Temporal Modeling and Missing Data Estimation from MODIS Vegetation Data

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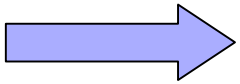
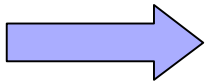
Backgrounds

- Spatio-temporal data mining from Earth observation satellite data is a powerful approach for Phenology study, and the other application field such as detection of famine, deforestation.
- The common obstacles are, noises, missing data, and the sparseness of the data
- How we can build a temporal model accurately for such dataset?



Model fitting by Maximum a posterior (MAP) approach

- How we can utilize spatial information to improve the accuracy of temporal modeling?



Integration of MAP estimate and spatial information by Random Forests

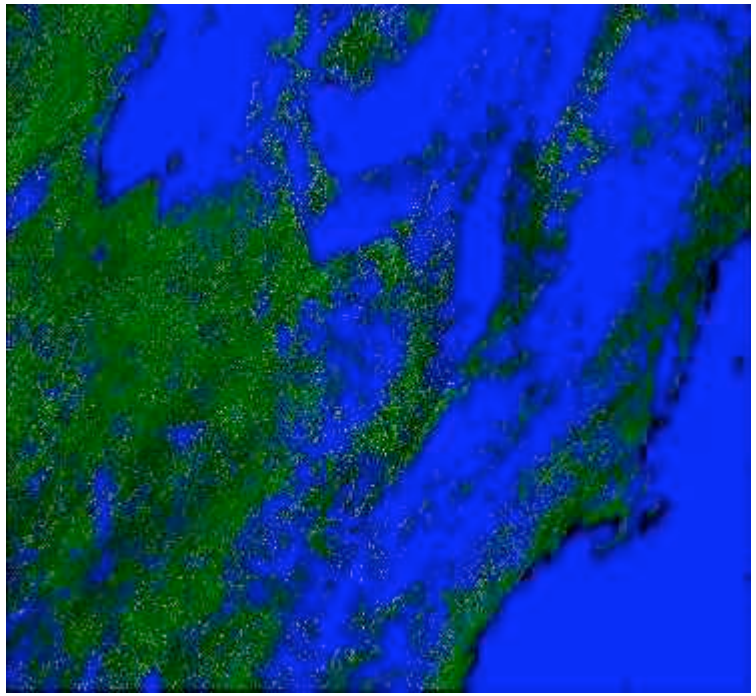
Outline

- Dataset.
- Temporal modeling of MODIS EVI by MAP.
- Missing value estimation by Random Forests by using both MAP estimate and the other and spatial information as the input.
- Conclusion.

Dataset

- The enhanced vegetation index (EVI) of Moderate Resolution Imaging Spectroradiometer (MODIS)
  - Produced globally over land at 500m/1km resolutions and 16-day compositing periods.
  - Optimized index with accurate calibration of atmosphere influences and effect of canopy, etc.
  - Useful for study of global phenology, ecosystem, etc.

Example of MODIS EVI Data



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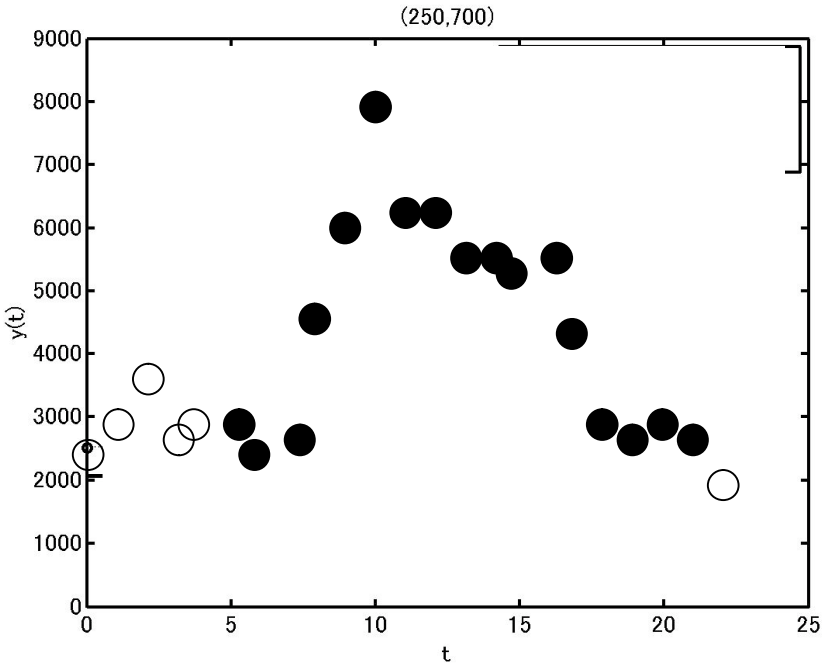


