A stakeholder-driven impact-based forecasting framework for Tropical Cyclones

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18/06/2025

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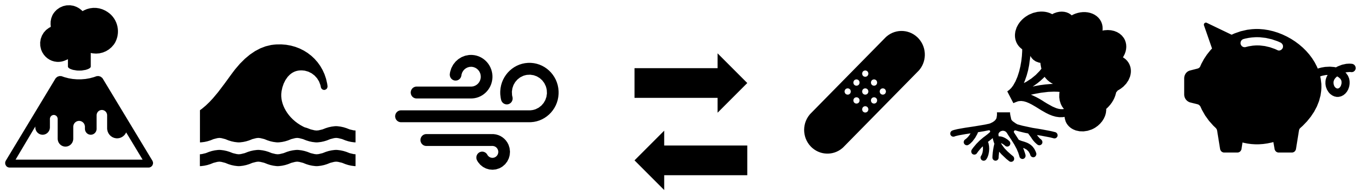
What is Impact-Based Forecasting?



Rather than asking "what will the weather be?", impact-based forecasting (IbF) aims to address the question: **"what will the weather do?"**

Why is IbF Important?

Early warnings

Exploring alternative scenarios

Understanding disaster impacts

Data-driven IbF uses historical impact data and machine learning (ML) to understand the complex, non-linear relationship between impacts and corresponding environmental conditions.

Challenges of Early Warnings

Warnings historically based on meteorology

Warning's content, communication, and language

"Boy who cried wolf" effect

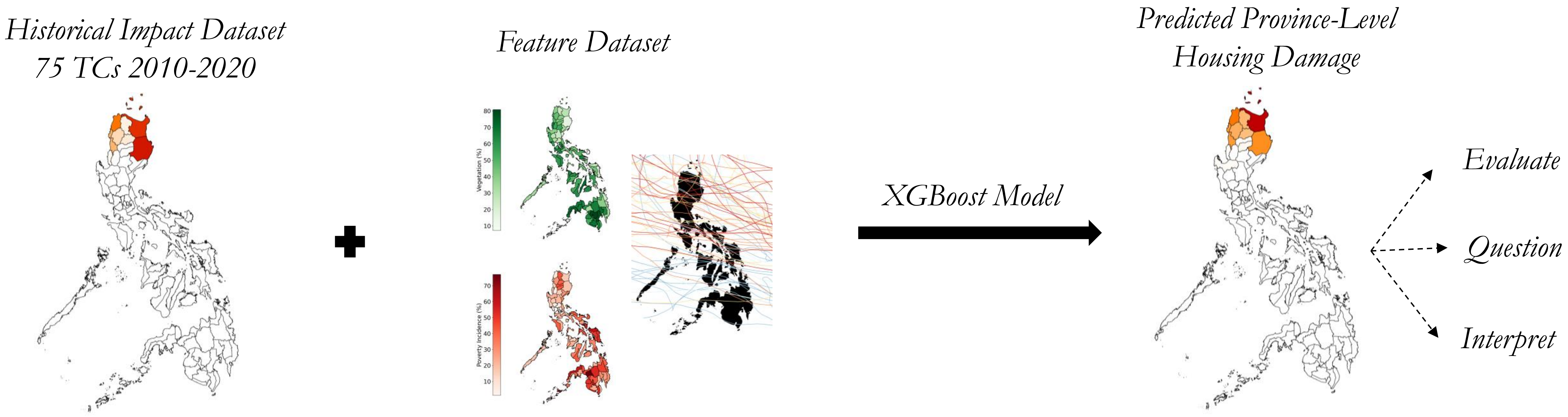
Overly general warnings

Uncertainty

Recent shift towards collaborative, people-centered warning design… but **what does that look like in practice**?

