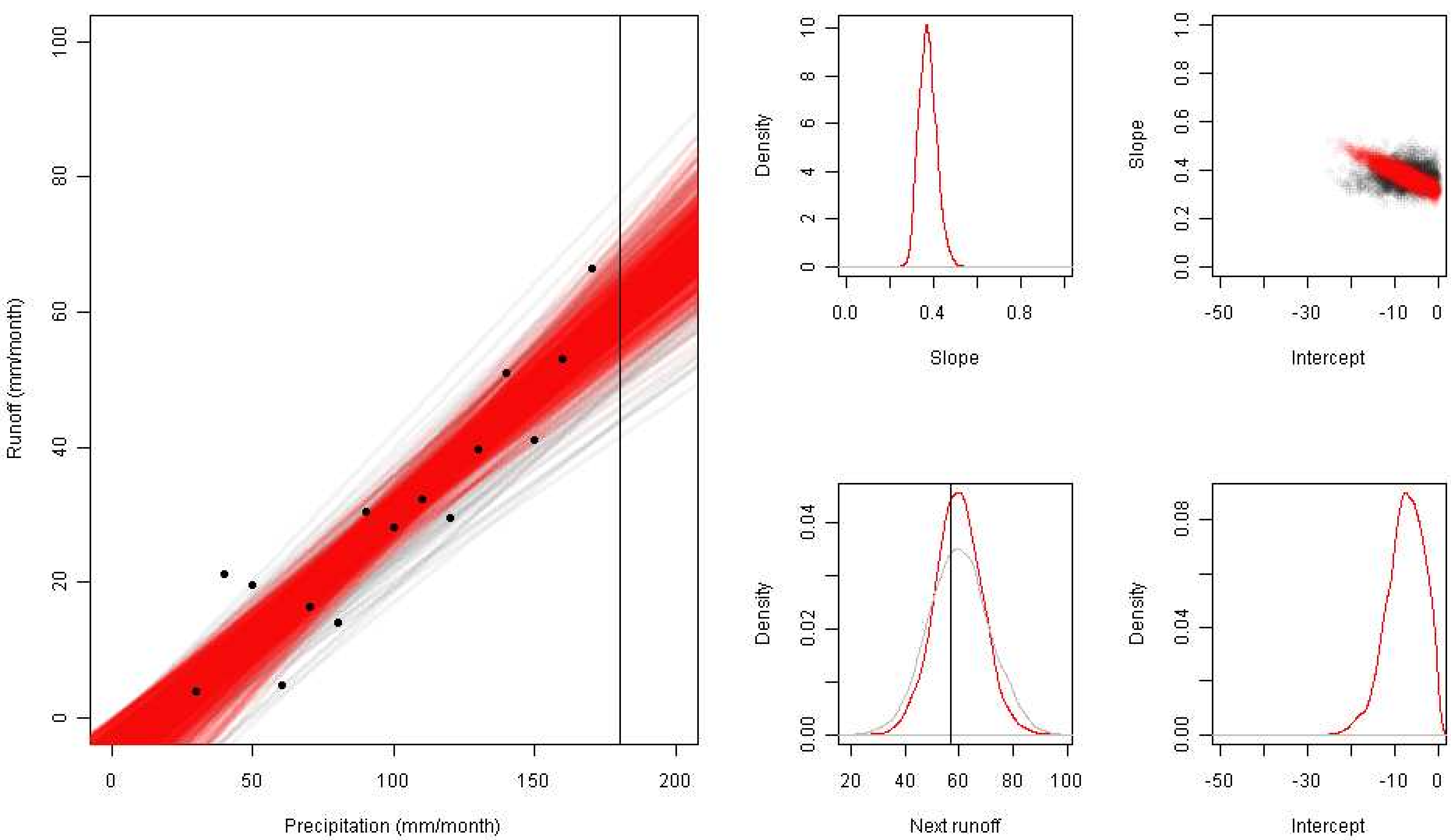
Regression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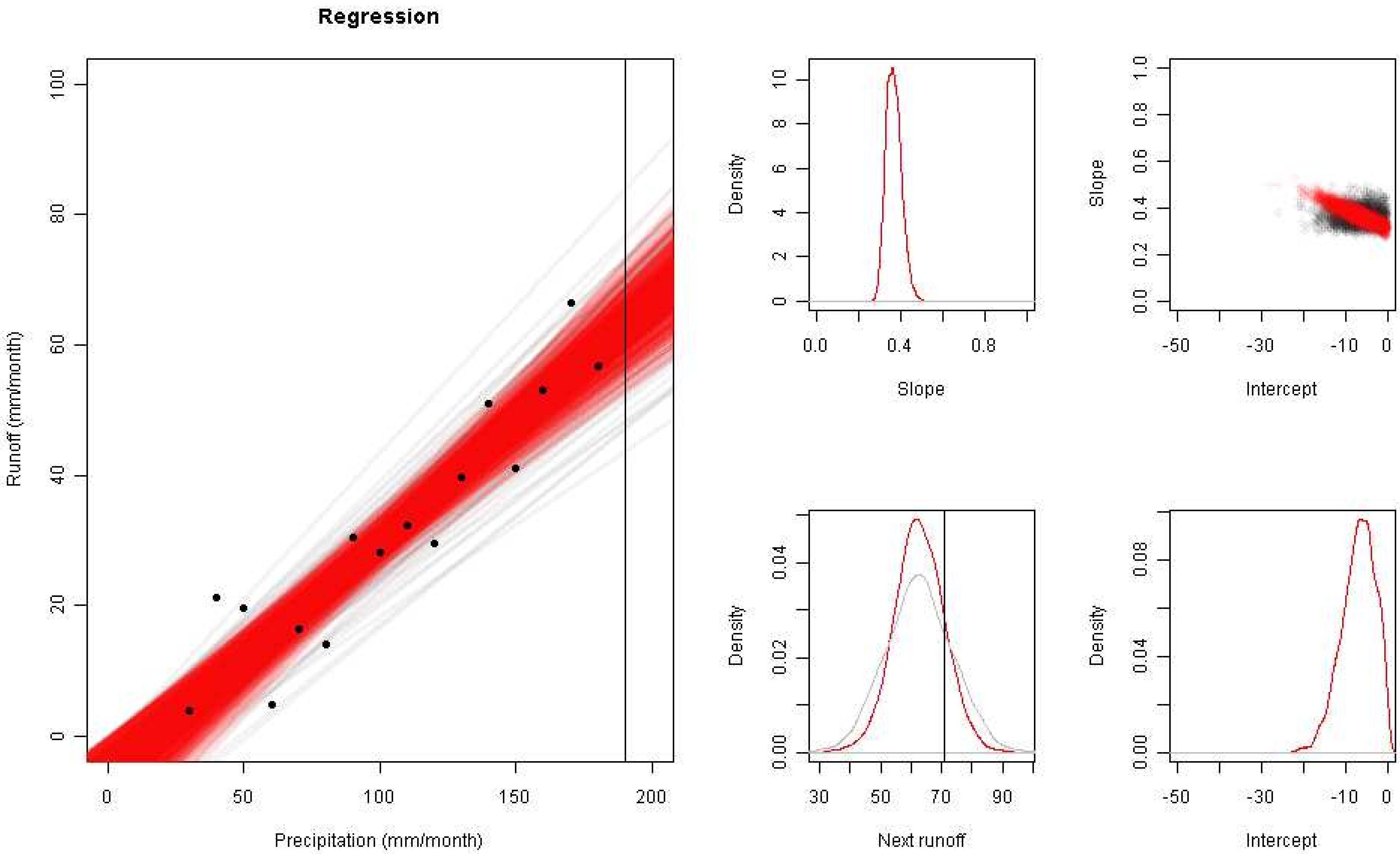

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Density
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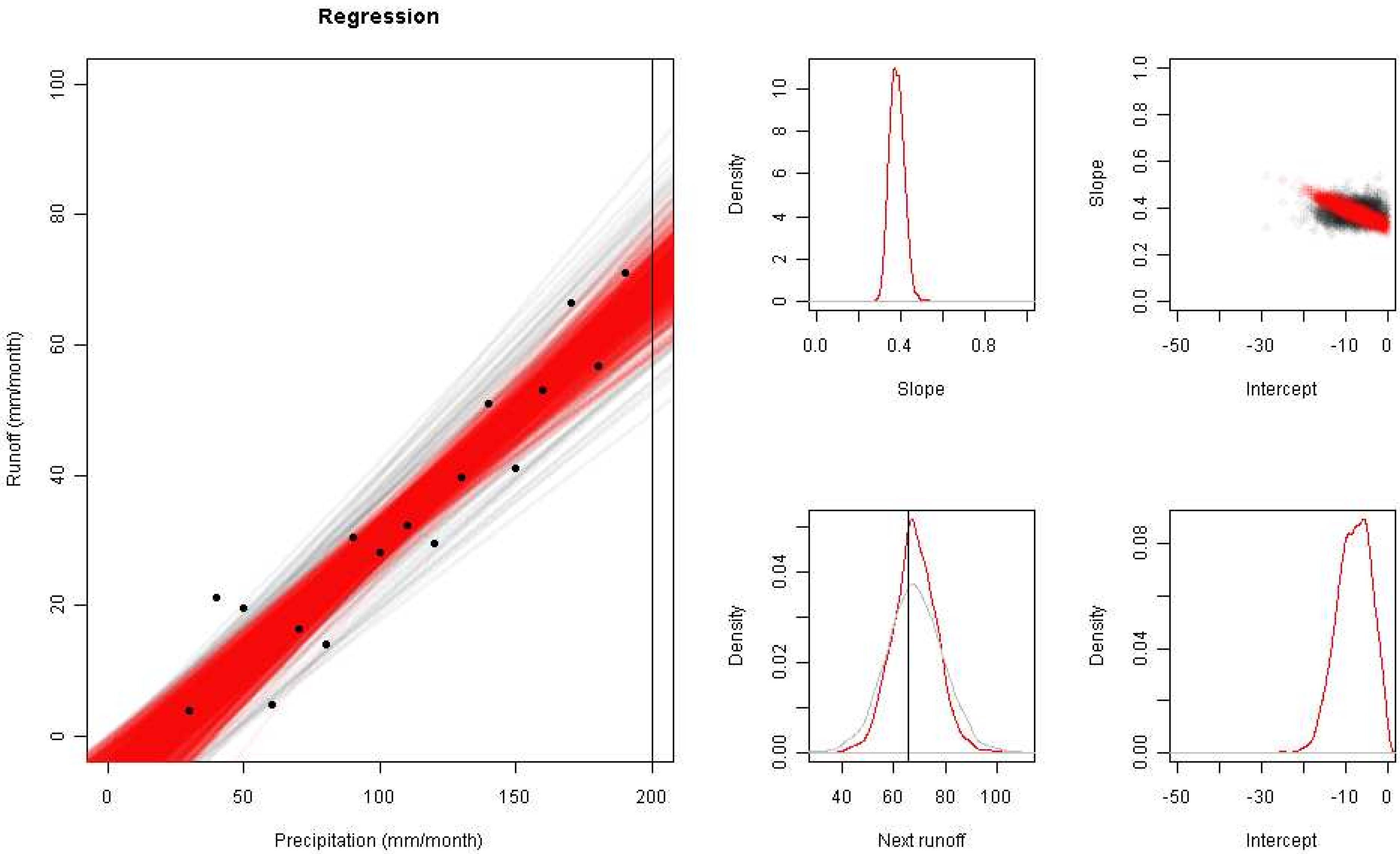

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Part II: Summary

- Correlation is information
- Include correlation when predicting, not just the marginal distributions
- Report the correlation of your parameter estimates, so that others can use it
- When using expert knowledge to formulate priors for prediction, try to assess the combinations of variables.

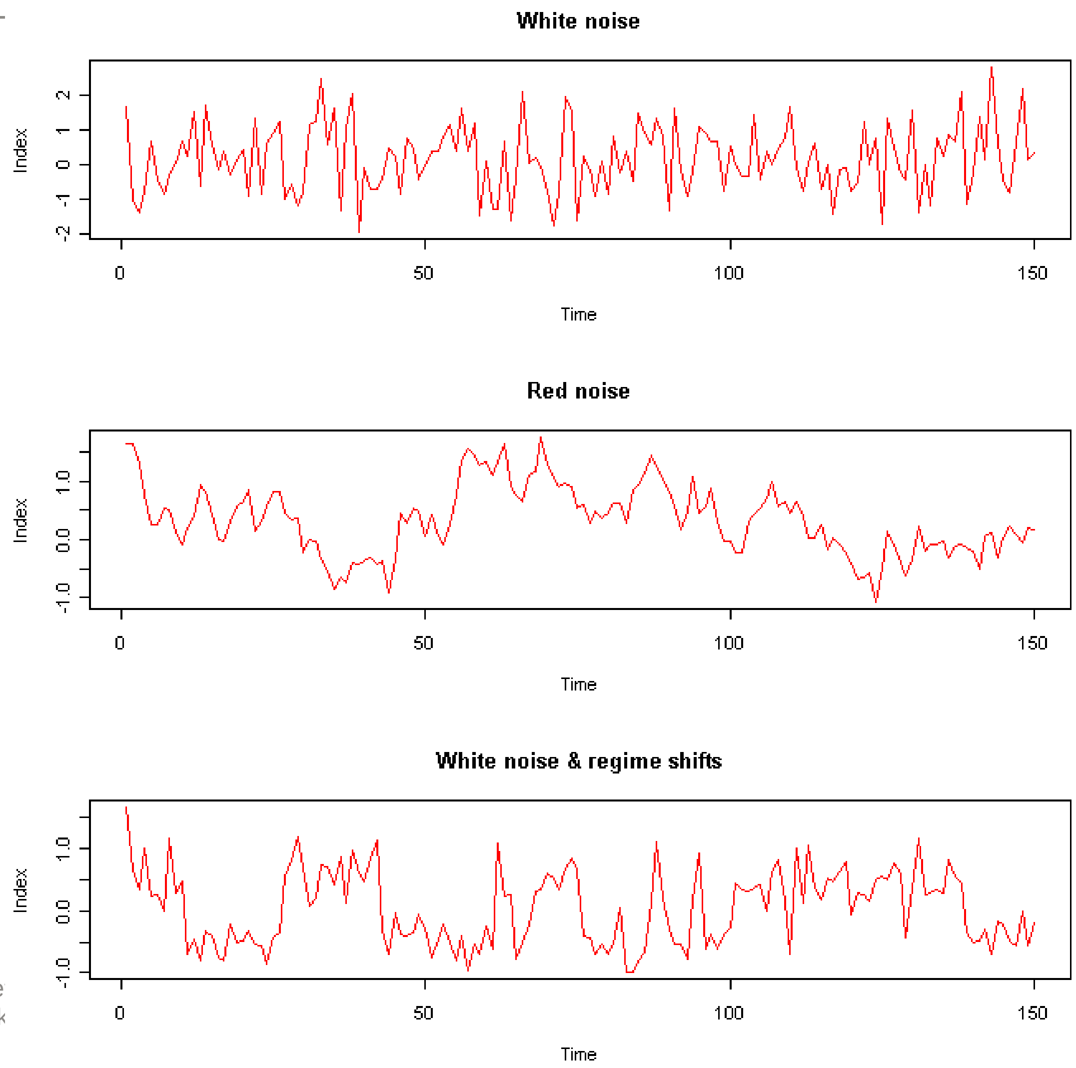
Part III: model averaging

- Multiple models
- Each model gives different prediction
- Not sure which model is ”true”
- How to take this uncertainty into account?