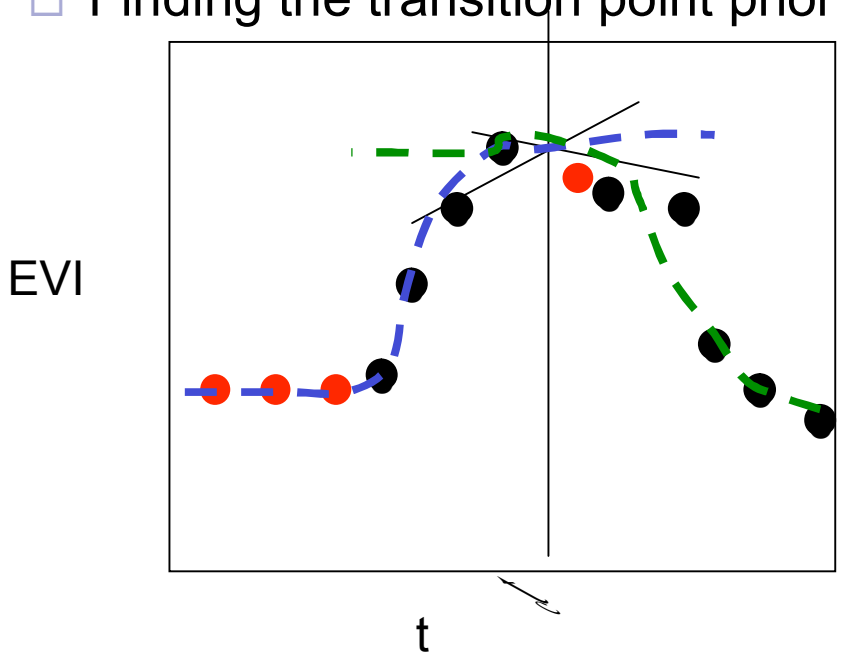
valid data
data in snow

- Problems
  - Numerous data are missing due to cloud or snow coverage (particularly in the winter time).
  - Data are noisy and data points exist temporally sparsely.

Method used in the previous study

- Zhang et al. (2003) adopted the piecewise logistic function model and fitted the data to the model by least-square-error method.
- Preprocessing was required prior to the fitting
  - Filling missing values by the temporal neighbors
  - Finding the transition point prior to the fitting

These may cause a biased solution.