Research Aims

1. Build an IbF forecasting model using data-driven ML to predict tropical cyclone (TC) housing damage in the Philippines



2. Identify ML-based techniques to help address the challenges seen in impact-based early warning
3. Use ML techniques in a way that is responsive to the current challenges and flexible to potential future needs and improvements

ML Approaches

1) Evaluation Metrics

2) Uncertainty (Quantile Regression)

3) Interpretability (SHAP)

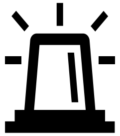
1) Evaluation Metrics

$$F1\ Score = \frac{2TP}{2TP + FP + FN}$$

1 = Highest Performance
0 = Lowest Performance

Adapts to individual user's concerns, for example:

One user may be concerned about the 'boy who cried wolf effect' and want to evaluate provinces where an impact is predicted but did not occur

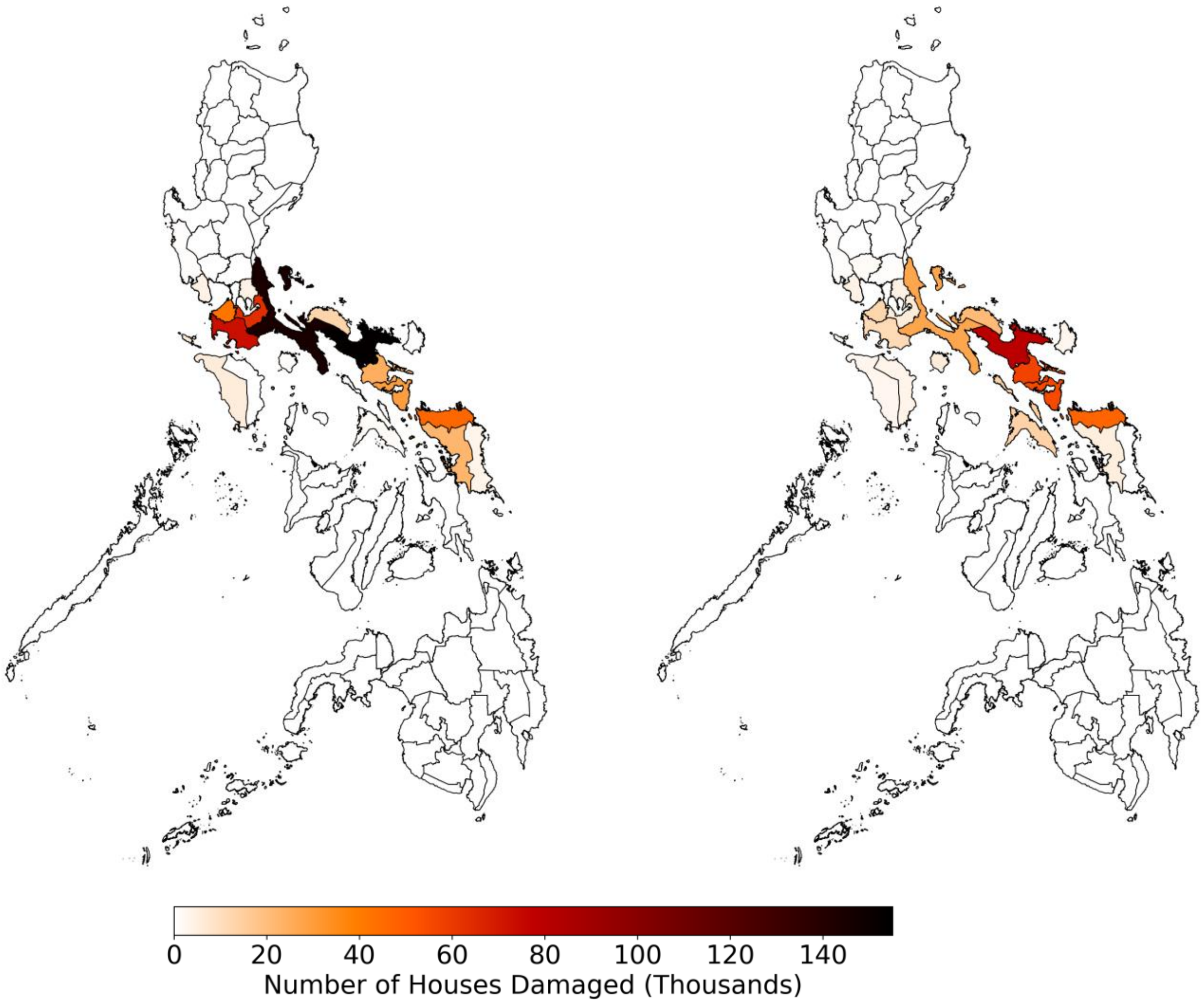


Another user may want to know if the model can identify the highest impacts, and evaluates how well the model identified provinces with over 10,000 houses damaged

