

Fire Prediction in Southeast Asia Using Remote Sensing

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1. Motivation

1. Peatlands in Equatorial Asia are one of the world's major carbon sinks.
2. Land use change over the last 20 years has directly resulted in increased CO₂ emissions and large fires.
3. During high fire years, tens of millions of people are exposed to unhealthy smog conditions.
4. Regional-scale investigation of peatland hydrology difficult due to inaccessibility of peat forests.

5. Can we predict fires using satellite data?

2. Methods

1. Where: Tropical peatlands in Equatorial Asia, which includes Sumatra, Borneo, and Peninsular Malaysia.

2. When: 2015

3. Data:

a) Features: soil moisture, vegetation optical depth, temperature, specific humidity, precipitation, potential Eand actual evapotranspiration. All features scaled between 0 and 1.

b) Response: Class variable based on fraction of grid burnt.

| | | |
|---------------------|------------|-------------|
| no fire | small fire | large fire |
| 0 | (0, 0.01] | (0.01, 0.4] |
| Burnt area fraction | | |

Fig. 1 Definition of fire classes. Color for each class used henceforth to label classes. Burnt area fraction is area of a cell affected by fire relative to total area of grid cell.

4. Model:

a) Classification problem: predicts whether a grid has no fire, small fire or large fire. Multinomial logistic (Softmax) regression chosen to classify response because of simplicity and robustness (data not linearly separable).

b) Regularization parameter λ tuned using 10-fold CV.

c) Model performance evaluated on test set (30% of data).

3. Results

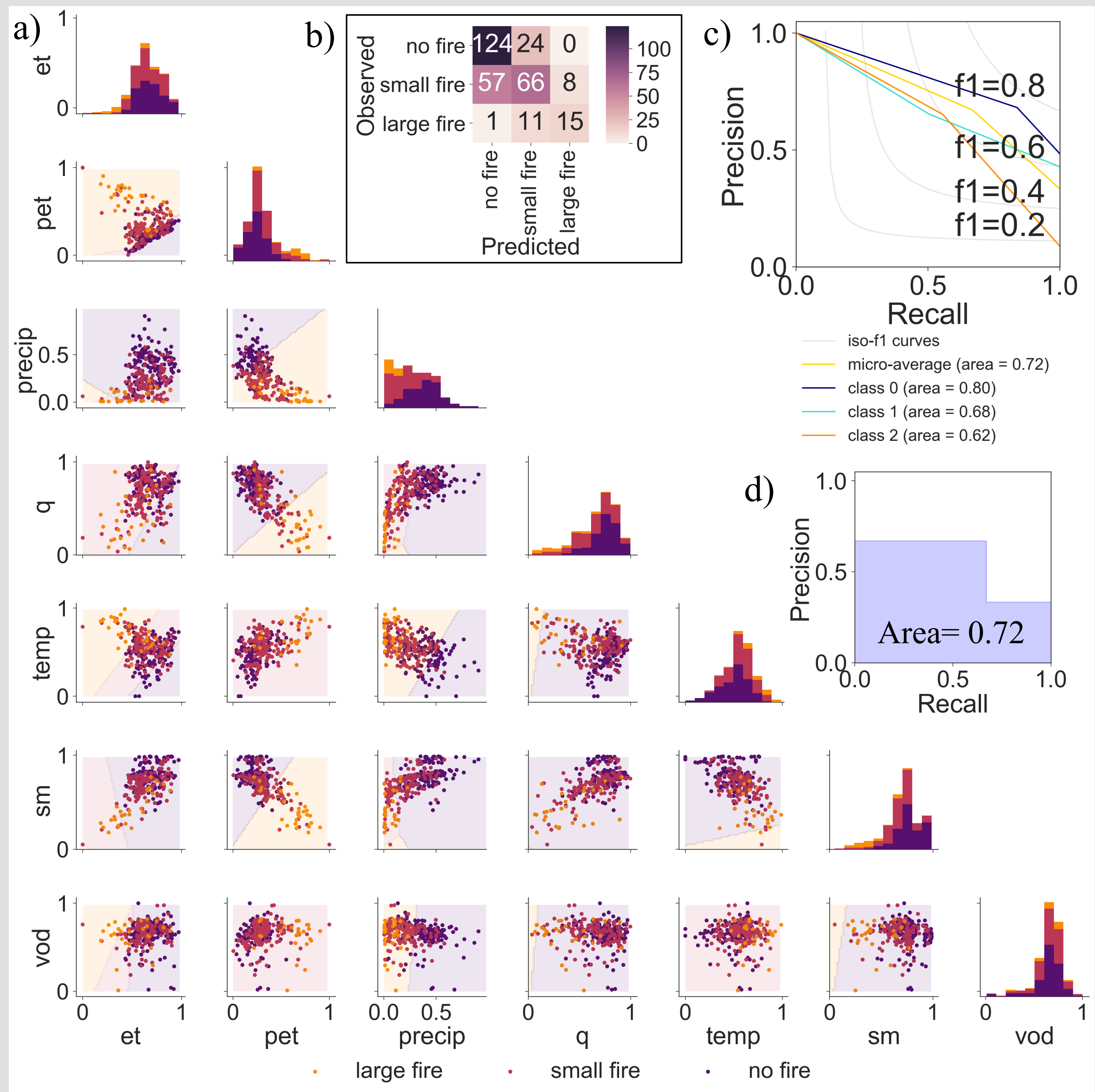


Fig. 2 (a) Scatter plot of all features with predictions; model predictions shown as background color in scatter plot, diagonal contains histogram of row variable colored according to fire label. (b) Confusion matrix of actual and predicted labels. (c) Precision-recall curve (harmonic mean of precision and recall) of predicted labels. (d) Precision and recall micro-averaged overall all 3 labels by considering each label as a binary prediction.

4. Key Takeaways

1. Climatic and geographic features measured by satellites hold valuable information about hydrology.
2. Logistic regression model performs better than current approach based on generalized indices that are not tuned for local conditions.
3. Test set out-of-bag-error = 0.29.
4. Averaged precision-recall = 0.72.
5. Precipitation is the most important feature in predicting large fires.
6. Modelling limited by poor resolution of passive radiometry. Radar could allow future improvements.

5. References

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