







Joel Nicolow¹, Peter Sadowski¹, John DeLay², James Juvik³, Han Tseng⁴, Thomas Giambelluca⁴

(1)University of Hawai'i at Mānoa, Information and Computer Sciences (2)Honolulu Community College, Geography and the Environment (3)University of Hawai'i at Hilo, Geography and Environmental Science (4)University of Hawai'i at Mānoa, Water Resources Research Center Contact: jnicolow@hawaii.edu

Site Description

This study utilized 13 trail camera sites located on the islands of Maui and O'ahu, two of the eight main Hawaiian islands. Of these sites, six were positioned on the slopes of Haleakalā, Maui. Haleakalā is an active shield volcano that constitutes approximately 75% of the island of Maui reaching an elevation of 3,055 meters. Two sites were situated on the windward slopes (north), while the remaining four were placed on the leeward slopes (south) Figure 3. The sites' elevations range from 1,045 m to 1,982 m. The remaining five cameras were installed on the windward (northeast) slopes and summit of Mount Ka'ala, the tallest mountain on the island of O'ahu. The three sites on the windward slopes were placed between 600m and

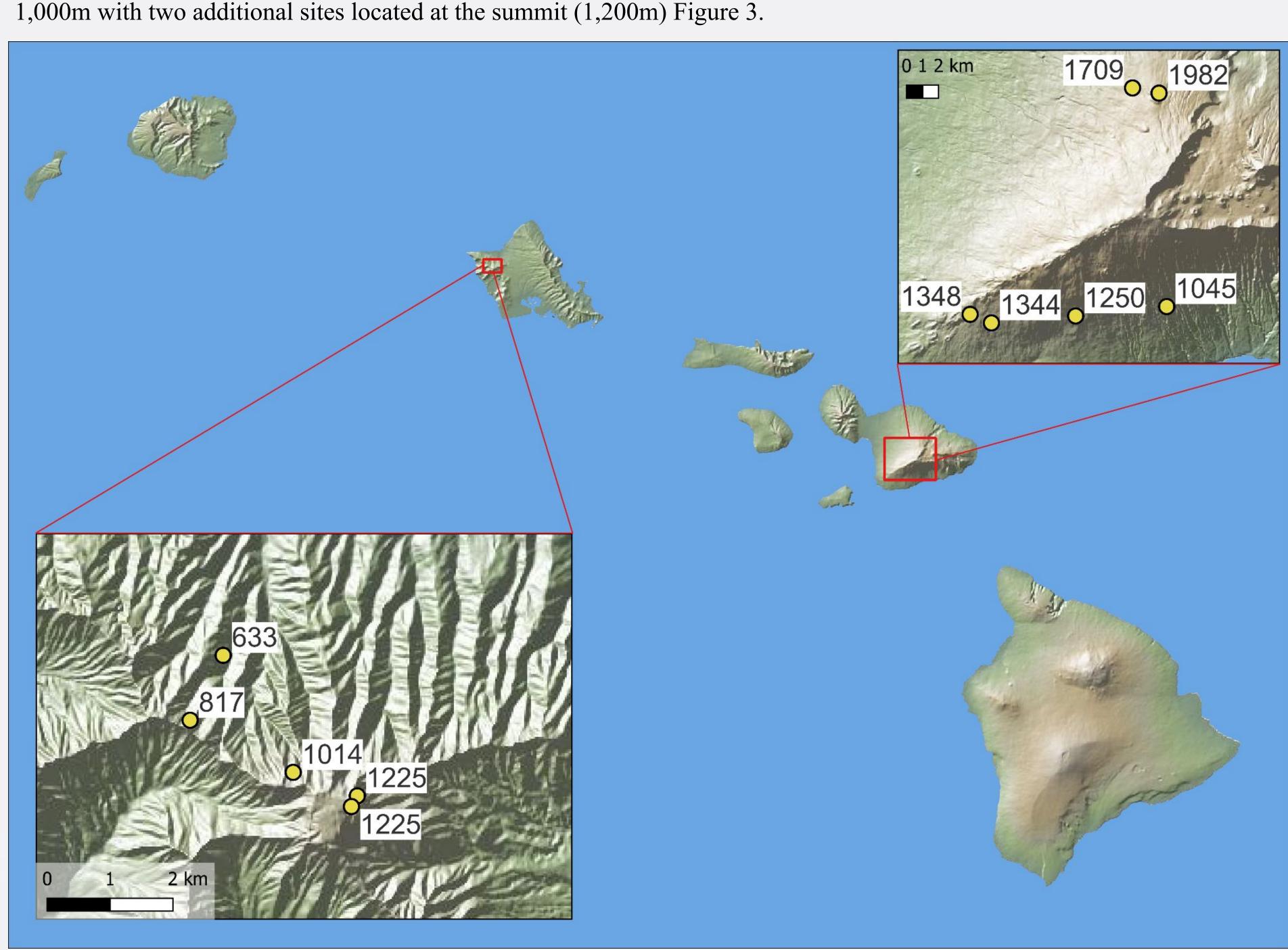


Figure 3: Site Locations and Elevations (m), O'ahu lower left Maui upper right

Fog Classification

Machine learning models were trained to classify images as "fog present" vs. "fog absent" from six image features that describe luminance and color statistics (Figure 4). Models were trained separately for diurnal and nocturnal imagery, and leave-one-out cross-validation was used for evaluation, where all the images from a particular site were held-out together to test how the models generalized to new sites. We also evaluated site-specific models that are trained and evaluated on data from the same site. Neural networks and random forests were both explored and we present results from the best model on each subtask.