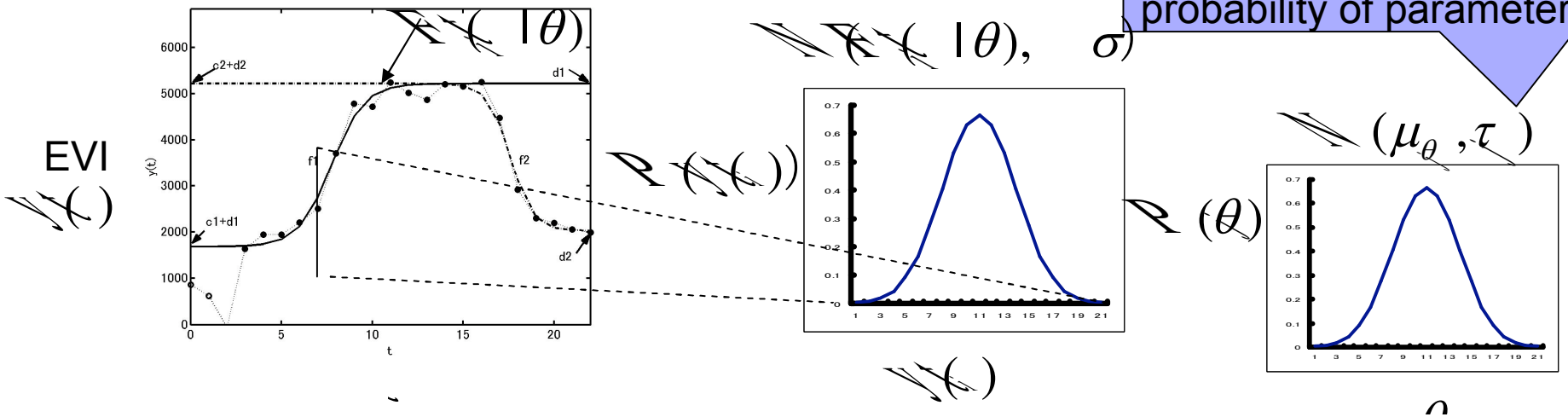
$$f(\ |\theta) = \begin{cases} f_1(\ |\theta_1) & \\ f_2(\ |\theta_2) & \end{cases}$$

$$f(\ |\theta) = \frac{}{1+}$$

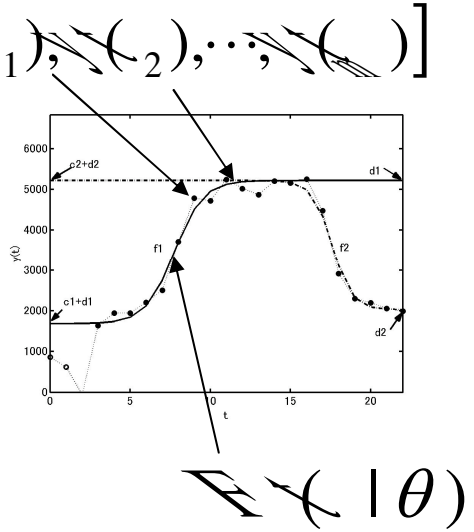
Features of temporal modeling in this study

- Following the Zhang et al's piecewise logistic function model, but statistically-sound method is used.
  - Maximum a Posterior (MAP) approach
  - Both probability distribution of observation including noise (σ), and the probability distribution of model parameter ((μ_θ, τ)) are incorporated in the model.

When the many of data are missing, MAP relies on the probability of parameters.



Method - Maximum a Posterior (MAP) Estimation -



- Equations.

$$P(\quad|\theta) = \prod \quad(\quad|\theta), \qquad \sigma),$$

$$(\theta) = \prod_{=1} (\mu_\theta, \tau)$$

Prior

$$(\theta) = \log \quad(\quad|\theta) \quad(\theta) \leftarrow \propto \quad(\theta|\quad)$$

Posterior Probability

$$\hat{\theta} = \arg\max_{\theta} \quad(\theta)$$

- Initial prior parameters are given explicitly.