Evaluation Metrics in Practice

TC Rammasun, 2014

Observed Housing Damage *Predicted Housing Damage*

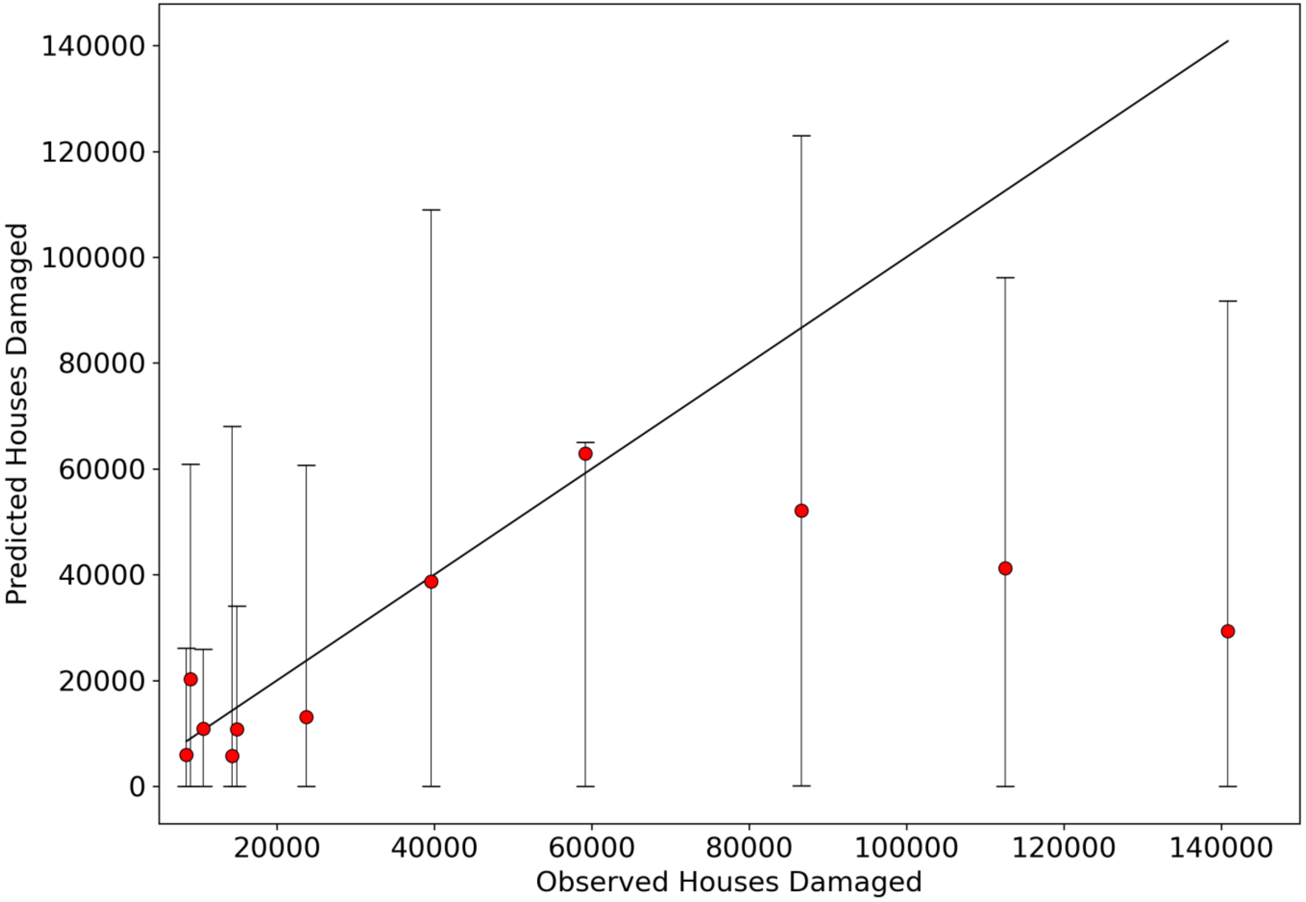


$F1$ (zero)	$F1$ (non-zero)	$F1$ (<100)	$F1$ (>100)	$F1$ (<1000)	$F1$ (>1000)
0.20	0.50	0.95	0.89	0.96	0.86