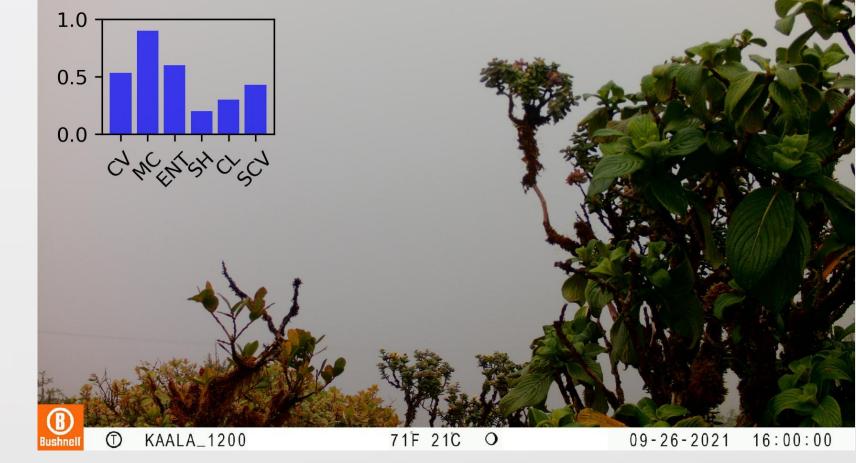


Figure 4: Images were described by luminance and color statistics features described in Bassiouni et al. (2017) and Choi et al. (2014)

Results

https://jnicolow.github.io/projects/AGU2

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- On never-before-seen sites, the model gets 86% accuracy (94 AUROC)
- o Diurnal: 81% accuracy, 94 AUROC

AGU23

- Nocturnal: 91% accuracy, 93 AUROC
- When site data is available, a site-specific model can be trained that improves performance.
- O Diurnal: 95% accuracy, 98 AUROC
- Nocturnal: 95% accuracy, 91 AUROC
- An analysis of performance vs. training samples shows how many annotations are needed to reach a particular accuracy.

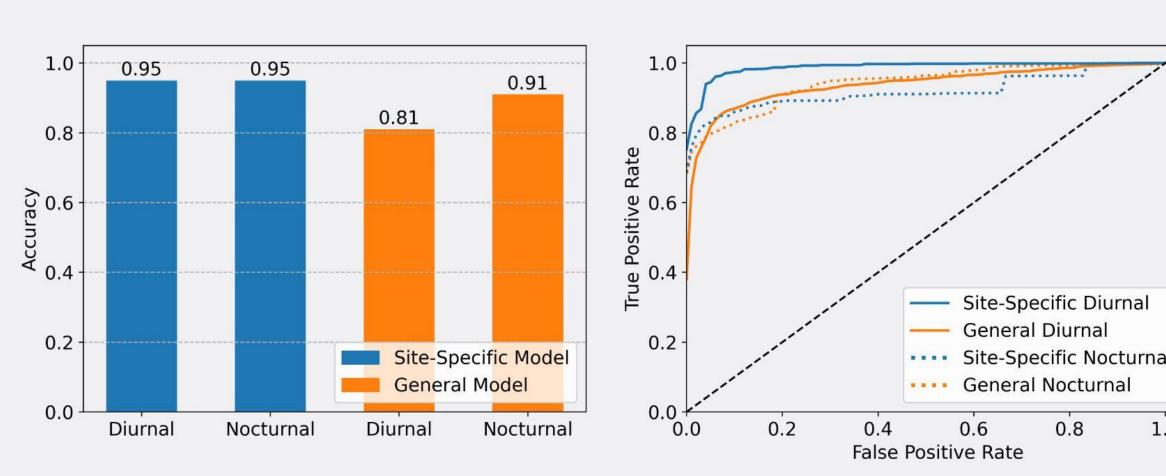


Figure 5: Model Performance

- General model performance can be improved by tuning the decision threshold with examples from the never-seen-before site
- Site-specific and General models with tuned decision thresholds perform better with more training images