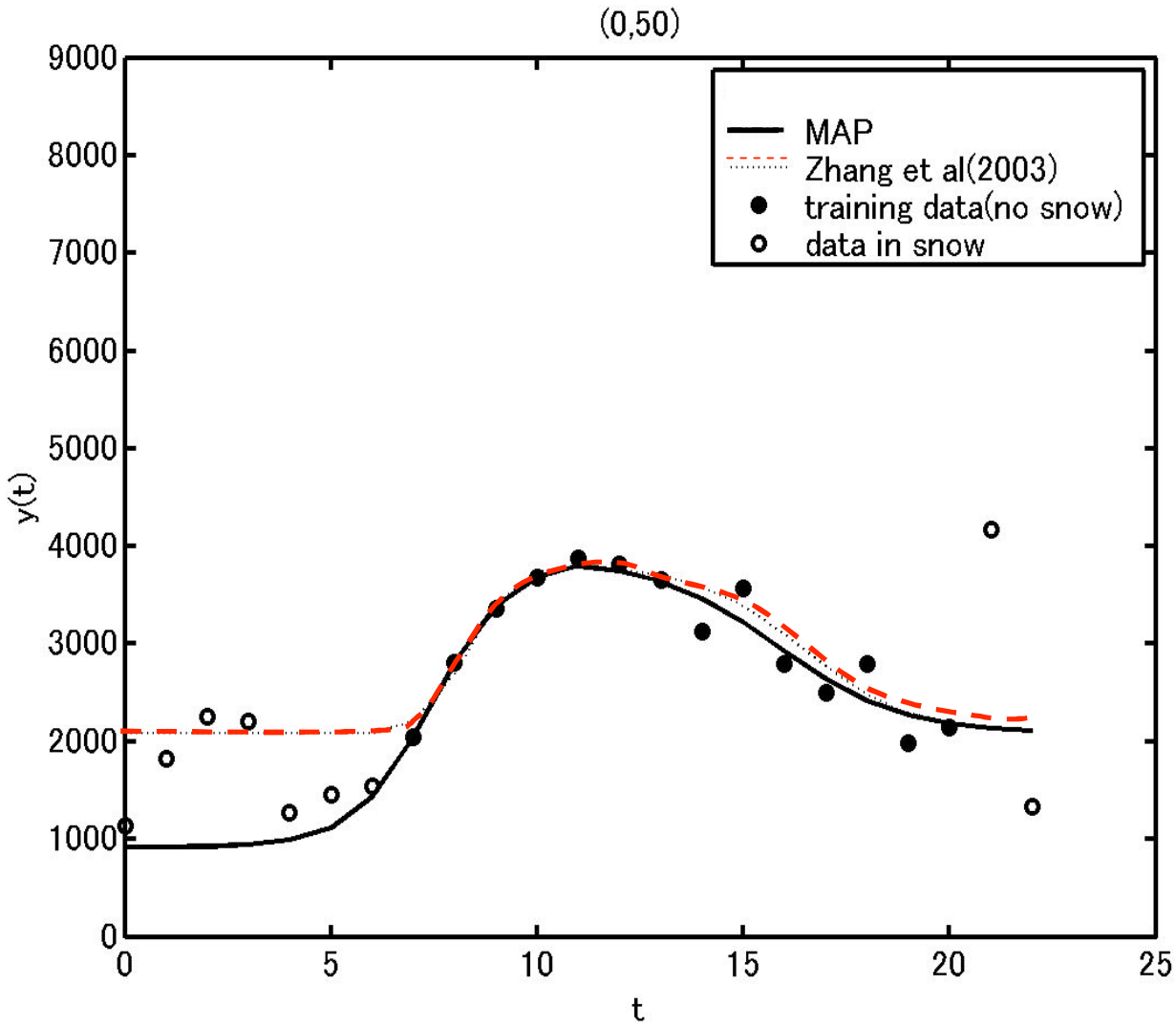
μ_θ : Mean of ML solutions for many pixels.

τ : Standard deviation of ML solutions for many pixels.

Positive effects

- Preprocessing of the data such as smoothing , guessing of missing data and segmentation are not required.
  - Still solutions are obtained accurately and robustly.
- Uncertainties of parameter estimates are assessed via confidence intervals
- Relevant prior information is introduced if it is available.

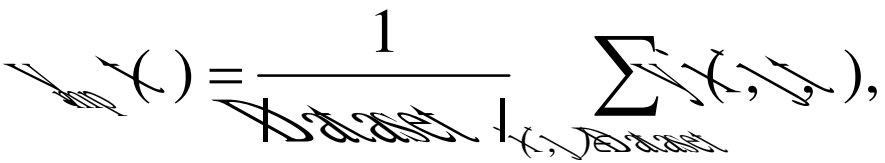
Example of fitting

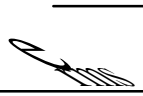


Performance of modeling by MAP

- Take one time point from each time series and guess that value from the model built from the rest of the data.
- Prediction accuracy measure
  - Normalized prediction error

