# Ghost Forest Detection with Sub-meter Resolution Satellite Imagery

February 27, 2025

**Stakeholder Names and Roles**

| Stakeholder | Role |
|---|---|
| *Professor Xi Yang* | *Sponsor: UVA Environmental Sciences Professor* |
| *Henry Yeung* | *Sponsor: UVA Environmental Sciences Graduate Student* |
| *Professor Heman Shakeri* | *Mentor* |
| *Mahin Ganesan* | *Member* |
| *Brendan Jalali* | *Member* |
| *Tom Lever* | *Member* |
| *Nicholas Miller* | *Member* |


**Abstract**

We are interested in identifying ghost forests across the United States. A ghost forest is a region with more than 10 dead trees per hectare along the coast. The objective of our project is to dive deep into applying deep learning algorithms to image detection in order to be able to map individual dead trees. To accomplish this goal, we have developed, using an existing neural network for urban tree detection, a neural network that predicts the centroids of dead trees in test images with an F1 score of 0.59 (Ventura et al.). We hope to improve this neural network and allow it to predict geospatial layers not only of centroids of dead trees but also probabilities that pixels represent dead trees. We will deliver code for the neural network and for generating validation and testing performance metrics, annotated testing images, and geospatial layers based on inference images. We have created training, validation, and testing data sets based on satellite images of vulnerable lowland areas and annotation images. Satellite images depict areas a few hectares in area near the East Coast, Gulf Coast, West Coast, and Great Lakes of the United States. Overall, the goal of this project is for the members to participate in developing a data science pipeline to identify ghost forests, which will in turn provide us an understanding of where and why ghost forest hotspots may arise. The locations of ghost forests are presently unknown. Knowing where ghost forests are occurring, governments and localities can push for legislation to keep these forests from dying, allowing them to continue protecting the surrounding coastal communities and ecosystems.


**Outline of the Project**

For the study and preservation of coastal forests, our sponsors, who are researchers in the Department of Environmental Science at the University of Virginia, have taken an interest in developing a tool that will be able to identify the extent of ghost forests. Our sponsors are interested in looking at the creation mechanisms of ghost forests, and in being able to identify more locations, we are taking the first step towards coastal forest preservation. In order to satisfy these requests, we have developed a model that predicts the location of dead trees in ghost forests with an F1 score of 0.59. Our model is valuable in predicting the locations of ghost forests across the United States. With this base model and the future improvements that we will implement, this effort will lead to a better understand the systems that cause the death of these forests. We are assuming high quality information from satellite imagery in order to build our model. Our scope is to build a neural network that, by the end of this semester, will identify coastal ghost forests in the United States that have potential for saltwater intrusion.

**Success Criteria**

Our success criteria are defined in the following table.

| | |
|---|---|
| *SC1* | *Identify potential ghost forest locations that can be used to expand training and testing* |
| *SC2* | *Build data pipeline for initial supervised model* |
| *SC3* | *Build and train supervised model that successfully meets expectations* |
| *SC4* | *Ensure that model predicts heat map of probabilities that pixels represent dead trees* |
| *SC5* | *Improve architecture of model for better performance in predicting dead trees* |

Green demarks completion

**Data Assumptions and Limitations**

The data we are using currently for training our supervised model is data provided by our sponsors that include satellite images from the East Coast of the United States. Along with this data, we received annotated images to accompany these satellite images. We have come across some limitations expanding this data set with satellite images of locations along the Gulf Coast, West Coast, and Great Lakes. We are searching for professionals who can create annotation images for new satellite images and accelerate expanding our data set. Part of our original task was expanding the data set from already gathered East Coast data points to include the Gulf Coast, West Coast, and Great Lakes Coasts. We are awaiting the annotation of our new data points, but for now we are moving forward with the East Coast data provided by our sponsors. If we expand beyond the East Coast data that we are working with currently, we may run into limitations with data storage, transfer, processing time, and time to run a neural network.

We are relying on annotated images correctly encoding polygons that circumscribe dead trees. We note that training images may consist of multiple 256 x 256 tiles going both left to right and top to bottom. Training and validation images are fully annotated. On the other hand, only central 166 x 166 sections of training images are annotated. Inference images are not annotated.

To date, we have progressed steadily and succeeded in:

- identifying potential ghost forest locations that can be used to expand training, validation, testing, and inference data sets
- Based on satellite images and annotation that our sponsor provided, creating 256 x 256 image tiles and tables of coordinates of centroids of dead trees that save as data for a neural network
- Using Rivanna GPUs, training, validating, testing, and inferring with a neural network.

**Summary of Data Processing and Data Aggregation**

Our data processing pipeline begins at the data source provided by our sponsors, and whose source is the NAIP (National Agriculture Imagery Program). We have pulled that folder into Rivanna and built a structure that takes greyscale images representing red, green, blue, and near infrared channels of satellite images, and their corresponding annotation images. We create RGBN images based on the channels, and corresponding data tables of centroids of coordinates of dead trees. We tile images and tables of centroids as required by the neural network. These pairs of tiled images and data tables of marked dead trees then serve as the input for the training, validation, and testing of our model.