Bayesian Model Averaging

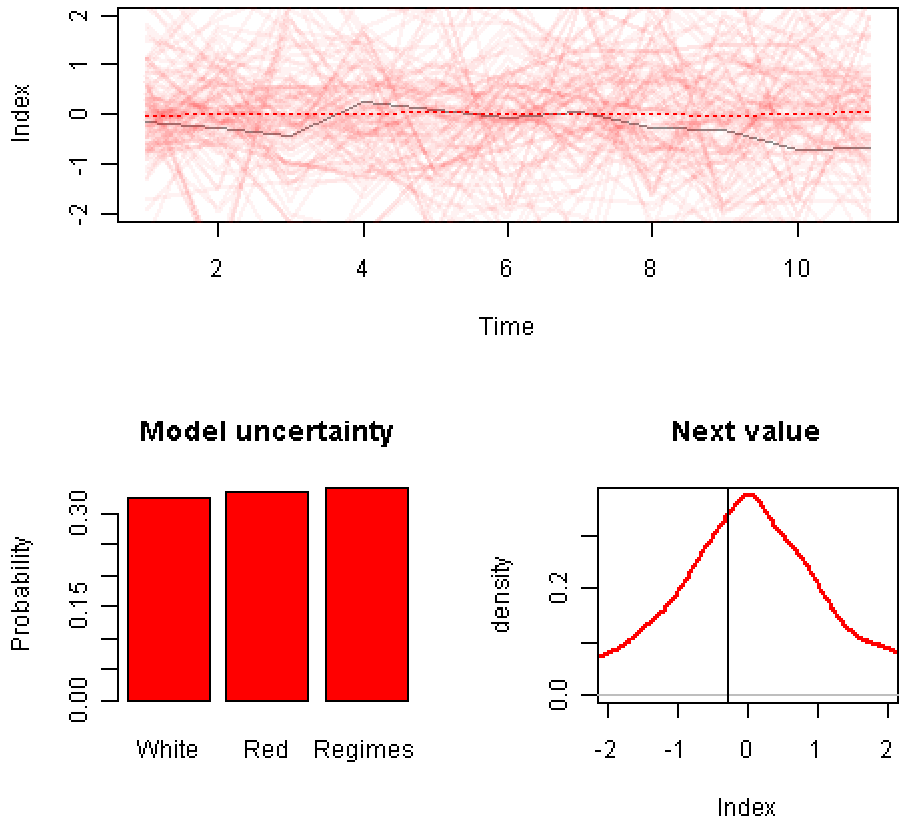
- Each model represents a hypothesis
- Baye's rule: probability of a hypothesis | data
- Just use it!
  1. Give prior weights to models before seeing the data
  2. Predict the next time step
  3. Update the weights based on observed data
  4. Go to (2)

Example: three models for an environmental Index



Uncertainty: which model is ”true”?

- Bayesian approach: assing prior probability for each model before seeing the data
- In this example: pretend that ”nothing” is know a priori
- P(model=white noise) = 1/3
- P(model=white noise | data) = ?
- Demonstration
  1. Predict upcoming data
  2. Observe data
  3. Update P(model | data), use as prior for next case
  4. Go to (1)



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Time
Model uncertainty
Probability
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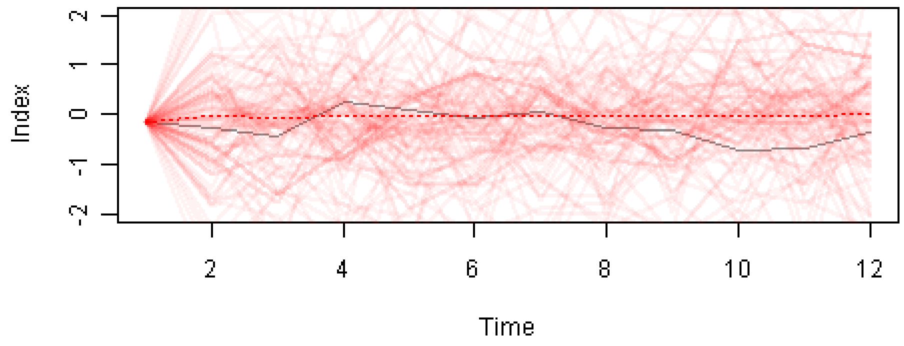

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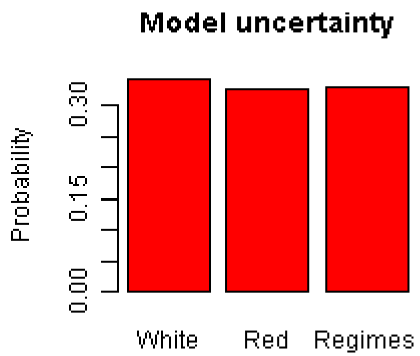

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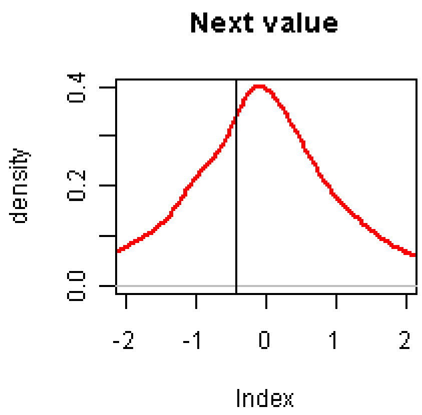

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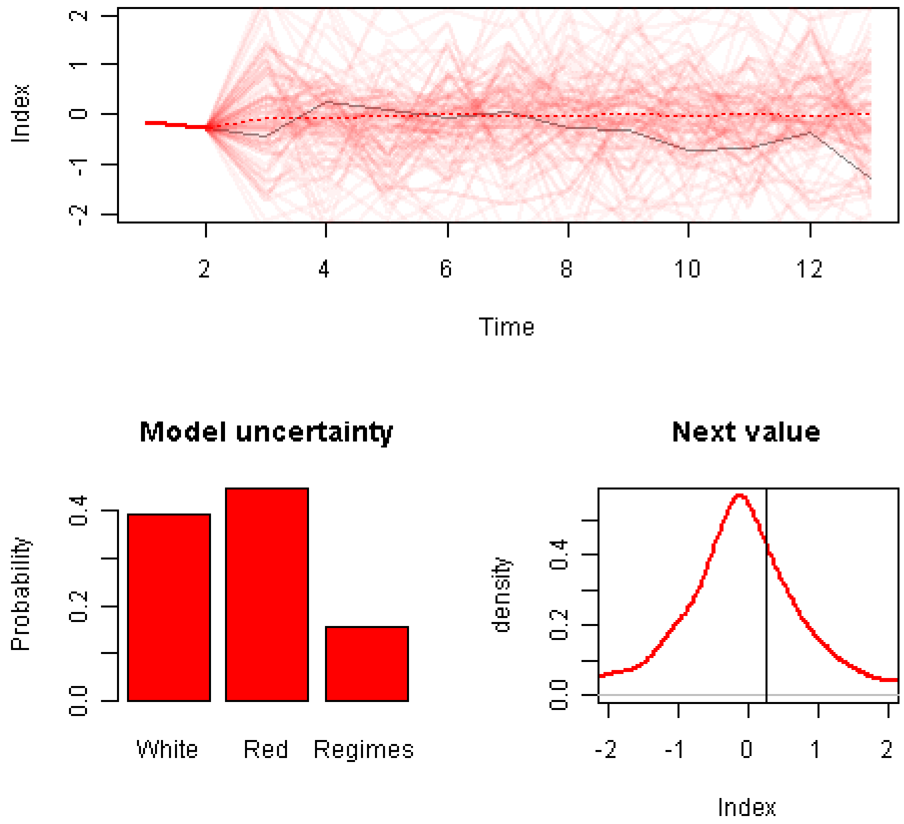
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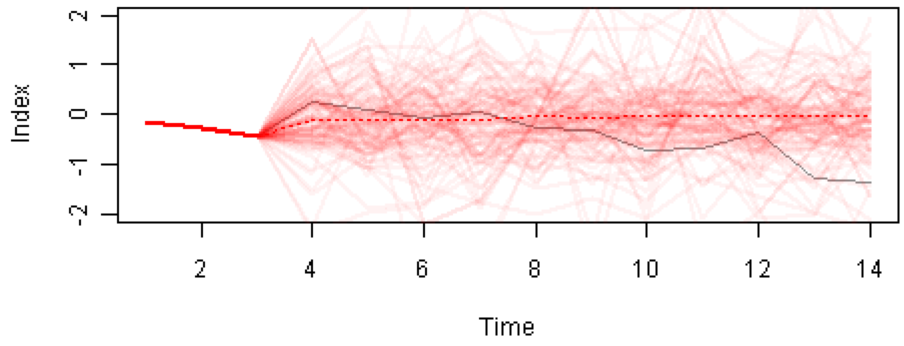
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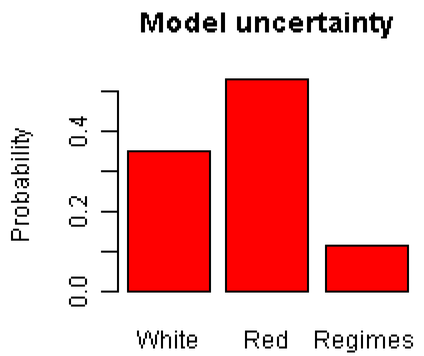
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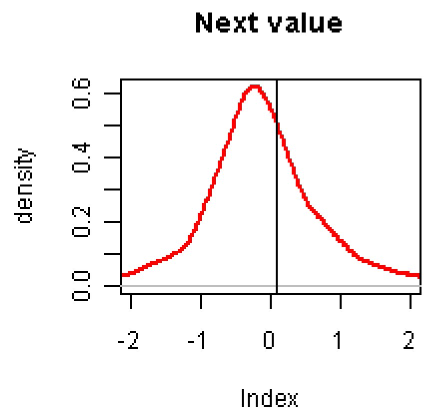
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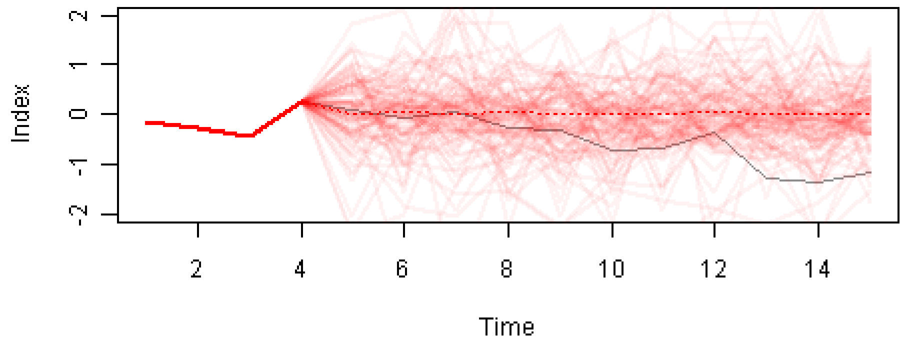
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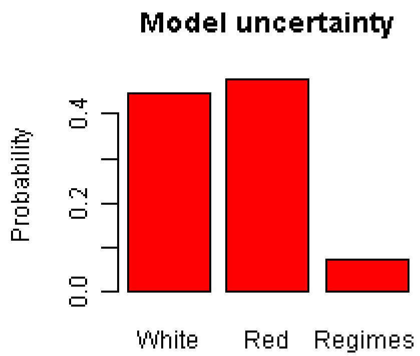
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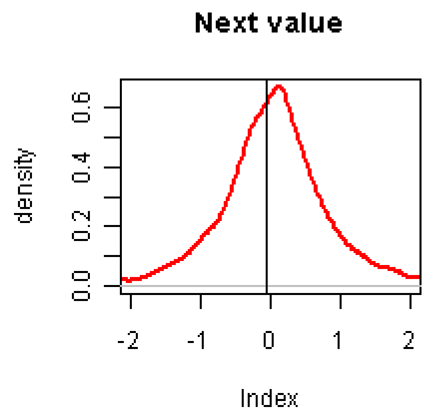
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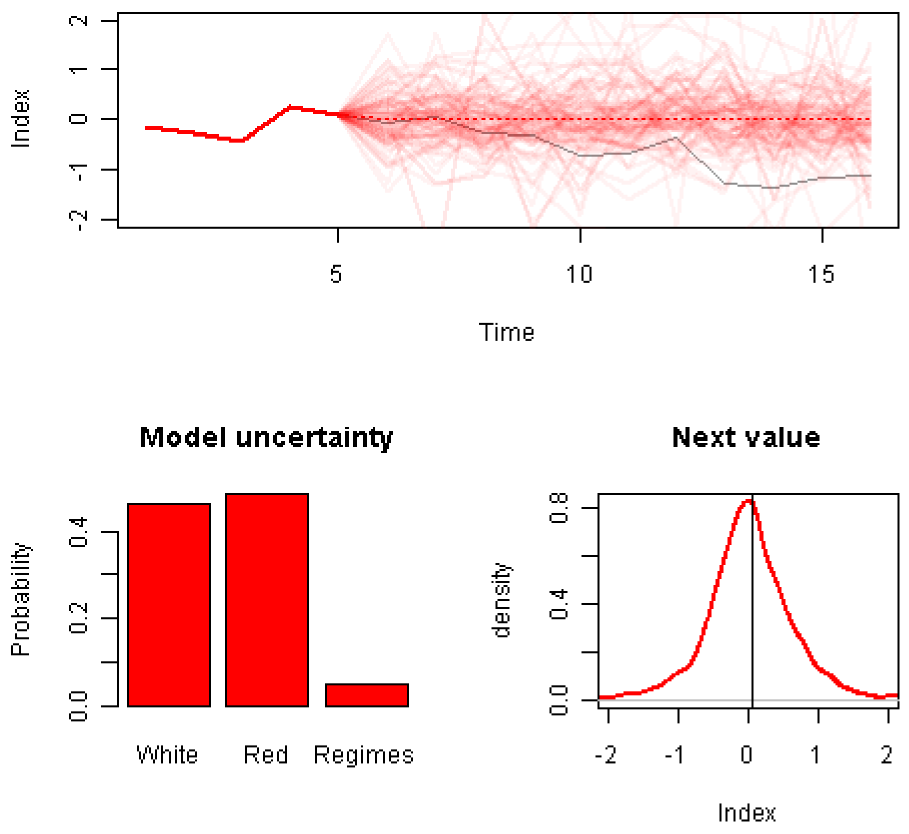
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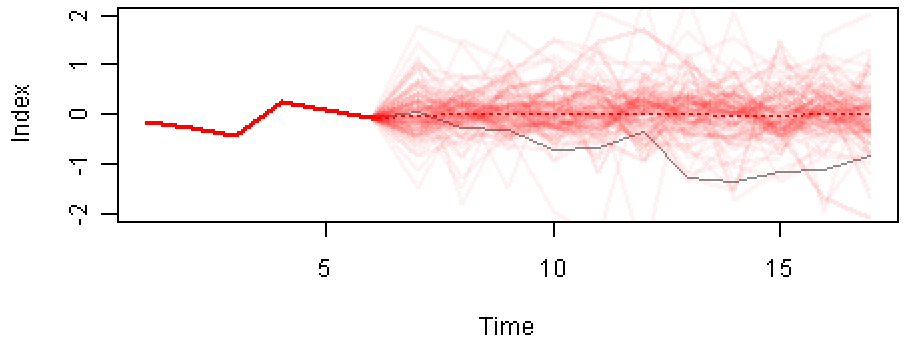
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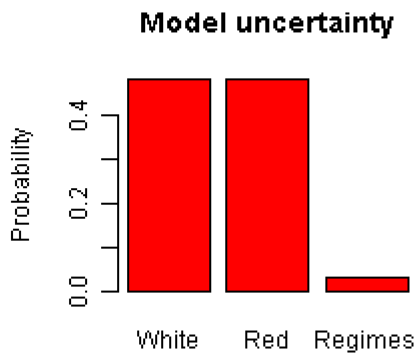
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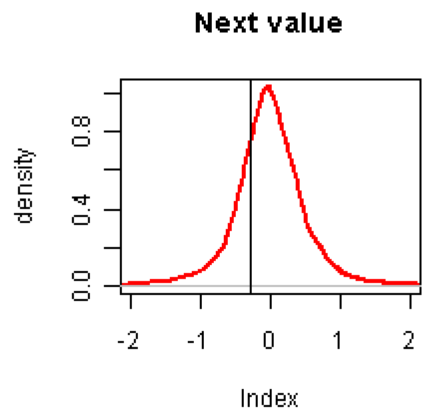
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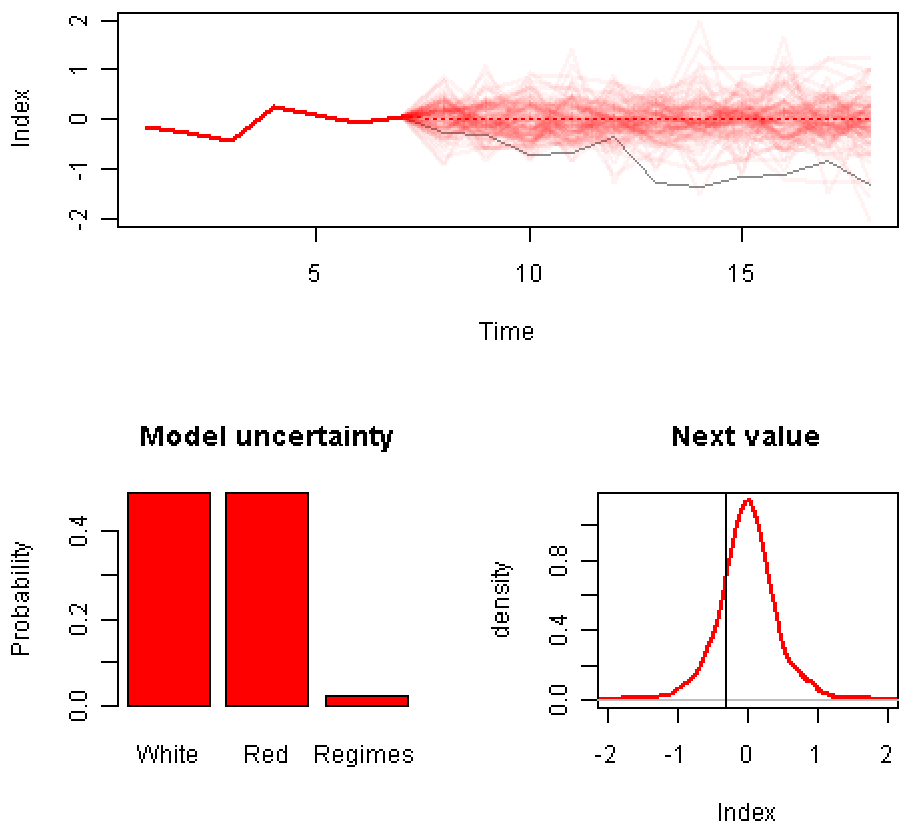