  - Mean predictor

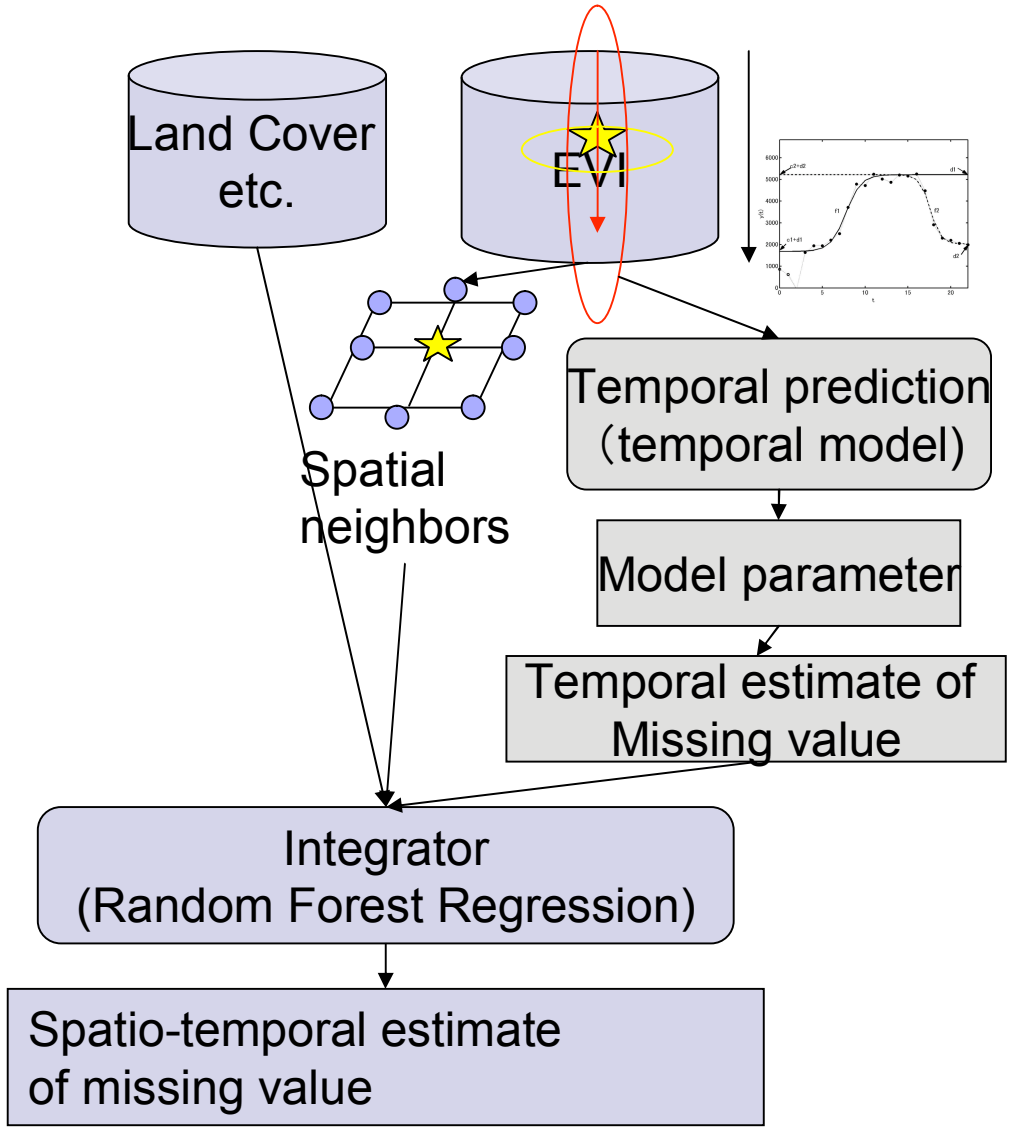


	MAP	Zhang et al (2003)
	0.135	0.209*

* Fitting error (not a prediction error)