We ultimately intend to predict not only geospatial layers with centroids of dead trees but also heat maps of probabilities that pixels in satellite images represent dead trees. For training, validation, and testing, our model ingests 256 x 256 tiles of satellite images and tables of coordinates of centroids of dead trees. For inference, our model ingests satellite images with arbitrary dimensions. For training and validation, our model outputs logs and performance metrics. For testing, our model outputs logs, performance metrics, and annotated satellite images. For inference, our model outputs logs and a JSON file that can be laid over a satellite image in QGIS and used to visualize centroids of dead trees.

**Data Visualizations**

Figure 1: Tile-able Satellite Image

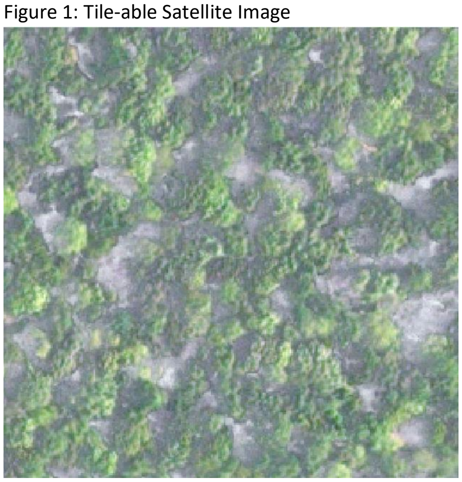


Figure 2: Qualitative, Testing, False Color Visualization w/ Predicted Annotations

Figure 3: Original Testing Blue Channel

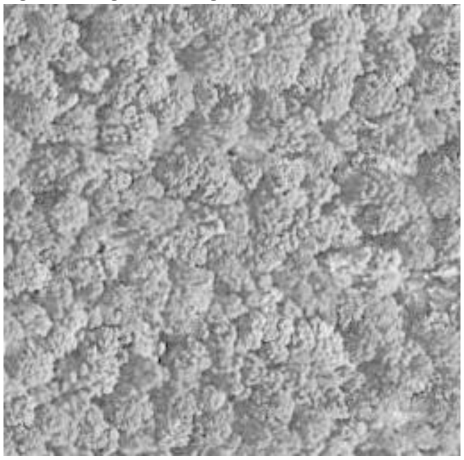
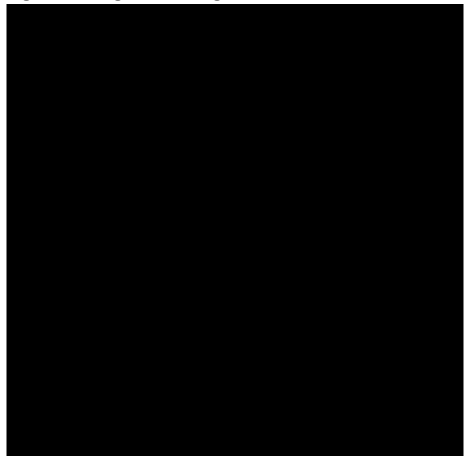


Figure 4: Original Testing Ground Truth Annotation Image



**Summary of Modeling and Analysis**

Our sponsors directed us to adapt a neural network that detects trees in urban environments to detect dead trees in satellite images. The article by Ventura et al. published in 2024 called, "Individual Tree Detection in Large-Scale Urban Environment using High-Resolution Multispectral Imagery" describes the architecture of the neural network that we adapted. We have processed data to be compatible with this neural network. We intend to ensure that our model predicts not only geospatial layers of centroids of dead trees but also heat maps of probabilities that pixels represent dead trees, to improve our architecture. The baseline architecture can be described below in Figure 1.

Figure 5: Architecture

**Appendix A. HR-SFANet architecture**

Here we provide pseudo-code to exactly describe the architecture of our HR-SFANet network, which is a modification of the original SFANet architecture Zhu et al. (2019). The pseudocode makes use of the following standard neural network operations:

- Conv$(n, k, x)$: 2D convolution on input $x$ with a filter size of $k \times k$ and $n$ output channels.
- ReLU$(x) = \max(0, x)$: Element-wise rectified linear unit.
- Sigmoid$(x) = 1/(1 + \exp(-x))$: Element-wise sigmoid function.
- BatchNorm$(x)$: Batch normalization (Ioffe and Szegedy, 2015).
- MaxPool$(x)$: 2x2 max pooling with a stride of 2.
- Concatenate$(x, y)$: Channel-wise concatenation of $x$ and $y$.
- Upsample$(x)$: $2\times$ upsampling of input $x$ using bilinear interpolation.