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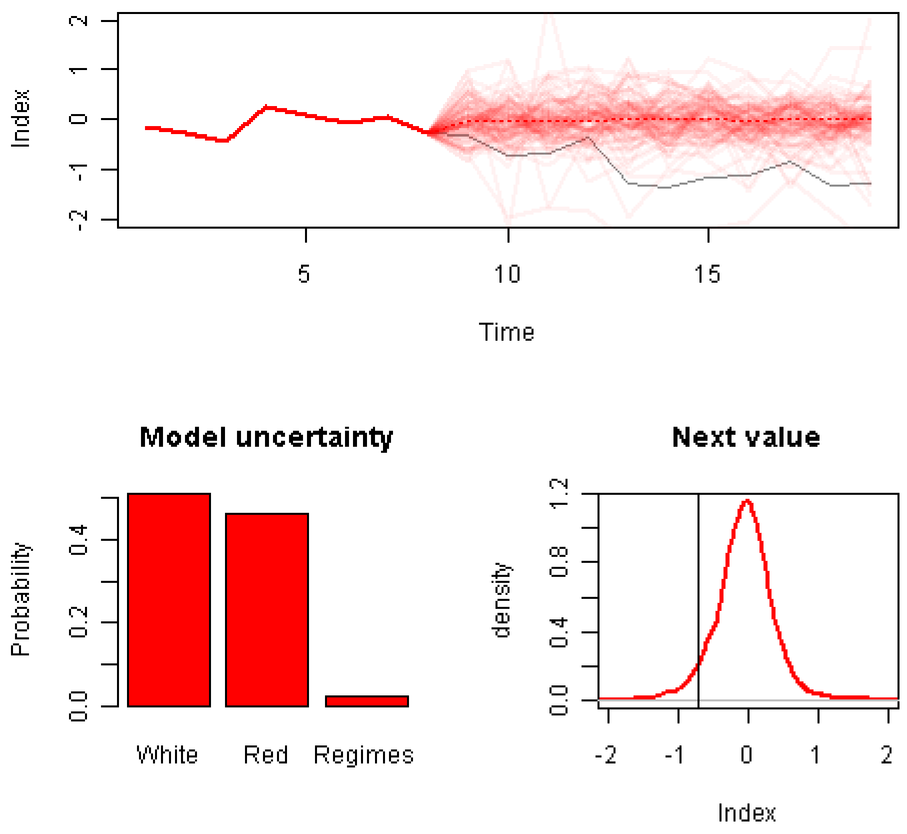
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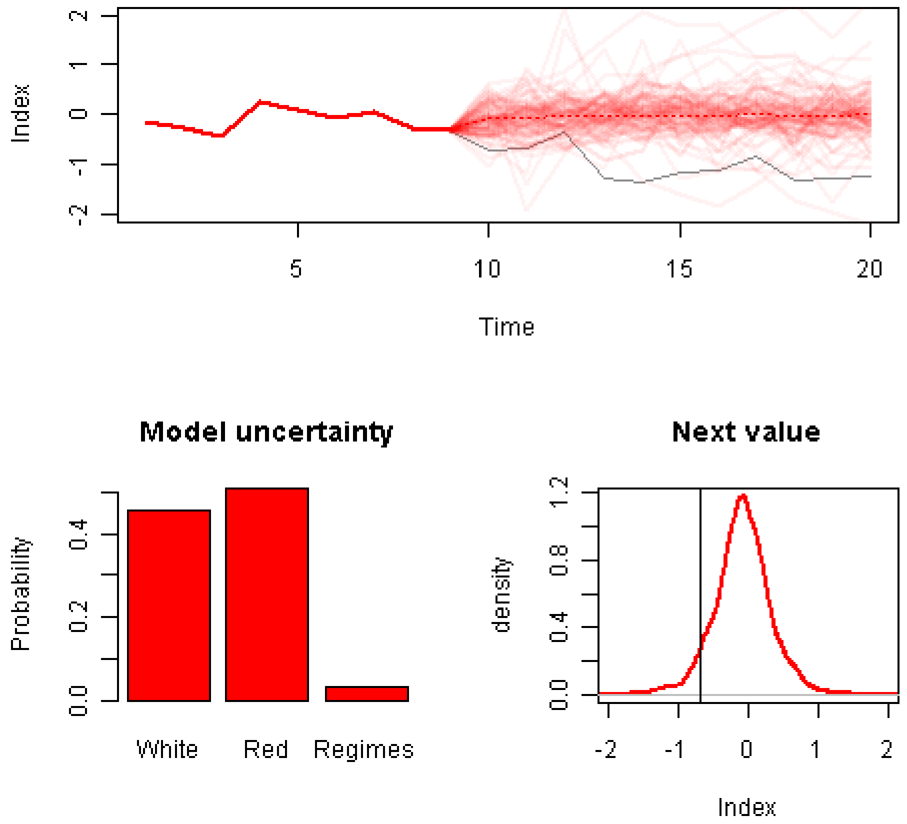
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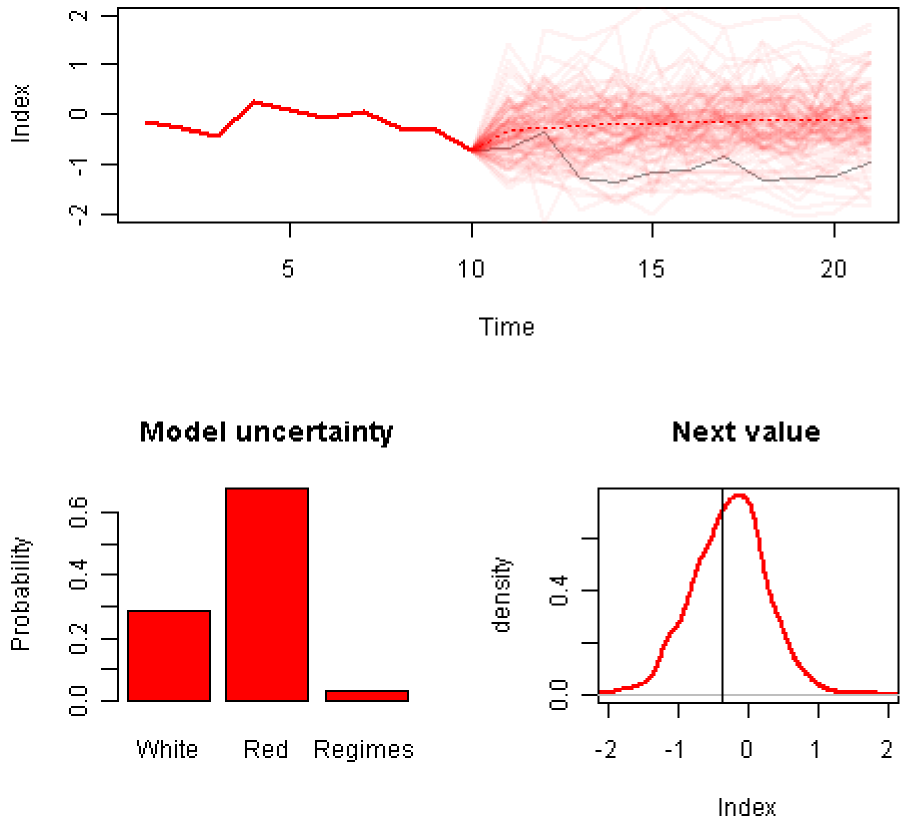