- Poor F1 (zero) caused by predicting impacts where there weren't any
- High F1 scores for thresholds of 100 and 1000 houses damaged show model replicates high-impact provinces
- Early warnings are generally categorical

2) Uncertainty

90th Percentile Prediction Intervals for TC Kammuri, 2019

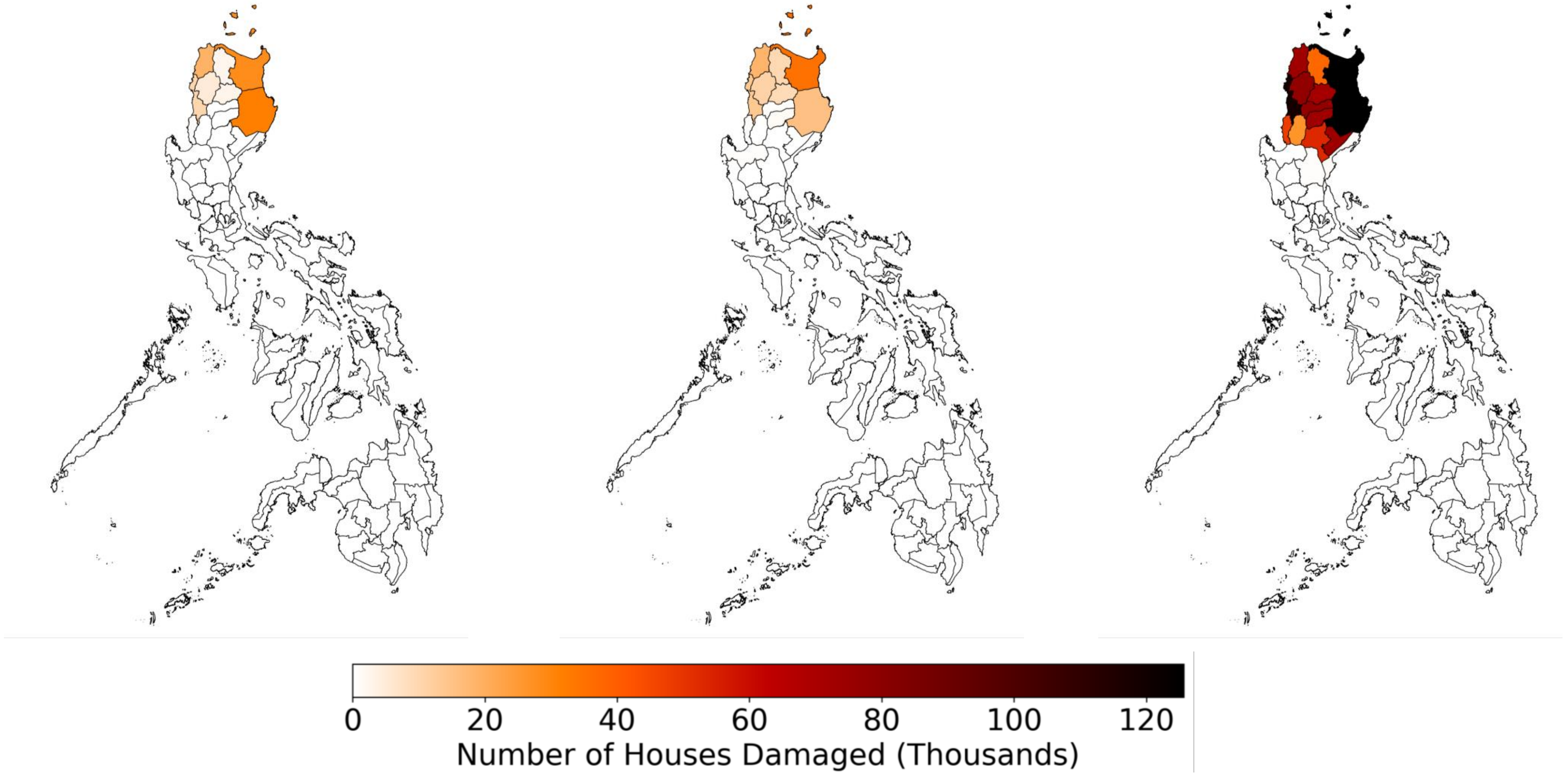


- ➢Quantile regression gives predictions at the chosen percentile of the distribution
- ➢Provides users flexibility of percentile choice
- ➢Places the prediction in the context of the training data