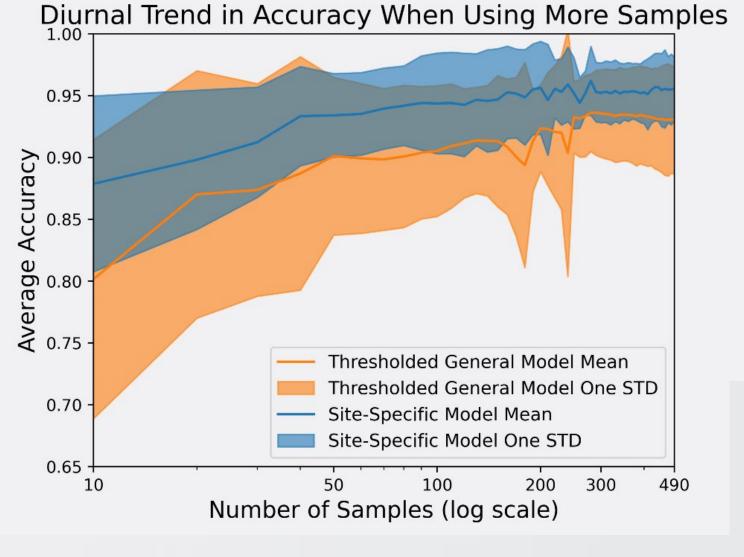


Figure 6: Trend Between Performance and Dataset Size

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References

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Highlights

- Machine learning detects fog in trail cam images with 95% accuracy
- 24,000 images were annotated by hand and used for training
- Code will be publicly available soon

Motivation

Fog plays a significant role in the hydrology and ecology of diverse mountain ecosystems. Trail cameras offer a low-cost alternative approach to observing fog presence. The aim of this study is to create a machine learning model that can detect fog in trail camera images.

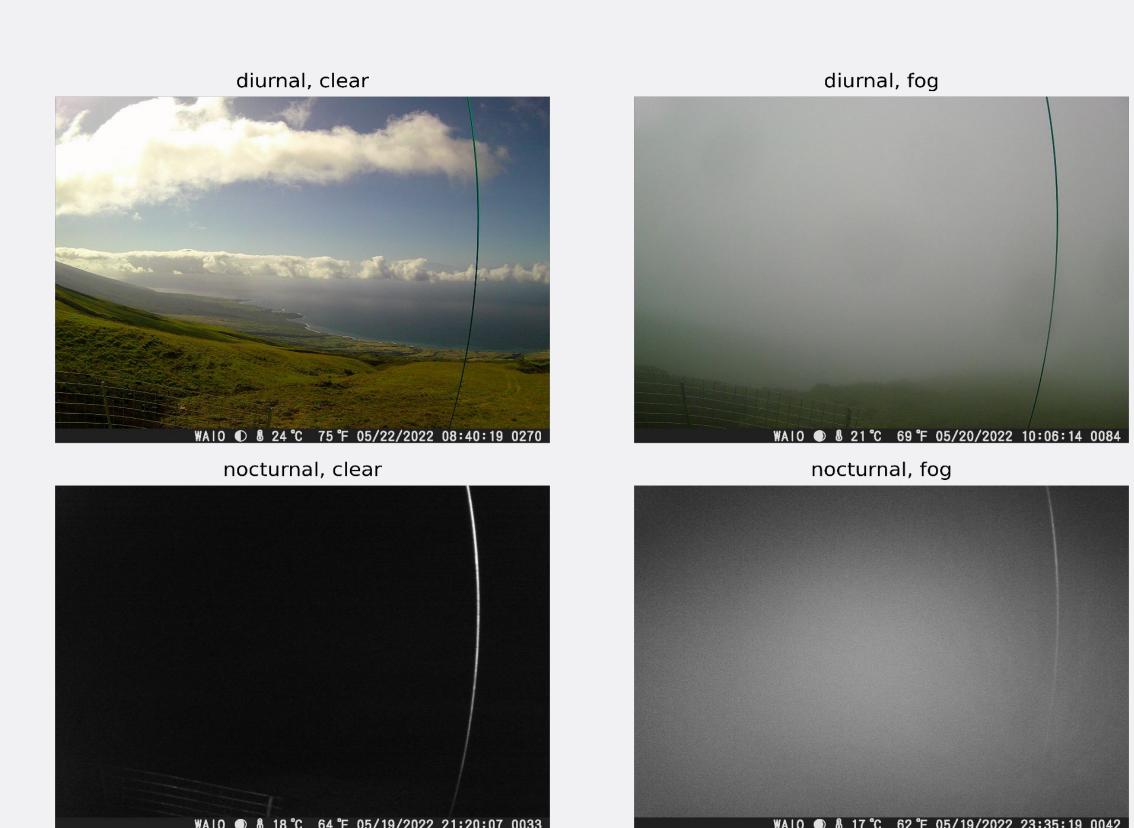


Figure 1: Image Examples From Leeward Haleakalā,

Equipment



Figure 2: Trail Camera Site Leeward Haleakalā, Maui

- Fence Post
- Game camera mount
- Trail camera
- Plastic hood shade
- Captures images every 15 minutes 24/7
- Images stored on SD cards
- SD cards manually collected every two to three months