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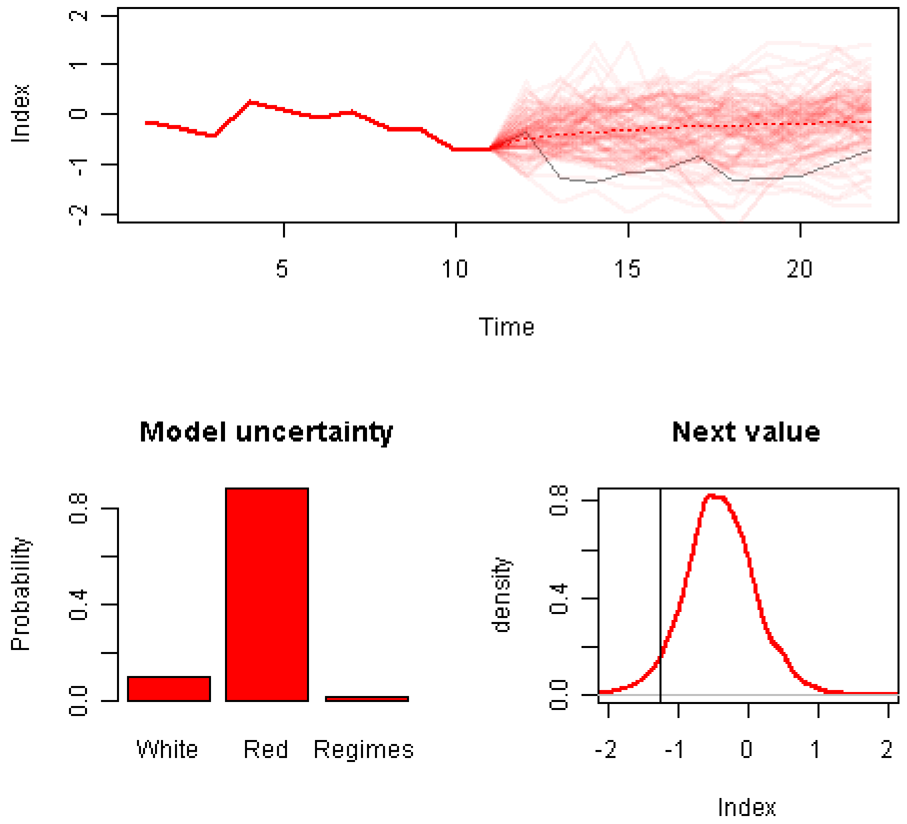
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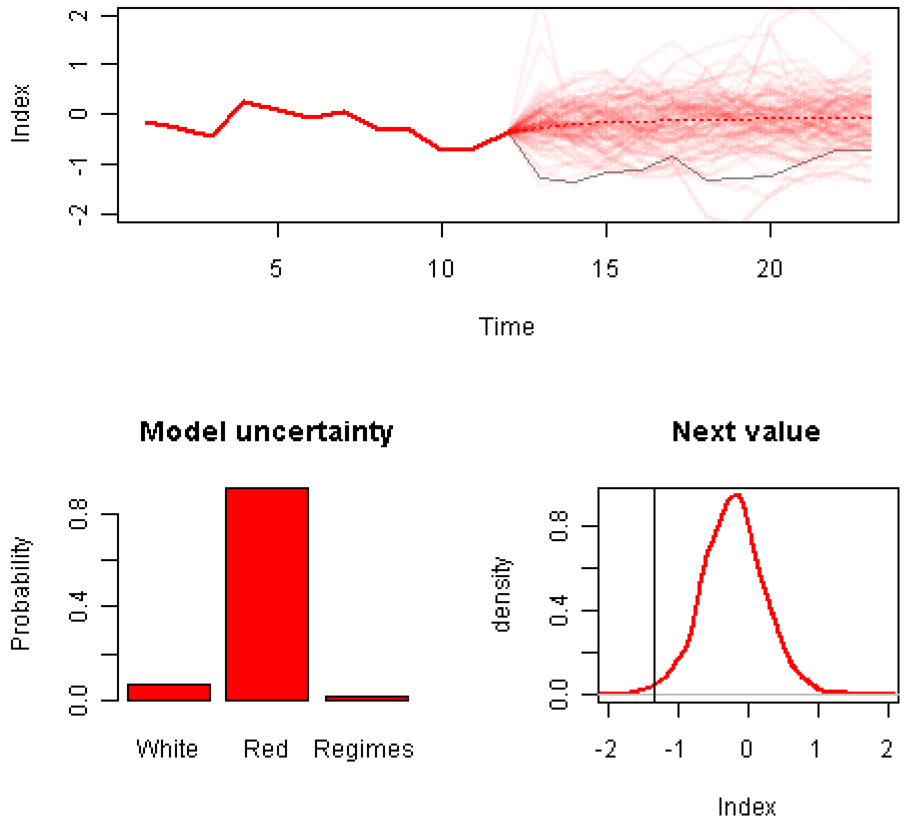
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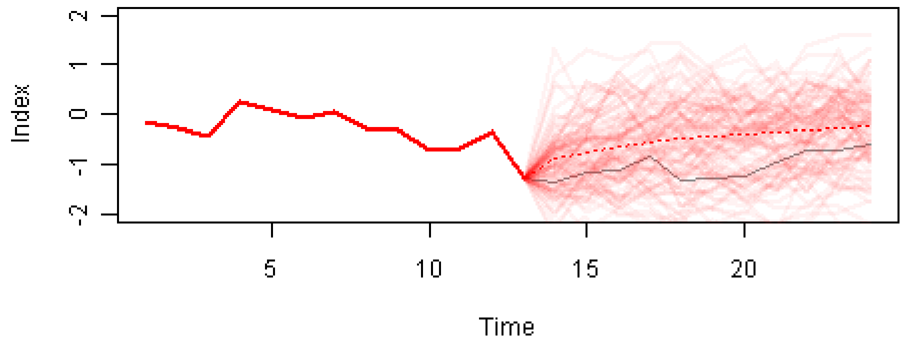
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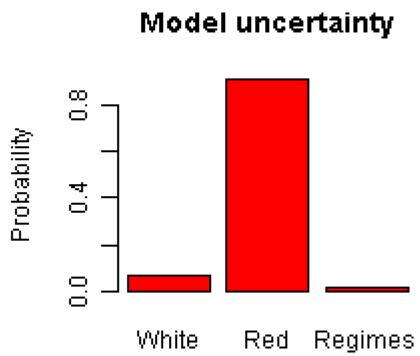
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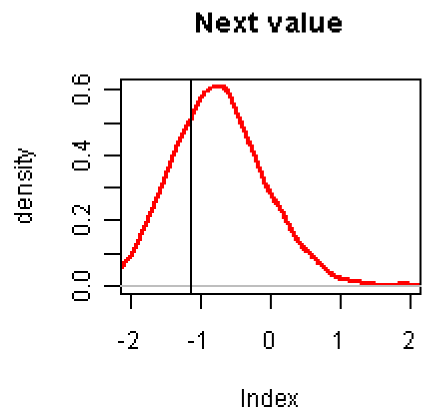
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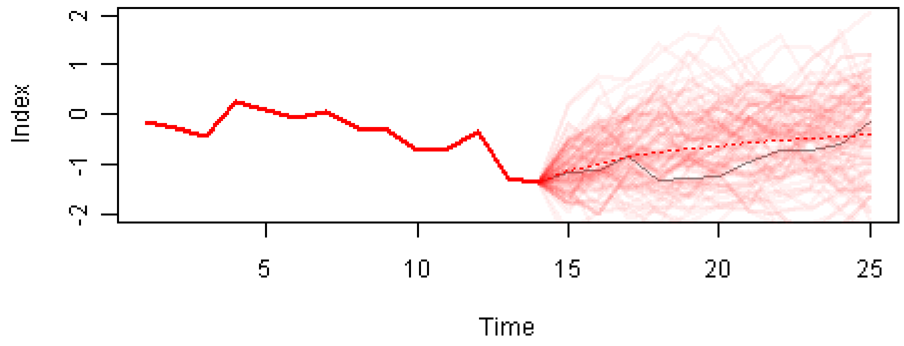
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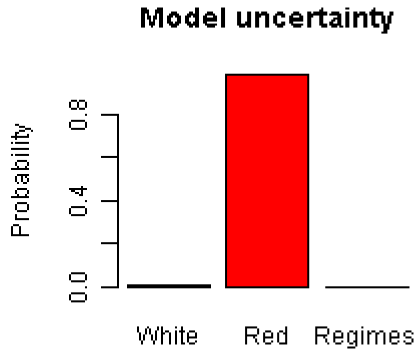
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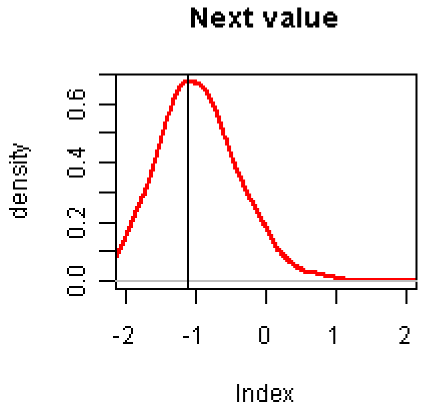
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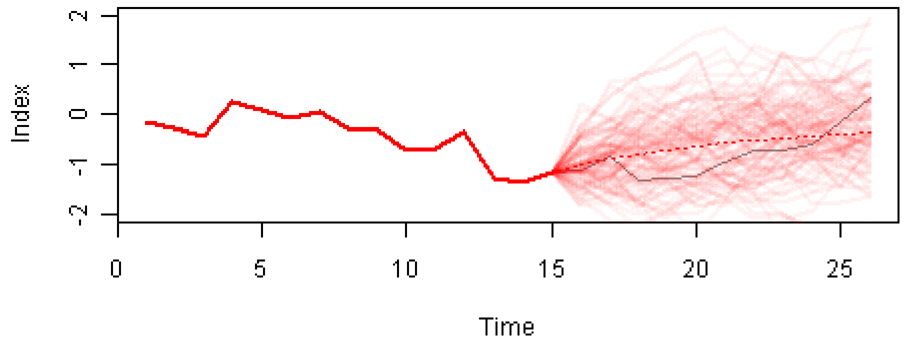
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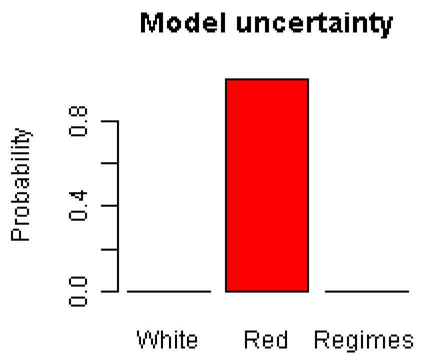
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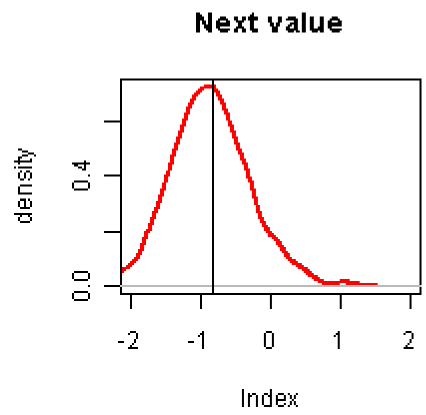
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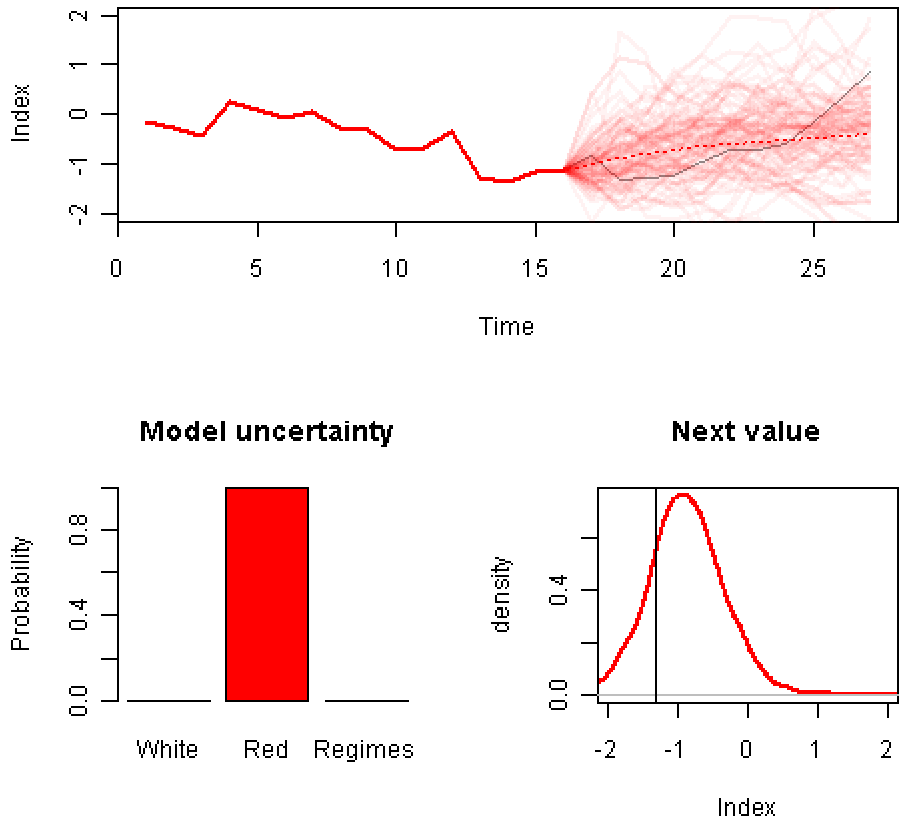

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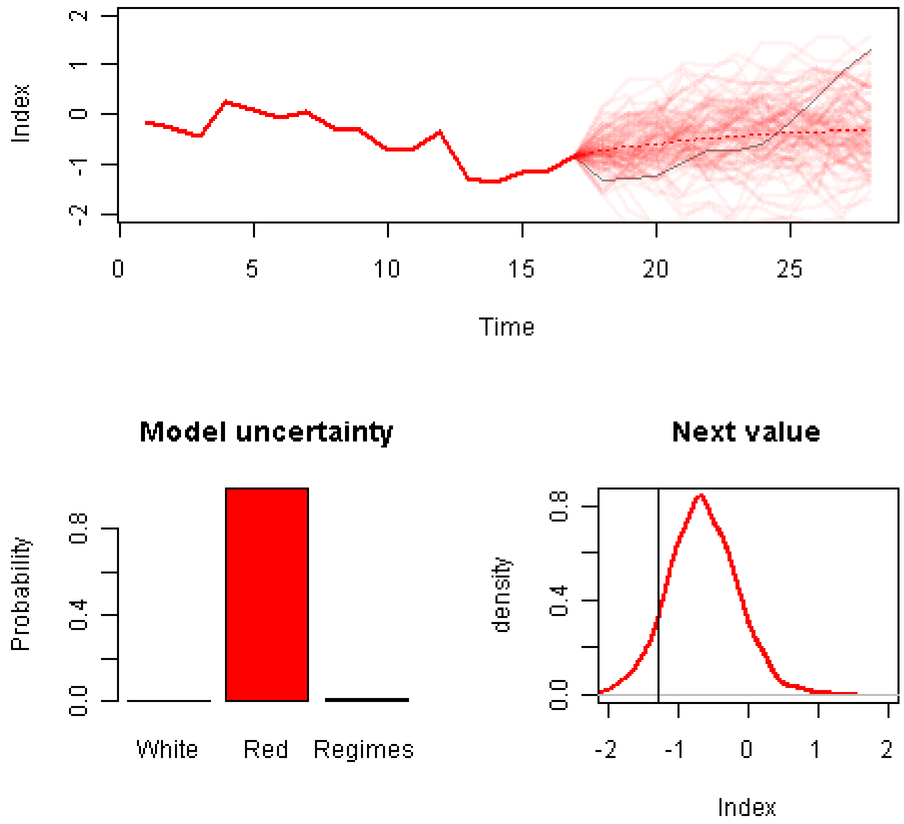
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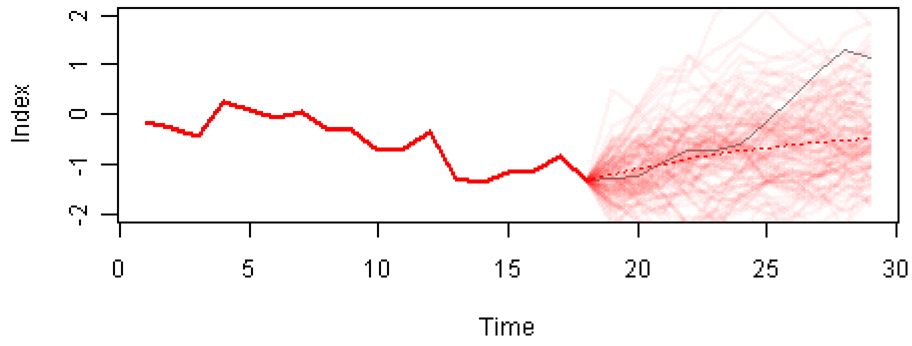
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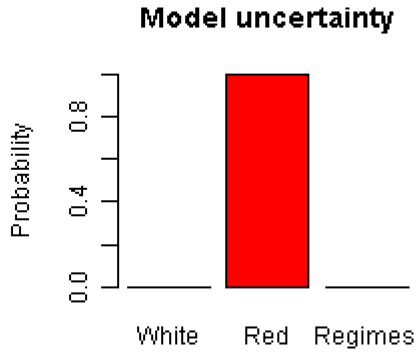
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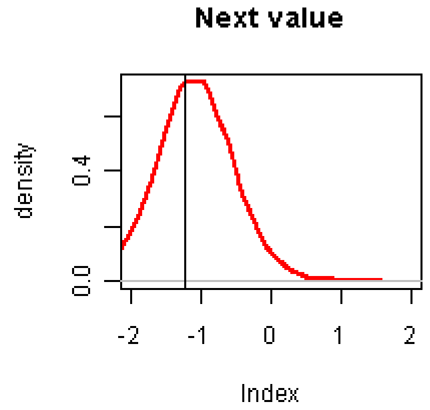
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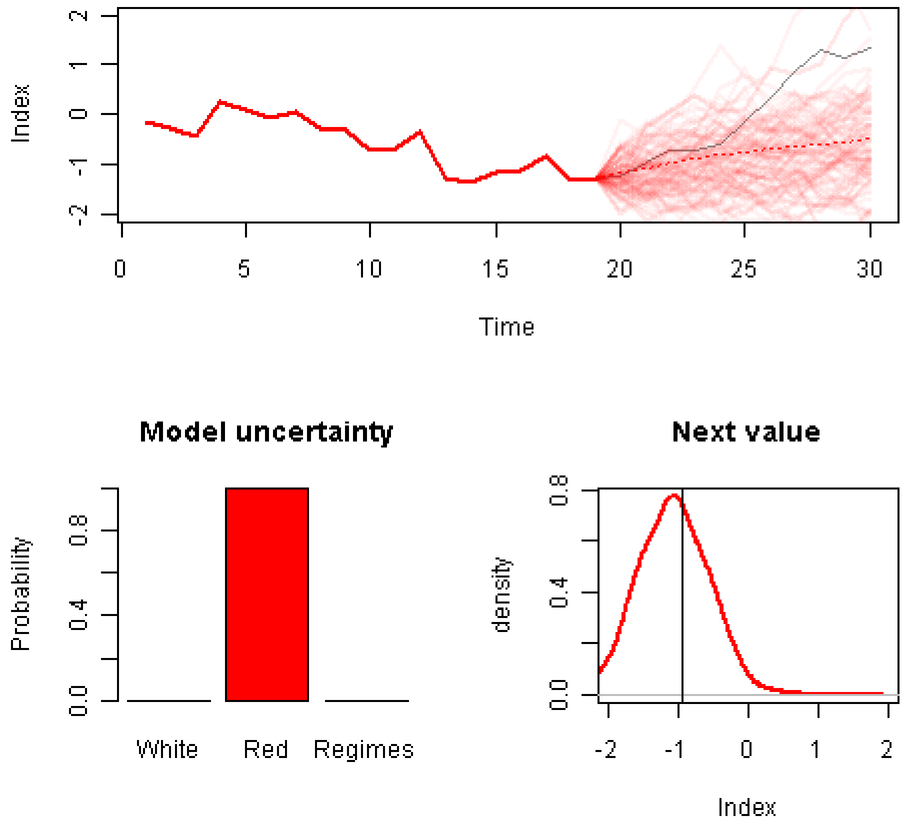
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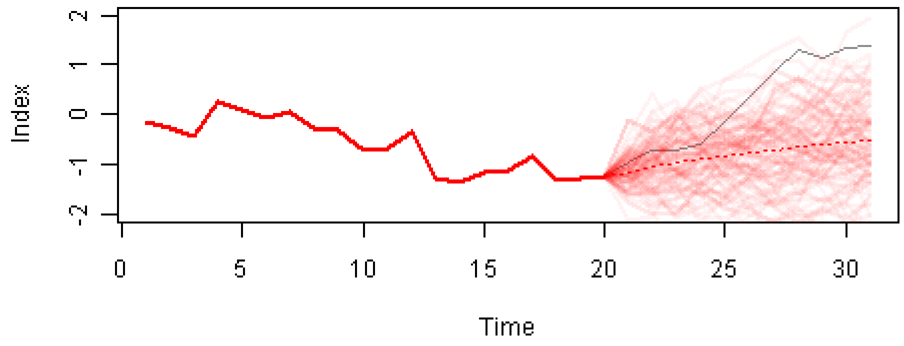
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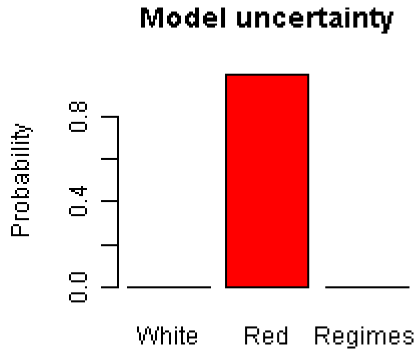
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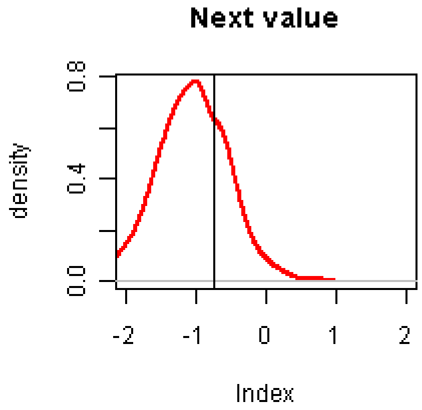
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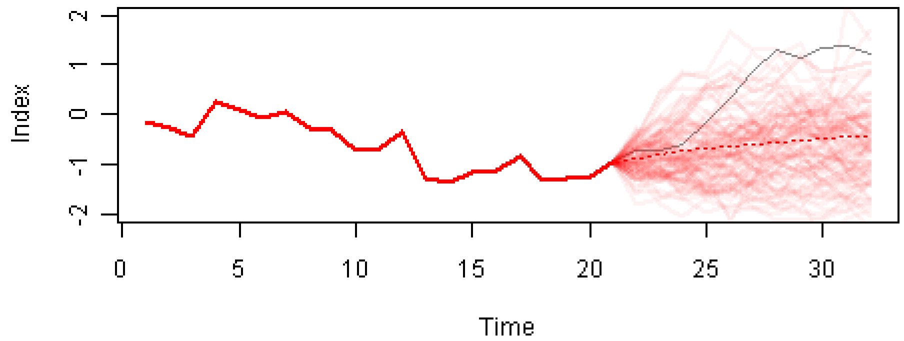