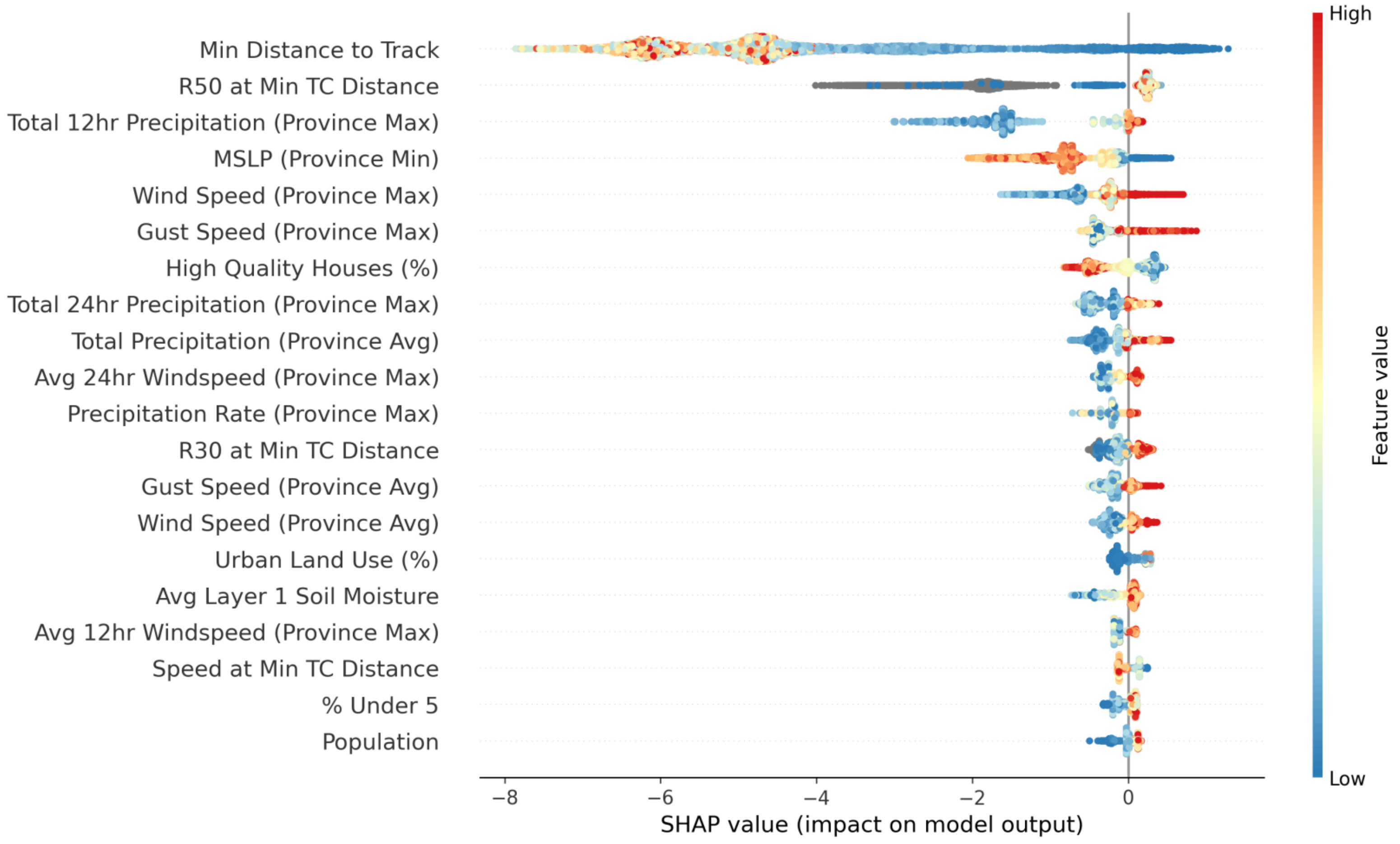
Uncertainty in Practice

TC Haima, 2016

Observed Housing Damage | *Predicted Housing Damage* | *95th Quantile Prediction*