Spatio-temporal estimation

- Missing value estimation by use of both temporal model, spatial neighbors and other information

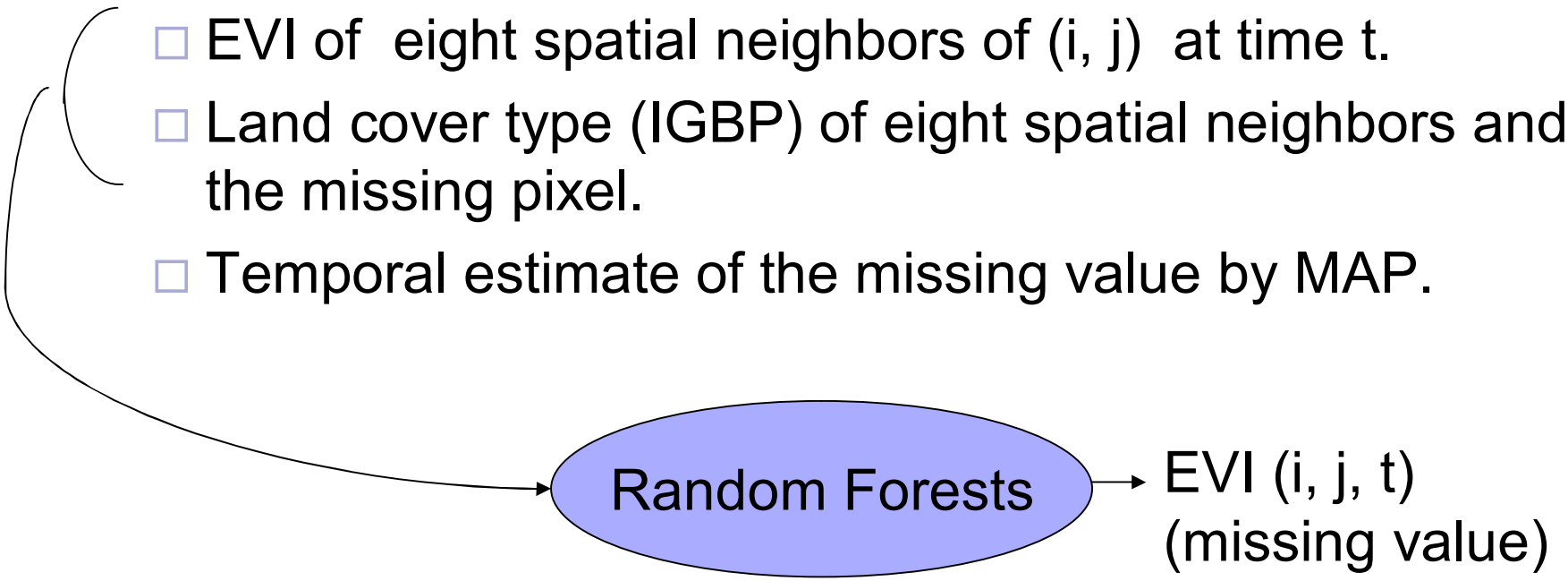


Random Forests (Breiman, 2001)

- An ensemble of unpruned classification or regression trees induced from bootstrap samples of the training data, using random feature selection in the tree induction process.
- Prediction is made by aggregating (majority vote for classification or averaging for regression) the predictions of the ensemble.