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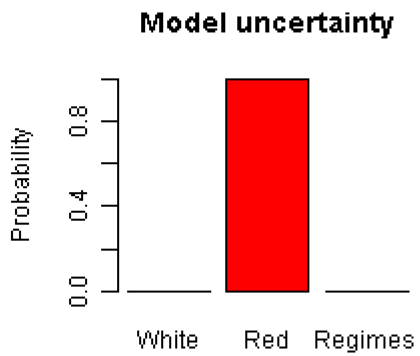

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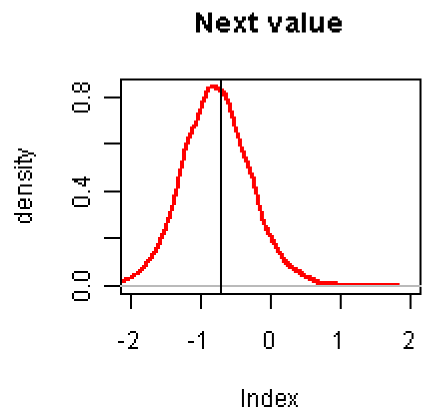

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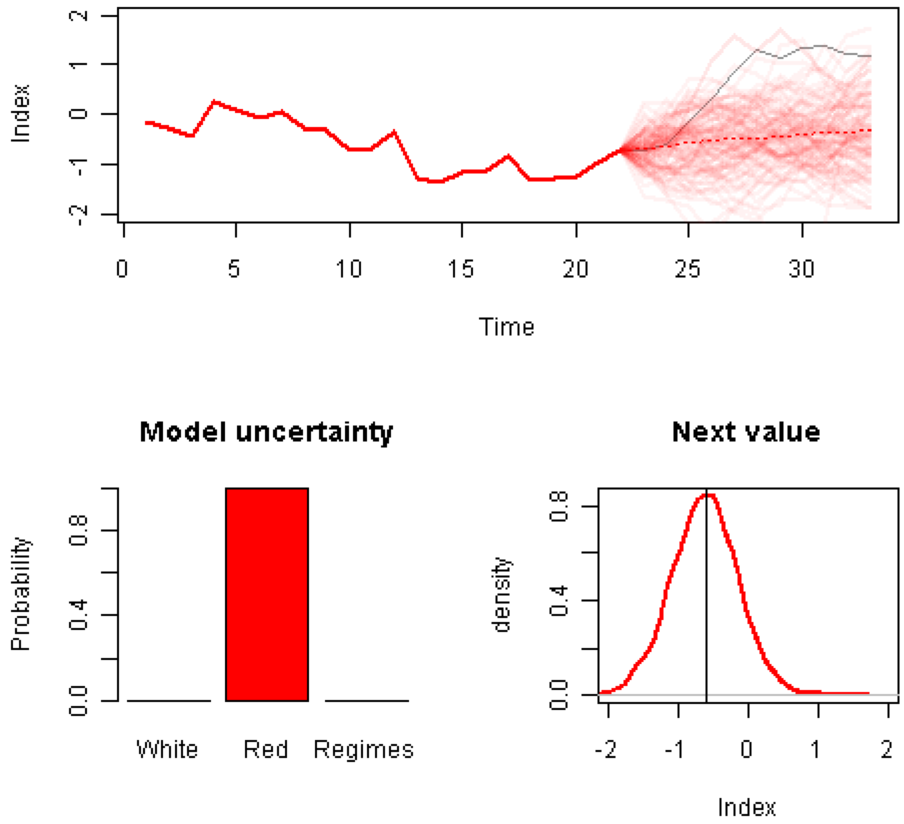