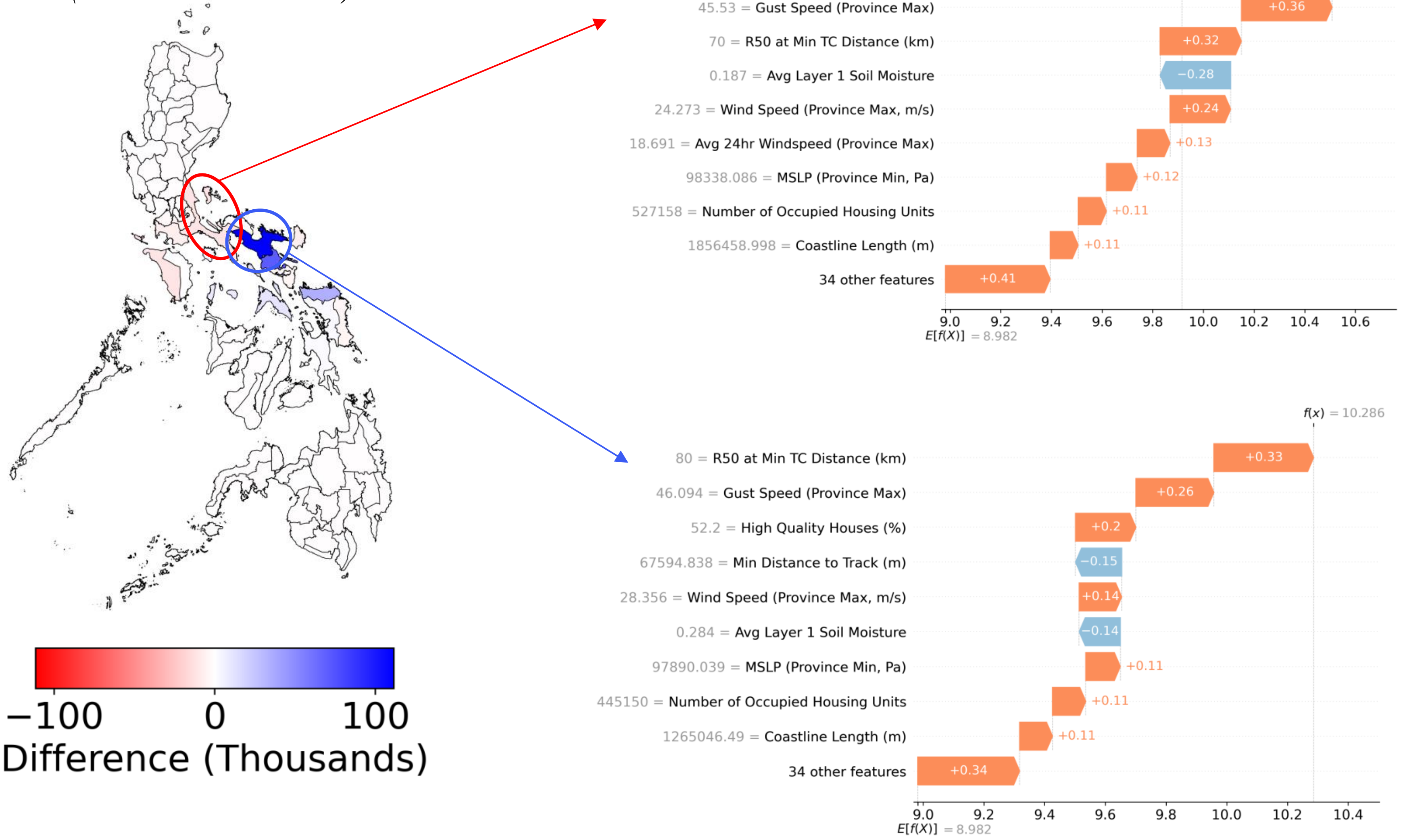
3) Feature Importance



- SHAP analysis tells you how the features are being used by the model to make predictions

Feature Importance in Practice

Prediction Error for TC Kammuri
(Observed - Predicted)



- Useful for model developers and those with expert knowledge to support an iterative model design

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Thank You
For Listening

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