Hail Size Prediction Using Machine Learning Techniques Applied to Storm Scale Ensembles

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1. Introduction

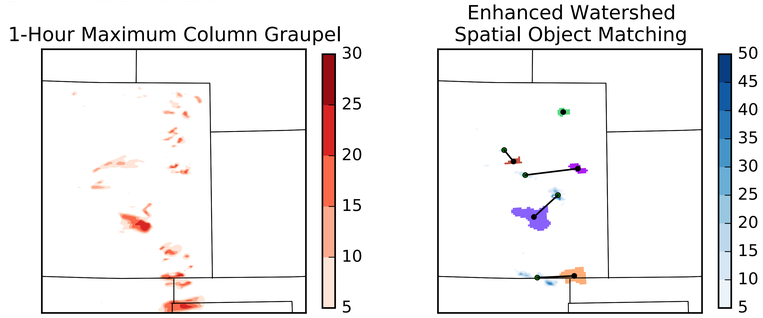
Hail has caused billions of dollars in damage. More people are living in hail-prone areas. Some hail damage could be avoided with more accurate and precise warnings. Current hail forecasts forecast threats over large areas and time ranges, resulting in very large false alarm areas.

Goal: evaluate techniques for producing day-ahead, hourly forecasts of hail diameter using storm-scale models and machine learning. This poster is based on work that will appear in the 2015 IAAI conference [1].

2. Data Sources

NOAA NSSL Multi-Radar Multi-Sensor (MRMS)
Maximum Estimated Size of Hail (MESH)
CAPS Storm-Scale Ensemble Forecast System (SSEF)
Training Dates: 26 April-5 June 2013
Evaluation Dates: 15 May-6 June 2014
Forecasts initialized at 00 UTC
Evaluated forecast hours 18 to 30

3. Methods



Left: 1-Hour Max Column Graupel from the M8 member of the SSEF.
Right: Objects identified in the column graupel field by the enhanced watershed technique, observed MESH in blue, and black lines connecting observed and forecast hail areas.

Storm Identification and Matching

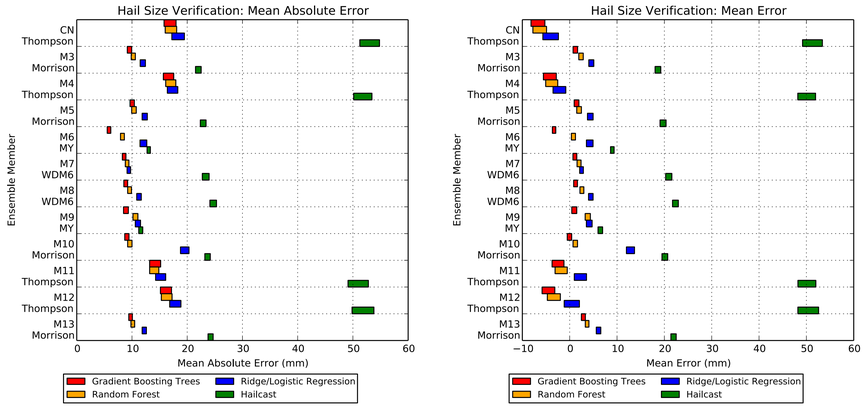
1. Enhanced watershed image segmentation [2] applied to column graupel and observed MESH. Enhanced watershed finds local maxima and grows objects until they reach a size or lower intensity threshold. Small objects are filtered.
2. Forecast and observed objects matched by distance.

Machine Learning

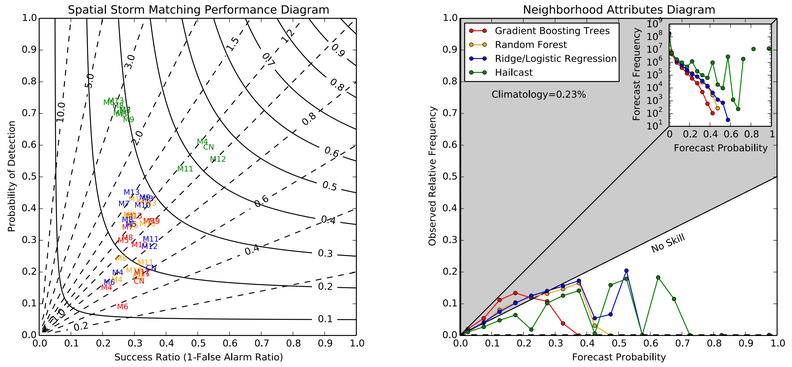
Hail occurrence models and hail size regressions are generated.