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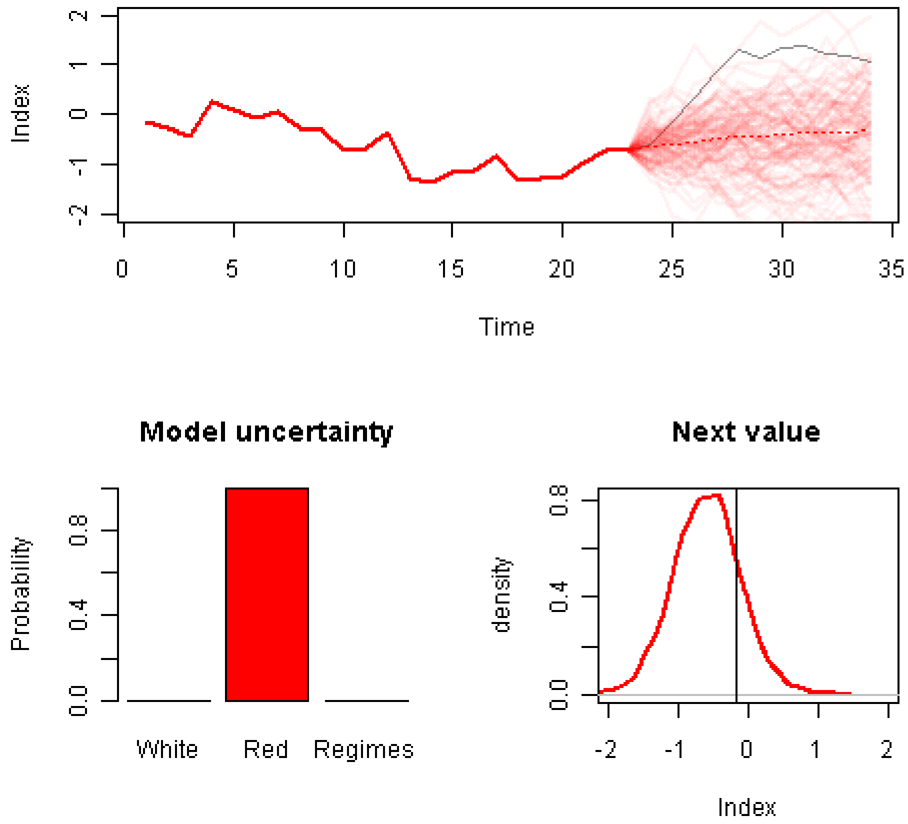
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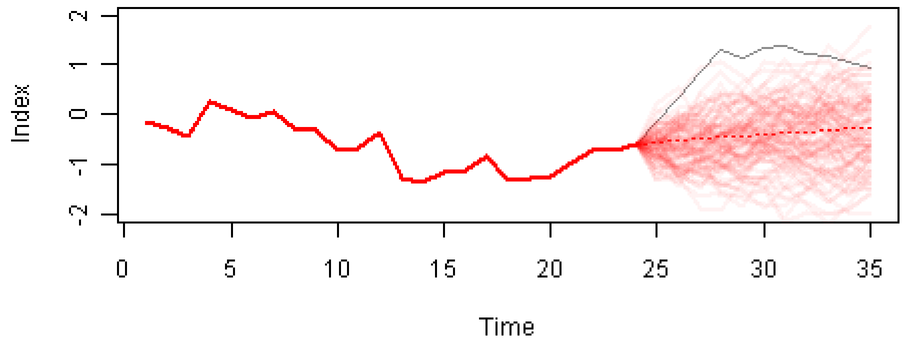
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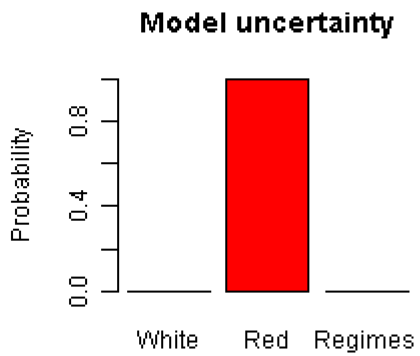
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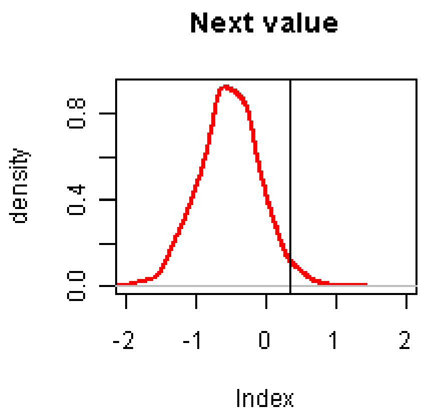
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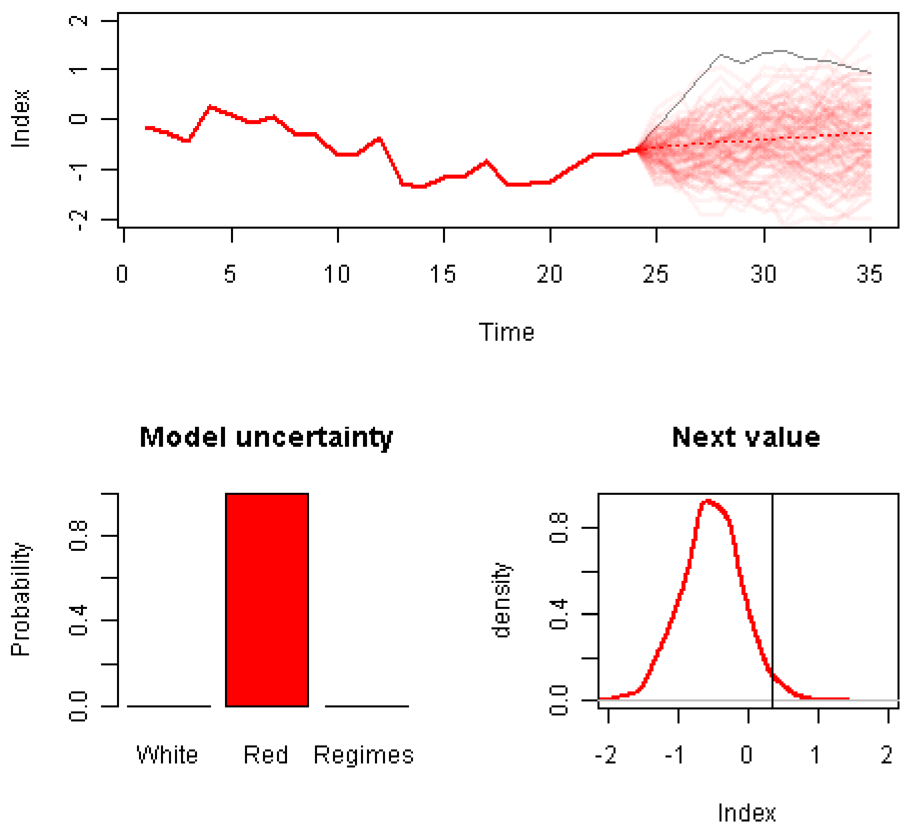
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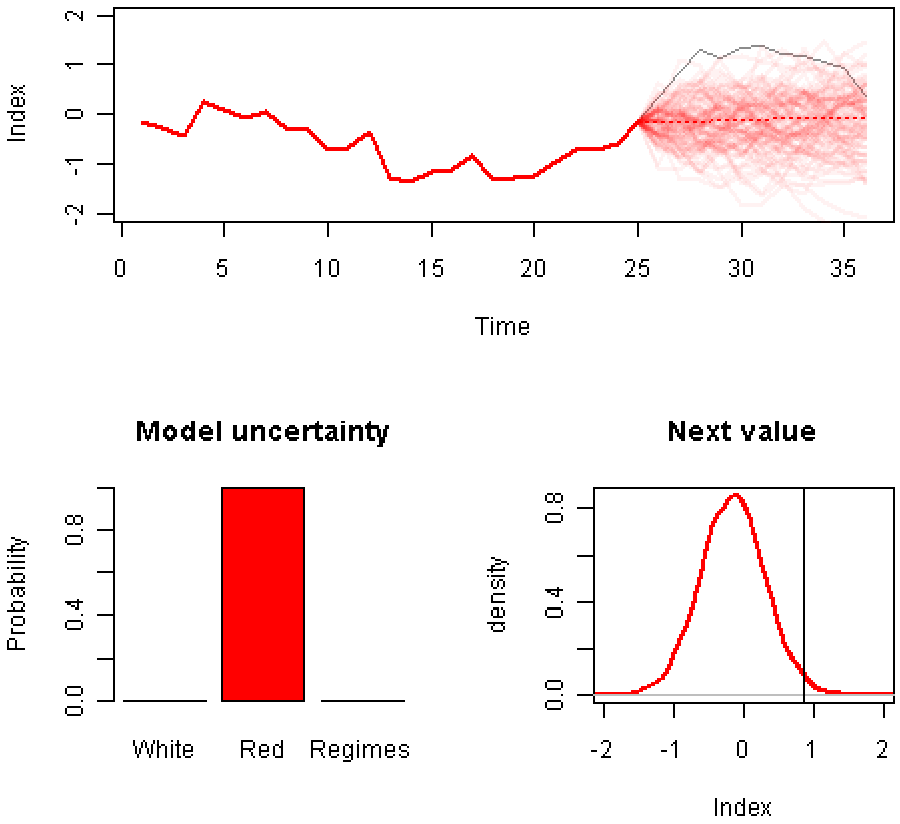
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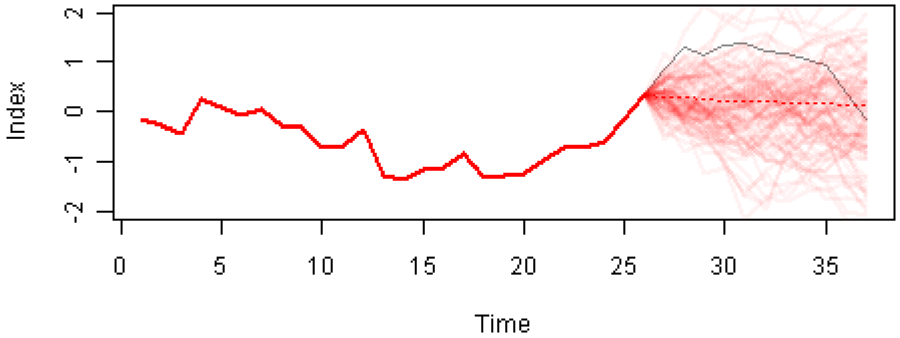
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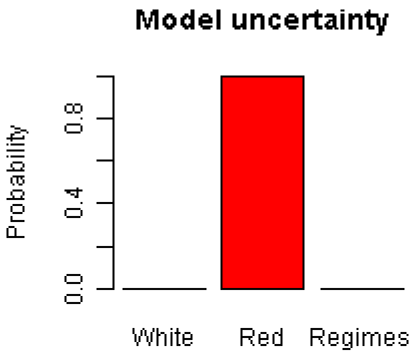
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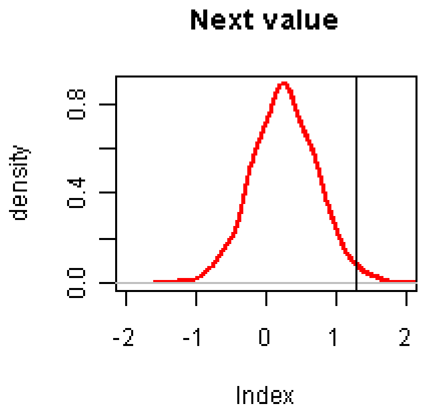
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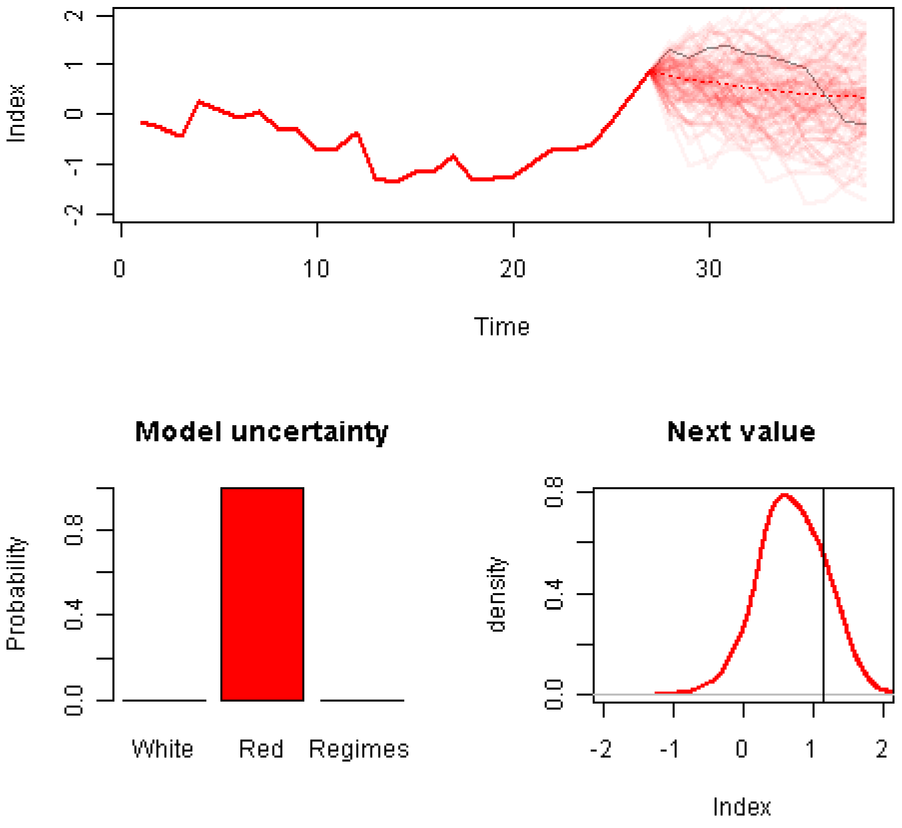
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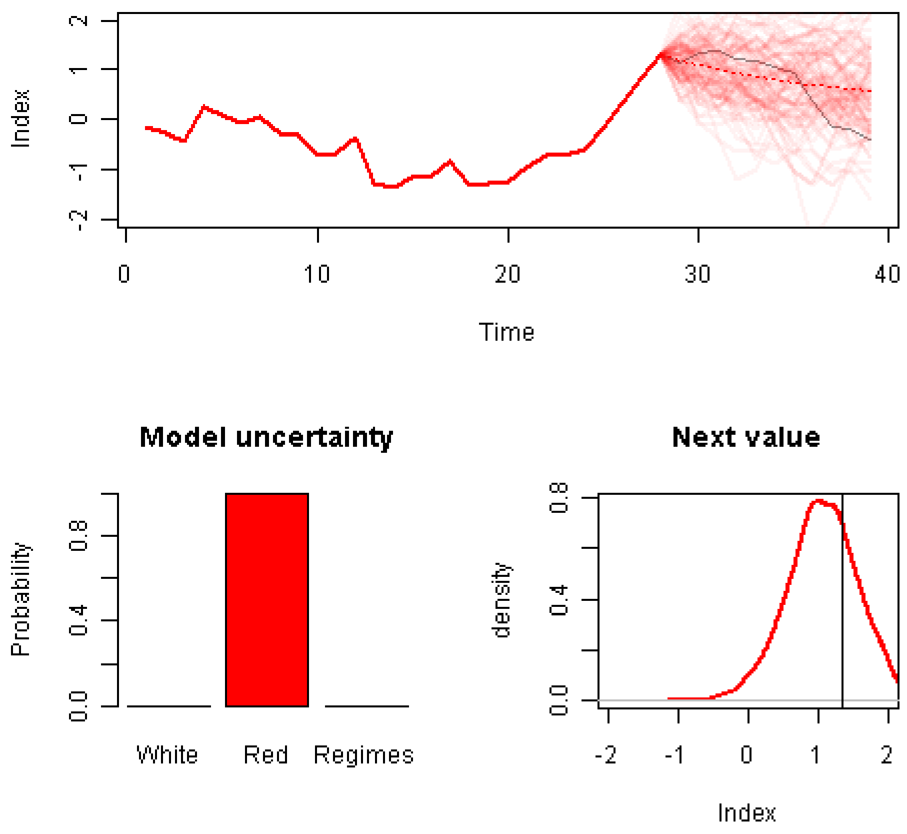
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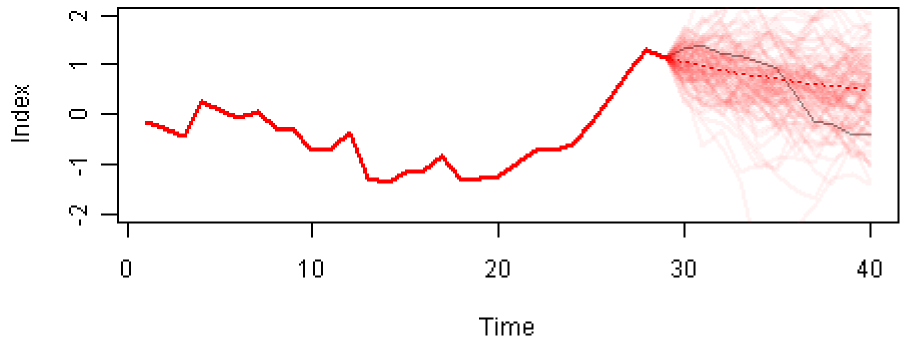
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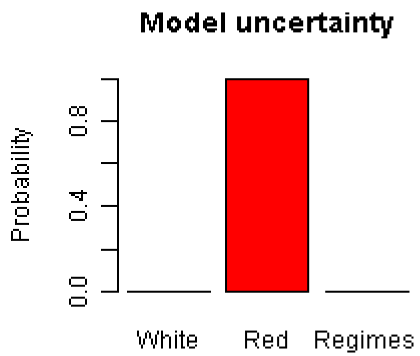
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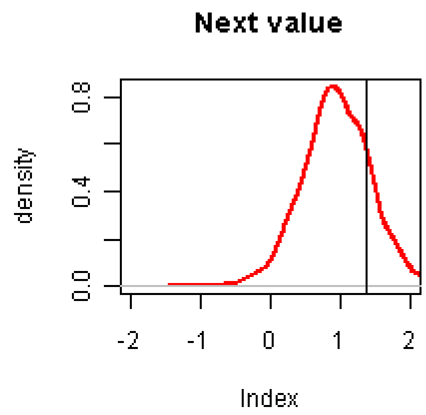
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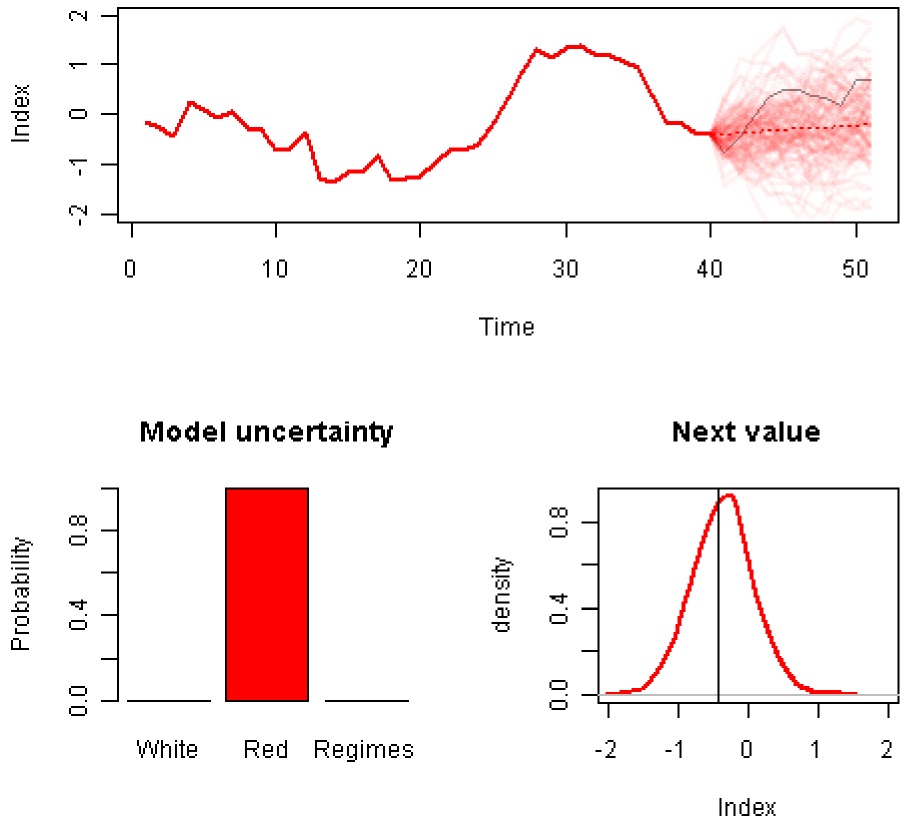