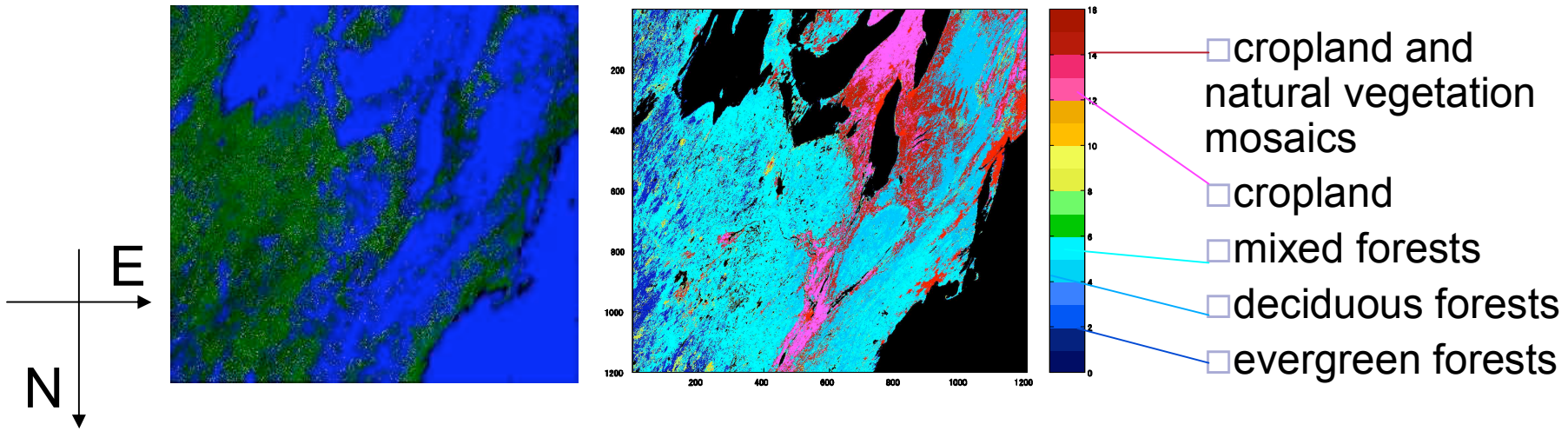
Input and target attributes of Random Forests

- Target
  - EVI of the (i, j) pixel at time t. (the missing value)
- Input
  - EVI of eight spatial neighbors of (i, j) at time t.
  - Land cover type (IGBP) of eight spatial neighbors and the missing pixel.
  - Temporal estimate of the missing value by MAP.