1. Random Forest: randomized decision tree ensemble
2. Gradient Boosting Trees: weighted decision tree ensemble
3. Ridge / Logistic Regression: linear regression variants
4. HAILCAST: physics-based column hail growth model

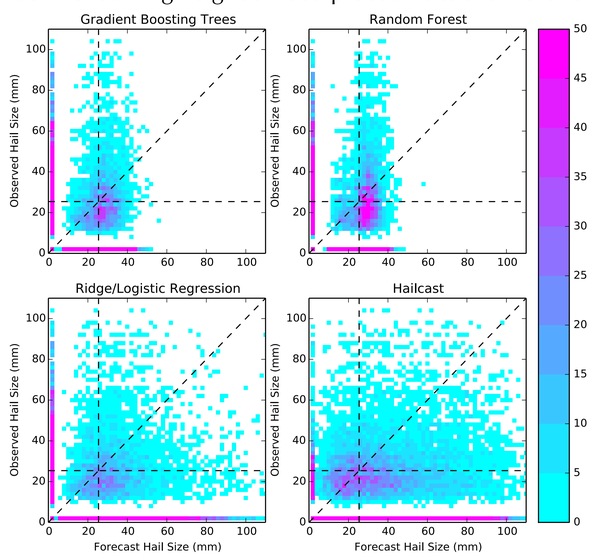
4. Forecast Evaluation



Bootstrap 95% confidence intervals for Mean Absolute Error and Mean Error. Members using Thompson microphysics perform significantly worse than others.

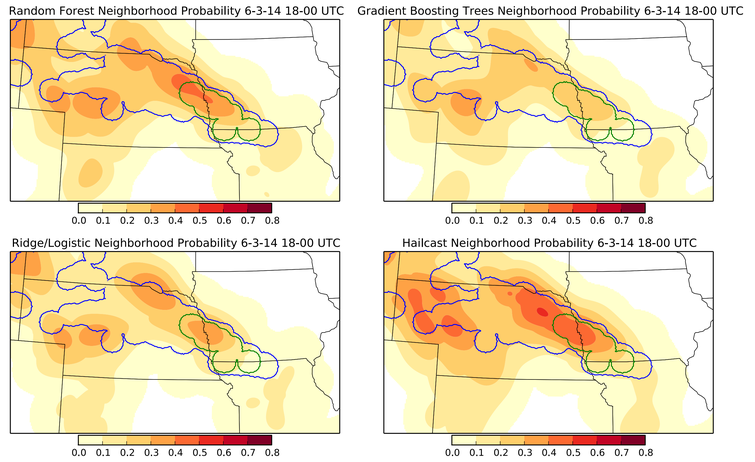


HAILCAST correctly identifies more hailstorms than other approaches. The machine learning neighborhood probabilities are more reliable.



Random forest and gradient boosting trees are best around the 25 mm threshold, but do not predict hail sizes over 50 mm. Ridge regression and HAILCAST have better sharpness but also have show little to no skill in predicting large hail sizes.

5. Case Study: 3 June 2014



Observed 25 mm hail is within blue contours and 50 mm hail is within green contours. All models showed elevated probabilties in eastern Nebraska and indicated the axis of motion correctly. High probabilities in western Nebraska were offest from the bulk of the hail.

6. Discussion

The machine learning hail forecasts were run during the 2014 Hazardous Weather Testbed Experimental Forecast Program. The neighborhood probabilities provided the most useful timing and location information. Currently, significant hail cannot be distinguished from severe hail accurately. Improving the hail size forecasts will require model improvements as well as finding storm matches in both space and time so that more intense model storms are associated with more intense hail sizes.

Conclusions

1. Machine learning reduces hail forecast bias.
2. The forecasts can identify hail threat areas.
3. The forecasts are best at distinguishing severe hail from small hail.

Acknowledgments

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References

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