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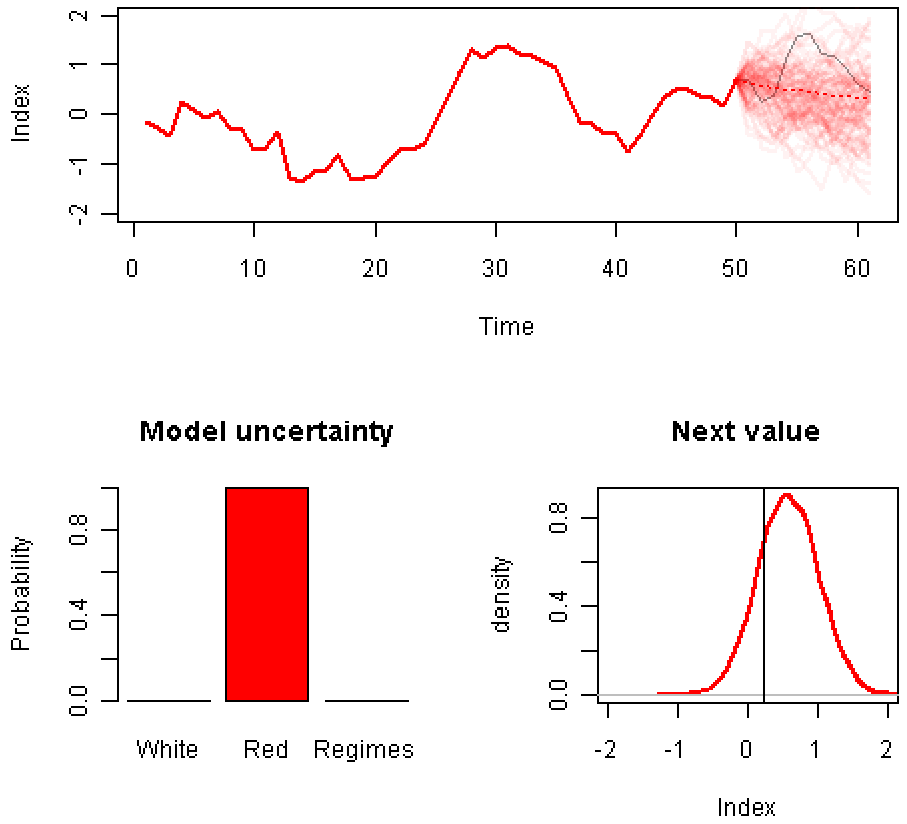
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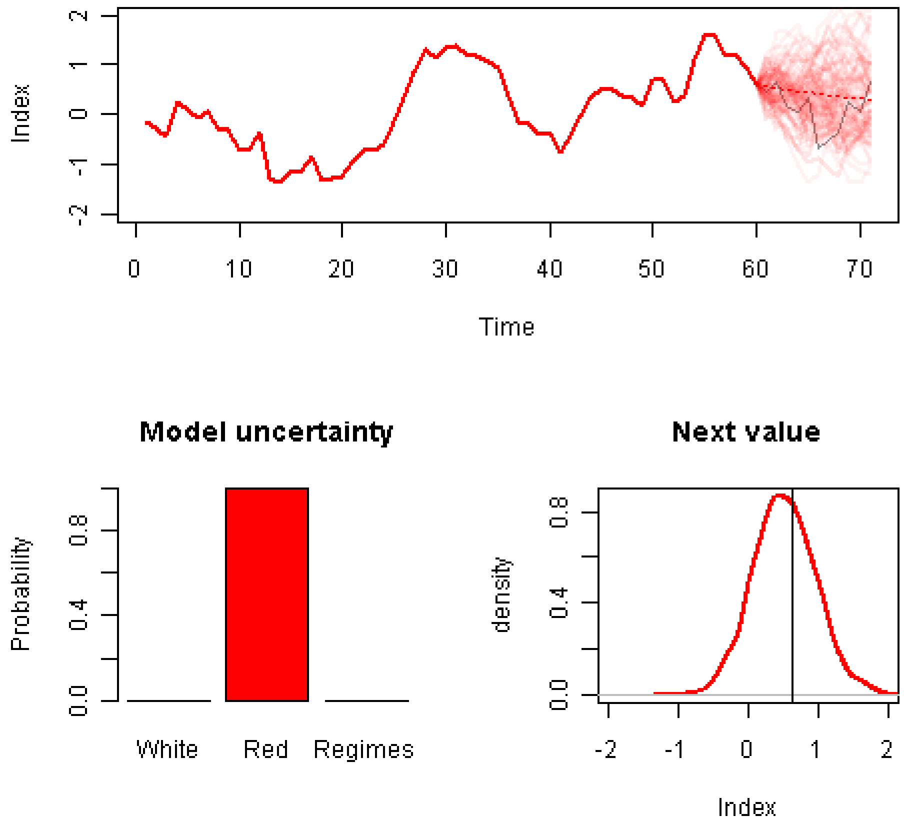
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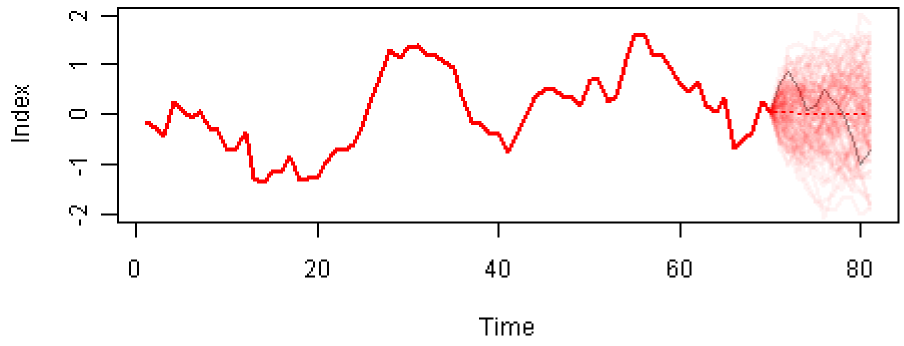
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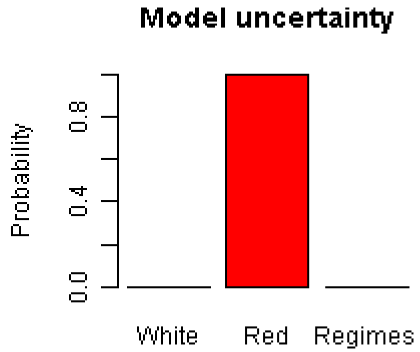
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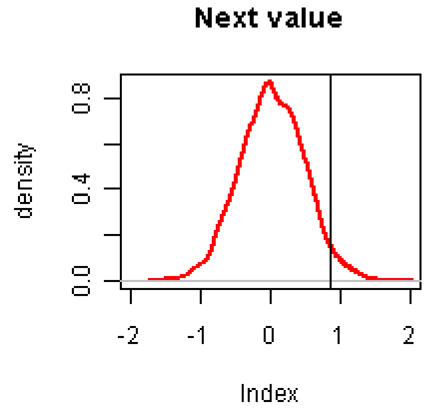
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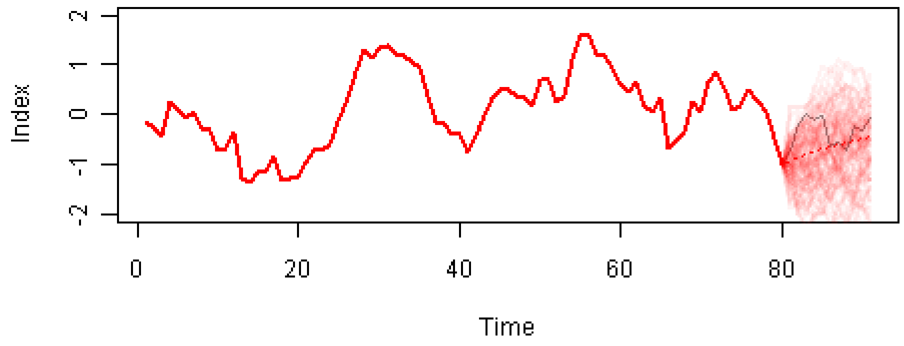
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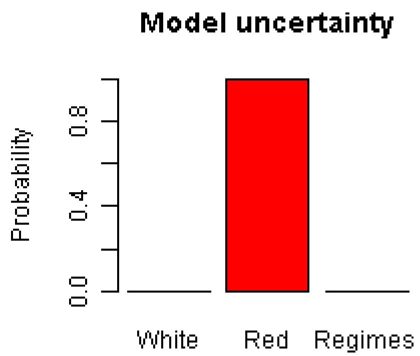
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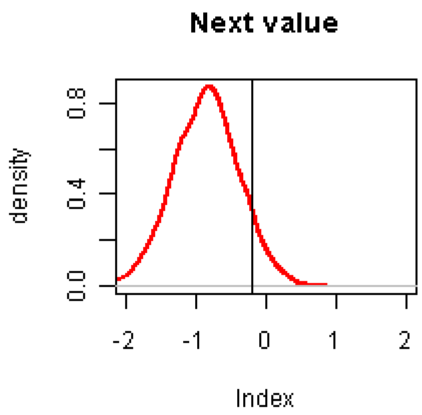
White
Red
Regimes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density
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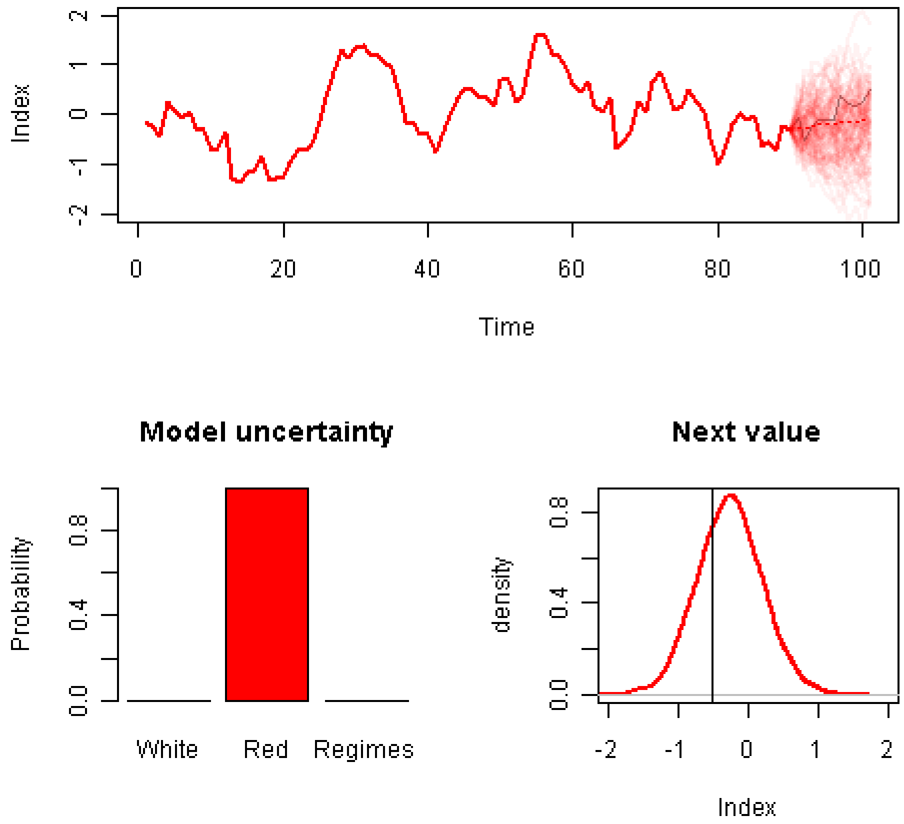
0.4
0.8
-2
-1
0
1
2
Index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2
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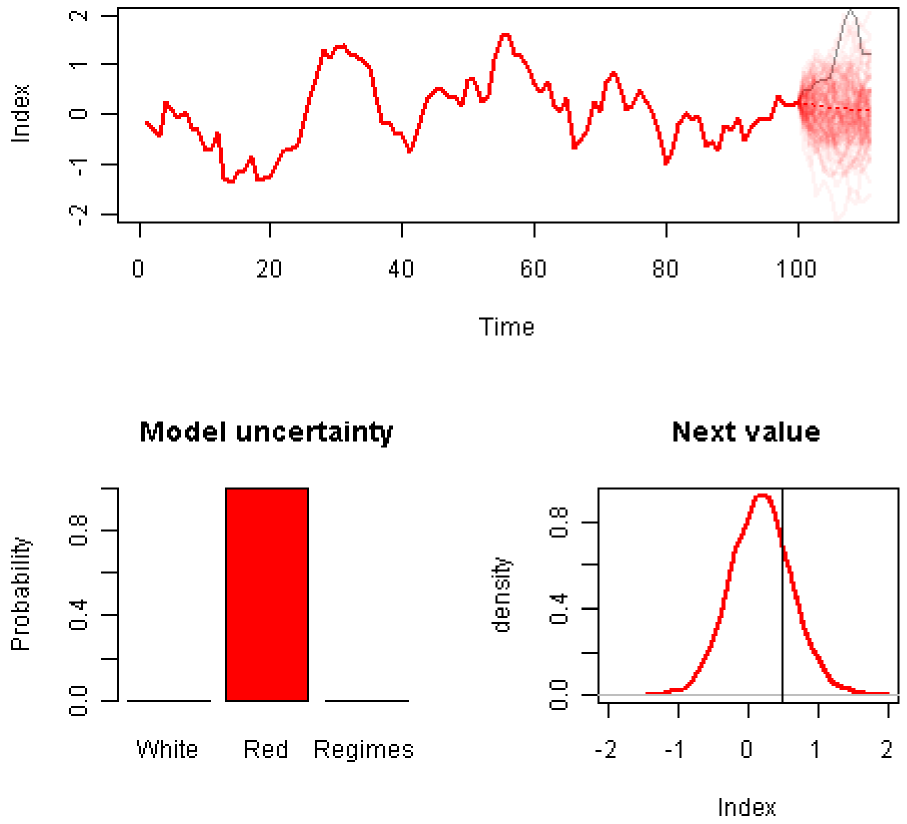
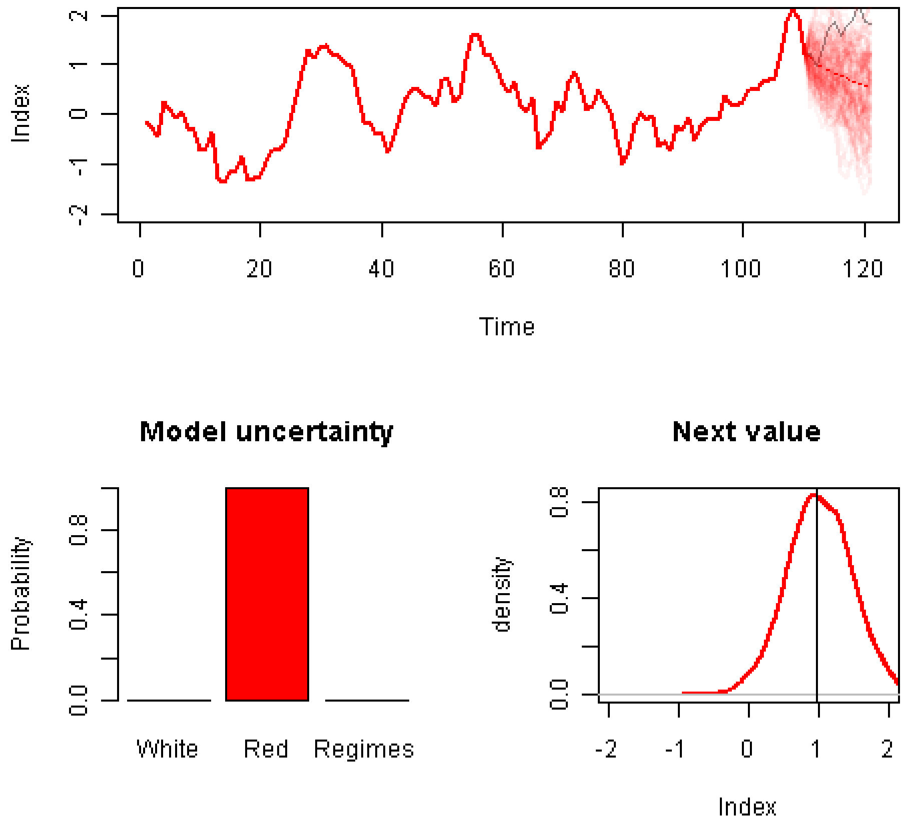
0
-1
-2
0
20
40
60
80
100
Time
Model uncertainty
Probability
0.0
0.4
0.8
White
Red
Regimes
Next value
density
0.0
0.4
0.8
-2
-1
0
1
2
Index