The dataset used for evaluation

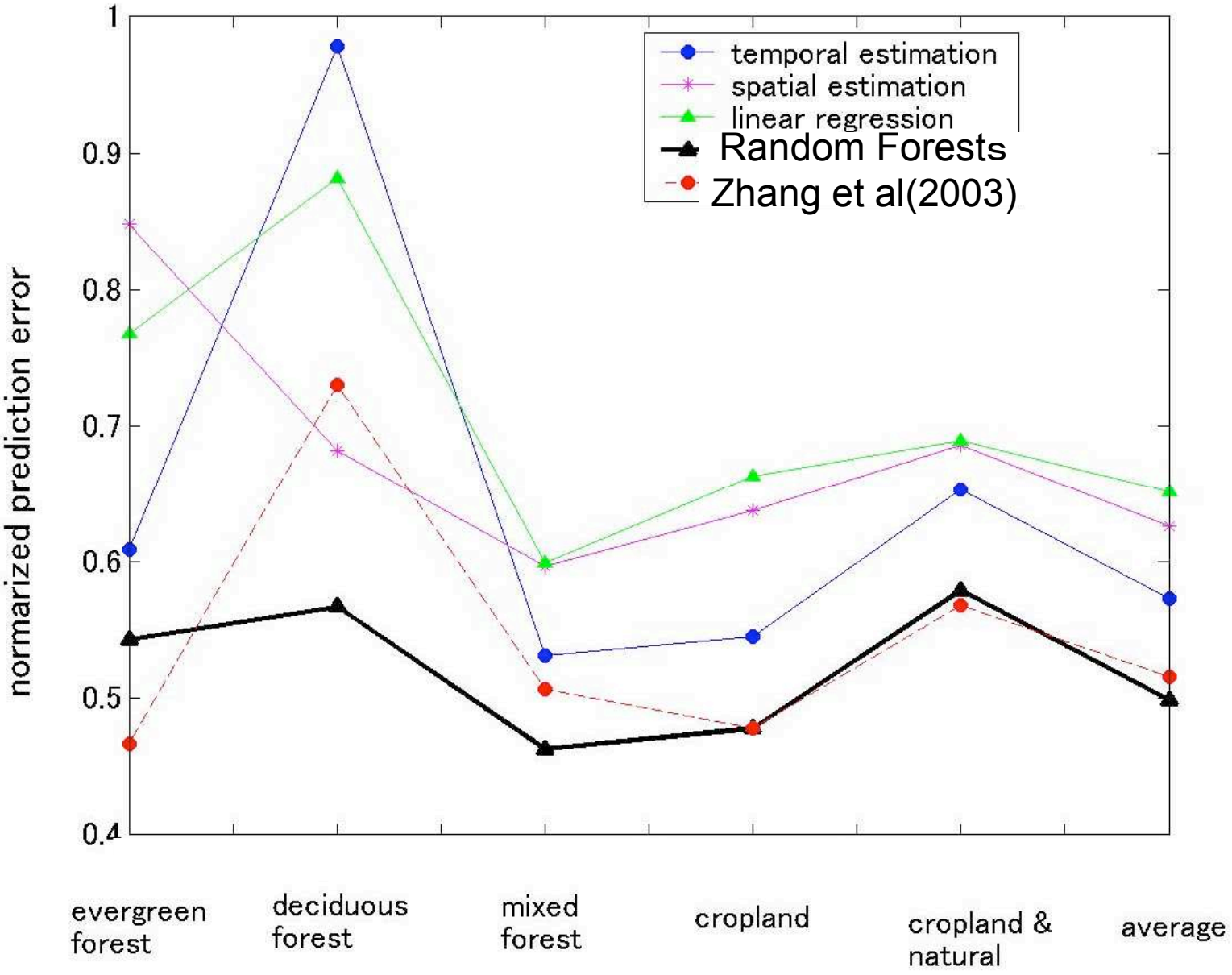
- MODIS data of Northeastern United States
  - EVI, “snow flag”, land cover type (IGBP) for each pixels
  - 16 days interval (January 2001 to December 2001)
  - A spatial resolution: 1km per pixel (1200 × 1200 pixels)
- Six datasets for evaluation
  - evergreen forests, deciduous forests, mixed forests, cropland, cropland and natural vegetation mosaics, and the mixture of five groups (about 1000 samples in each and 5000 for the mixture).



Evaluation Method

- The half of the data set was used for training of random forests and the rest was used for evaluation .
- Other Methods in comparison
  - Logistic model fitting via MAP (temporal prediction).
  - Four neighbor average (spatial prediction).
  - Linear regression by using all the attributes.

- Accuracy Measure
  - Normalized prediction error.


temporal estimation
spatial estimation
linear regression
Random Forests
Zhang et al(2003)
normarized prediction error
1
0.9
0.8
0.7
0.6
0.5
0.4
evergreen forest
deciduous forest
mixed forest
cropland
cropland & natural
average

Conclusion

- The effectiveness of MAP for temporal modeling for such dataset as MODIS EVI is confirmed.
  - No preprocessing (e.g., segmentation and filling of missing values) and required and still the solutions are obtained robustly.
- Random Forests is found to be effective to improve the temporal estimate.
  - Once the predictor is created, temporal estimation is improved promptly.
- Future study
  - Application to multiple-year data set, and detection of spatio-temporal pattern change.
  - Automatic detection of sub-seasonal pattern.
  - The models considering spatial distribution (e.g., mixture model for model parameters in the spatial domains) .

Acknowledgement

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Discussion Questions

- 1. What data mining or statistical methods were used?
  - Maximum a Posteriori, Random Forests
- 2. How were the techniques developed?
  - b) modified from another application or research project
- 3. What is the importance of the science question?
  - How we can deal noises, missing data and construct the temporal model robustly.
- 4. What scientific results were obtained that would have been
- difficult or impossible without data mining and/or statistics?
  - Robust fitting without pre-processing and improvement of estimation
- 5. What were the obstacles?
  - Missing values, noises.
- 6. Did this work result in a geoscience publication? If not, why not?
  - Not yet.

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