Figure 6: Loss Functions

$$L_{\mathrm{MSE}} = \frac{1}{N} \sum_{x,y} [C'(x,y) - C(x,y)]^2$$

$$L_{\mathrm{BCE}} = -\frac{1}{N} \sum_{x,y} [A(x,y) \log(A'(x,y)) + (1 - A(x,y)) \log(1 - A'(x,y))]$$

$$L = L_{\mathrm{MSE}} + \alpha L_{\mathrm{BCE}}$$

Let's consider the neural network architecture in depth. A batch of data for our model consists of a 256 x 256 satellite image with red, blue, green, and alpha channels, and an annotation image with non-black pixels representing vertices of polygons circumscribing dead trees. Our model uses 2D convolutional layers to detect features of dead trees that would not appear in other images (such as stems with no leaves), allowing for the model to locate images with dead trees. The model also uses pooling layers to look at specific areas of an image at a time and combine portions of the image to reduce the dimensions, ensuring focus on the most important features. Finally, the model adds an attention map to focus on regions where dead trees are likely to be located and a confidence map to show the likelihood of dead trees at any given pixel.

In the architecture we plan to use, the loss function is broken down into two parts, MSE and binary cross entropy. MSE is the main loss function and compares predicted and actual ground truth confidence maps. The ground truth map includes indicators that pixels represent centroids of dead trees. The ground truth map is compared to the model's predicted map of probabilities whose pixels represent centroids of dead trees. MSE loss is used to see how much the model differs from the ground truth when searching for dead trees in training and validation images. The binary cross entropy loss focuses on the attention map, seeing how well the predicted regions of dead trees match the actual locations of dead trees. Our final loss calculation adds the MSE loss to a weighted BCE loss (depending on how important we find each loss to be) to get our total loss function as seen in Figure 2 above.

We used the architecture of Ventura et al. as our starting point. We will apply our knowledge of Deep Learning to improve this architecture and our neural network's prediction of centroids of dead trees, and heat maps of probabilities of pixels representing dead trees. We can evaluate the performance of our model, and consider improvements to our model and its predictions, by examining loss curves derived during training and validation, and precision, recall, F1 score, and Root Mean Squared Error calculated during validation and testing. Below are some of our initial performance metrics:

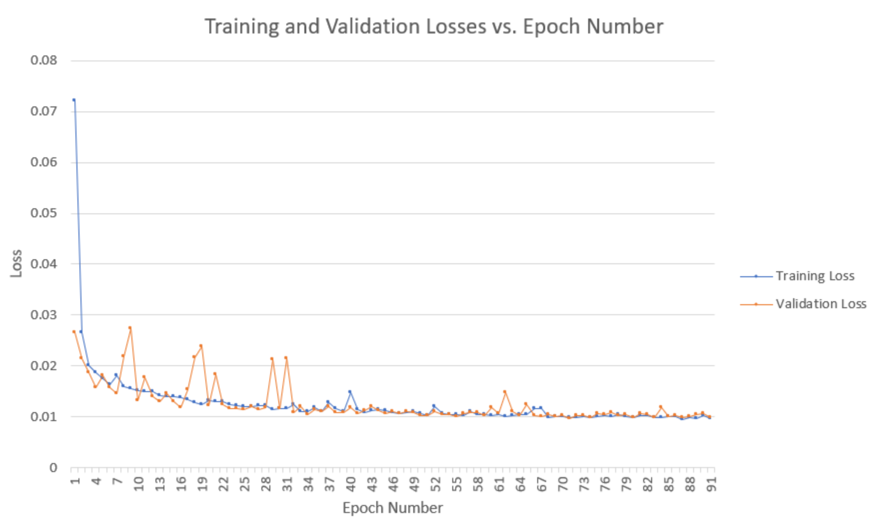



Figure 7

| Metric | Validation | Testing |
|---|---|---|

| | | |
|---|---|---|
| Precision | 0.413245 | 0.652947 |
| Recall | 0.511418 | 0.544284 |
| F-Score | 0.45712 | 0.593684 |
| RMSE [px] | 2.636964 | 2.451626 |

Our primary performance metrics are precision, recall, F1 score, and RMSE. Precision measures the number of true positives divided by the number of total positives in the model, both true and false. In the scope of our project, this means how many of the predicted dead trees are actually dead trees. Our initial precision score of about 65% indicates that about 65% of the model's predicted dead trees were indeed dead according to ground truth. Recall indicates our model's ability to capture as many dead trees as possible, for which we were able to get 54% using our initial model. Our F1 score of 59% represents the performance of the model when combining both precision and recall, for which we have room to improve. Finally, we are using RMSE to compare the distances between true positive predictions of dead trees and the ground truth map counterparts. We currently have an RMSE of 2.45, and a lower RMSE in future experiments would indicate that the model's predicted dead tree centroids are closer to the dead tree ground truth locations.

**Future Work Plan**

| **Task Description** | **Date** |
|---|---|
| Along with geospatial layers of centroids of dead, predict heat maps of probabilities of pixels representing dead trees. | End of March |
| Achieve better performance metrics by introducing image augmentation and architectural improvements like better a loss function. | Throughout semester, completed by end of Semester |
| Create an Architecture Diagram. | End of Semester |

**Potential Concerns [C] and Blockers [B]**

| **Identifier** | **Description** |
|---|---|
| C | Data Breadth: Do we have enough data? |
| C | Can we adequately adapt the model of Ventura et al. to Ghost Forest Detection? |
| B | Will we receive annotation images for satellite images of areas near the Gulf Coast, West Coast, and Great Lakes? |