Index
Time
0
20
40
60
80
100
-2
-1
0
1
2
Model uncertainty
Probability
0.0
0.4
0.8
White
Red
Regimes
Next value
density
Index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2
1
0
-1
-2
0
20
40
60
80
100
120
Time
Model uncertainty
Probability
0.0
0.4
0.8
White
Red
Regimes
Next value
density
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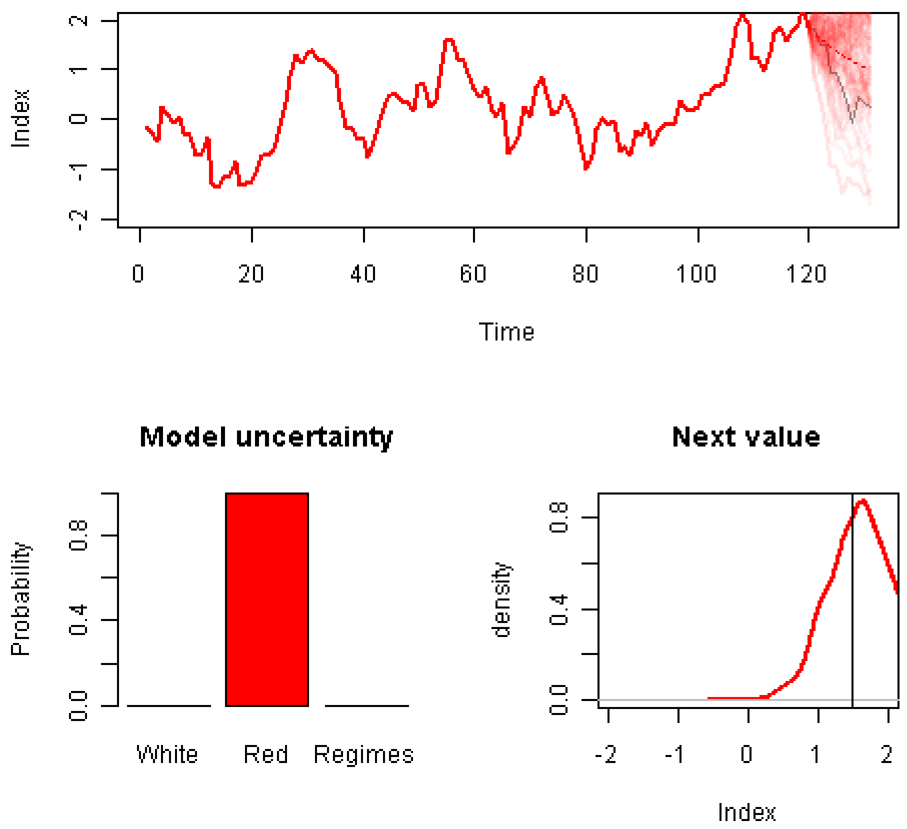
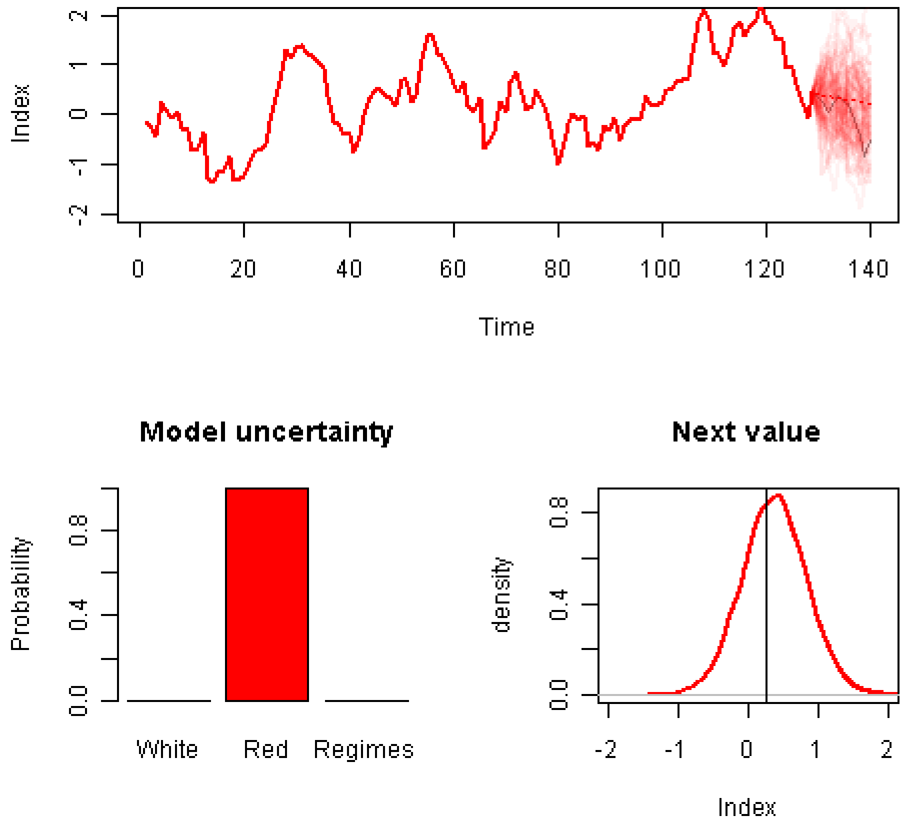
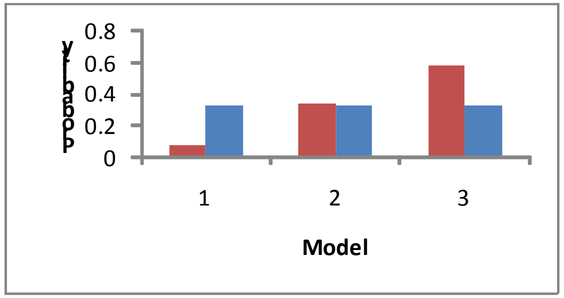
0.4
0.8
-2
-1
0
1
2
Index

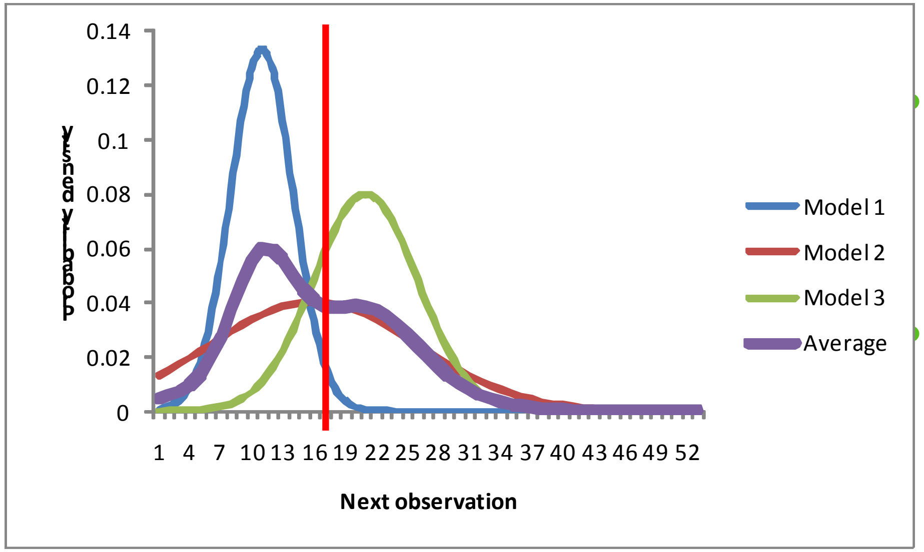


Index
2
1
0
-1
-2
0
20
40
60
80
100
120
Time
Model uncertainty
Probability
0.0
0.4
0.8
White
Red
Regimes
Next value
density
0.0
0.4
0.8
-2
-1
0
1
2
Index


Index
Time
Model uncertainty
Probability
White
Red
Regimes
Next value
density
Index

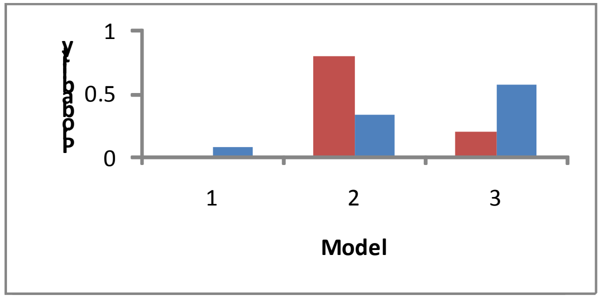
How it works?

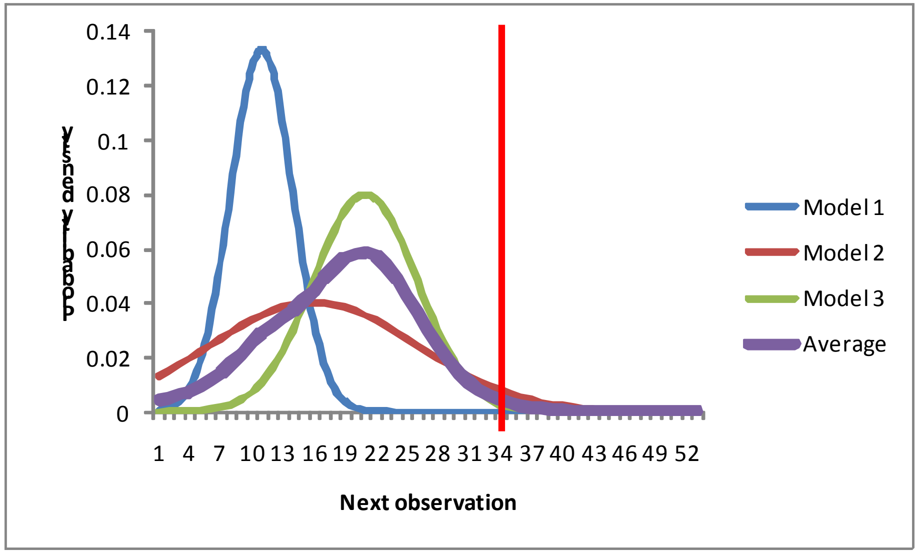




- P(data)=ΣP(data | model)P(model)
- In other words:
  - Predictive distribution of data is weighted average of model specific predictive distributions
- Weights are updated based on the predictive performance of individual models
- Just using the Bayes’ rule

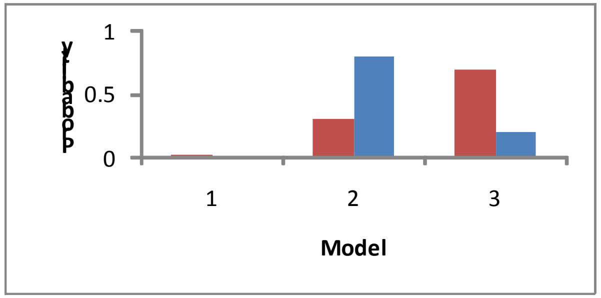
The next step

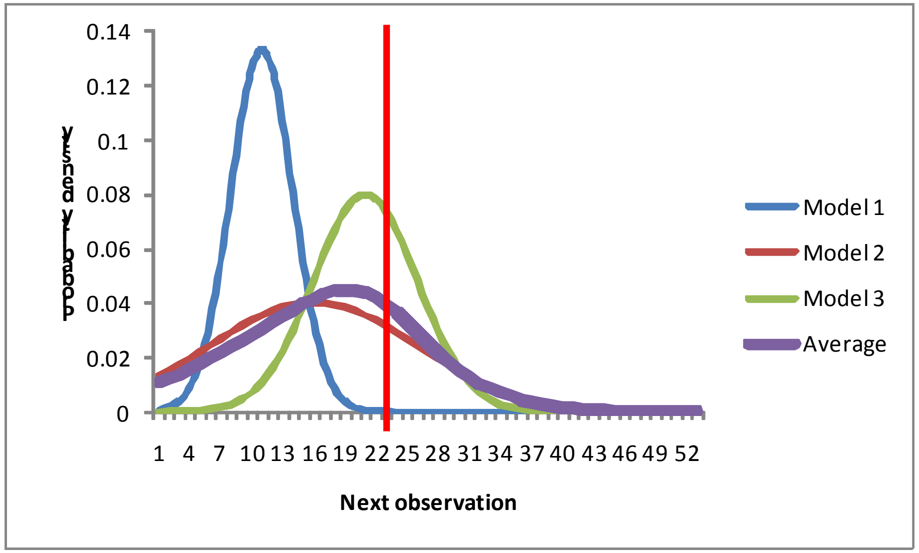




- Prediction using updated weights P(model | data)
- Update the weights again using a new observation

And so on…


1
0.5
0
1
2
3
Model


0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
1 4 7 10 13 16 19 22 25 28 31 34 37 40 43 46 49 52
Next observation
Model 1
Model 2
Model 3
Average

Part III: summary

- Bayesian Model Averaging : consistent way of accounting for model uncertainty
- Theory is very simple
- Practice can be difficult
  - Typically analytically intractable
  - Approximations needed
  - Ideal: parameters of each model should be updated after each new data point : ”Correlation is information”

Methods to estimate uncertainties of scenario simulations

- Bayesian framework
  - Structural & parameter uncertainty
  - Expert knowledge and data
  - Fit all models to all data using Baye's rule : full uncertainty accounted for, including the effect of correlations of parameter estimates
- Computational tools
  - Monte Carlo methods: parameter estimation & model uncertainty
  - Bayesian networks : Decision anlysis, integration of simulation output, interactive format

Possibilities to combine Bayesian risk analysis and climate change ensemble modelling?

- If the models in the ensemble provide probabilistic prediction:
  - Should be straightforward, in theory
  - Computational problems may arise
- If the models are deterministic
  - Not possible without changes to models
  - Predict a data set, learn residual variation -> use as uncertainty in further predictions
  - And/or use expert judegement to estimate the uncertainty

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Probabilistic Wind Speed Forecasting Using Ensembles and Bayesian Model Averaging

J. McLean SLOUGHTER, Tilmann GNEITING, and Adrian E. RAFTERY

The current weather forecasting paradigm is deterministic, based on numerical models. Multiple estimates of the current state of the atmosphere are used to generate an ensemble of deterministic predictions. Ensemble forecasts, while providing information on forecast uncertainty, are often uncalibrated. Bayesian model averaging (BMA) is a statistical ensemble postprocessing method that creates calibrated predictive probability density functions (PDFs). Probabilistic wind forecasting offers two challenges: a skewed distribution, and observations that are coarsely discretized. We extend BMA to wind speed, taking account of these challenges. This method provides calibrated and sharp probabilistic forecasts. Comparisons are made between several formulations.

KEY WORDS: ECME algorithm; Gamma distribution; Numerical weather prediction; Skewed distribution; Truncated data; Wind energy.

1. INTRODUCTION

While deterministic point forecasts have long been the standard in weather forecasting, there are many situations in which probabilistic information can be of value. In this paper, we consider the case of wind speed. Often, ranges or thresholds can be of interest—recreational sailors are likely to be more interested in the probability of there being enough wind to go out sailing than in simply the best guess at the wind speed, and farmers may be interested in the chance of winds being low enough to safely spray pesticides. Possible extreme values are of particular interest, where it can be important to know the chance of

(Brown, Katz, and Murphy 1984; Kretzschmar et al. 2004; Gneiting et al. 2006; Genton and Hering 2007). A detailed survey of the literature on short-range wind forecasting can be found in Giebel, Brownsword, and Kariniotakis (2003).

Medium-range forecasts looking several days ahead are generally based on numerical weather prediction models, which can then be statistically postprocessed. To estimate the predictive distribution of a weather quantity, an ensemble forecast is often used. An ensemble forecast consists of a set of multiple forecasts of the same quantity, based on different estimates of the initial atmospheric conditions and/or different physical

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Using Bayesian Model Averaging to Calibrate Forecast Ensembles

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(Manuscript received 18 December 2003, in final form 29 September 2004)

ABSTRACT

Ensembles used for probabilistic weather forecasting often exhibit a spread-error correlation, but they tend to be underdispersive. This paper proposes a statistical method for postprocessing ensembles based on Bayesian model averaging (BMA), which is a standard method for combining predictive distributions from different sources. The BMA predictive probability density function (PDF) of any quantity of interest is a weighted average of PDFs centered on the individual bias-corrected forecasts, where the weights are equal to posterior probabilities of the models generating the forecasts and reflect the models' relative contributions to predictive skill over the training period. The BMA weights can be used to assess the usefulness of ensemble members, and this can be used as a basis for selecting ensemble members; this can be useful given the cost of running large ensembles. The BMA PDF can be represented as an unweighted ensemble of any desired size, by simulating from the BMA predictive distribution.

The BMA predictive variance can be decomposed into two components, one corresponding to the between-forecast variability, and the second to the within-forecast variability. Predictive PDFs or intervals based solely on the ensemble spread incorporate the first component but not the second. Thus BMA provides a theoretical explanation of the tendency of ensembles to exhibit a spread-error correlation but yet be underdispersive.

Thank you!