Eastern Hemlock Mortality Risk Assessment Model

Based on Environmental Stressors and Hemlock Woolly Adelgid Infestation

Utilizing GIS and Logistic Regression Modeling

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1.0 Introduction

Eastern Hemlock (*T. canadensis*) is often referred to as a foundation species due to its ability to alter its local ecosystem, leading to an increase in suitable habitats for unique amphibian, fish, avian, and macroinvertebrate species (Ross et al., 2003; Snyder et al., 2002; Tingley et al., 2002). In 2011, Eastern Hemlock was categorized as a near-threaten species on the IUCN Red List due to the introduction and spread of the invasive defoliating insect, Hemlock Woolly Adelgid (*A. tsugae*) (IUCN, 2020; P McCarty & Addesso, 2019). The insect feeds on the base of hemlock needles which leads to needle loss, reduced water potential, and overall plant stress— ultimately, when combined with other environmental stressors, caused Eastern Hemlock mortality (Domec et al., 2013; Sivaramakrishnan, 1980). As a foundational species, the decline in Eastern Hemlock forests often lead to decrease populations of unique species that rely on the Eastern Hemlock services and ecosystem (Lemarie et al., 2000; Siddig et al., 2016). The rate of HWA spread has become a critical and ongoing issue. Since HWA spread is limited by cold winter temperatures, current climate projections have predicted increase rapid spread northern into more native Eastern Hemlock forests. (Cornelsen et al., 2024; Paradis et al., 2008).

The general introduction and spread of invasive species have significantly impacted native ecosystem biodiversity and services (Pejchar & Mooney, 2009). In response to the native effects, many countries have implemented invasive species management plans— typically involving multi-year management and monitoring efforts (Blossey, 1999; Keller et al., 2011). The United States alone, has invested over one trillion USD into these management plans, resulting in invasive species management and monitoring to be economically straining (Fantle-Lepczyk et al., 2022; Hoffmann & Broadhurst, 2016).

There have been ways to mitigate HWA infestations using biological and chemical control—both having limitations. Chemical management is costly and biological control results in unpredictable long term ecosystem effects (Cheah et al., 2004; Cowles et al., 2006). With ongoing issues concerning Hemlock population decline brought by HWA infestation, this project aims to develop a spatial risk assessment model to identify areas where Eastern Hemlocks face higher mortality rates, from HWA infestation and other Eastern Hemlock environmental stressors. The model aims to assist foresters and land managers prioritize resources to protect high-risk Hemlock stands to reduce the time and costs associated with invasive species management and monitoring.

2.0 Literature Review

2.1 Eastern Hemlock Stress: HWA Infestation and Environmental Stressors

Hemlock Woolly Adelgid infestation is a biotic stressor that increases the risk of Eastern Hemlock mortality. The combination of both HWA infestation and other environmental stressors has been found to be the most probable cause of Eastern Hemlock decline(Livingston et al., 2017; Sivaramakrishnan & Berlyn, 2000). Terrain, temperature, and soil moisture are all factors that play a role in Hemlock susceptibility to HWA and mortality. Areas that are warmer and more susceptible to drought are more likely to experience higher Hemlock mortality (Narayanaraj et al., 2010; Orwig & Foster, 2000). Understanding how environmental conditions influence Eastern Hemlock stress is essential to identify vulnerable areas and predict where Hemlock decline is more likely to occur. Incorporating these spatial variables into a risk assessment model can aid in prioritizing management efforts and effective resource allocation and reduce Eastern Hemlock population decline.

2.2 Invasive Species Management: Risk Assessment Model

To help mitigate costs and maintain effective management efforts, risk assessment models have become a common tool to assist in creating invasive species management plans (Lodge et al., 2016). These models can incorporate a combination of spatial environmental factors to help identify higher risk areas (McMahon et al., 2021; Yan et al., 2024). Incorporating a risk assessment model with Eastern Hemlock environmental stressors would be beneficial to identify stands that are more susceptible to mortality.

By spatially modeling areas of higher concern, the model allows management officials to prioritize resources and create more cost-effective management and monitoring strategies (Cohen et al., 2024; Robertson et al., 2021). With costly chemical HWA management, utilizing a risk assessment model can help foresters allocate resources to higher susceptible areas— reducing cost and stand decline.

2.3 Forest Defoliation Detection: Remote Sensing Methods

Remote sensing is a valuable tool for monitoring forest health and detecting changes caused by both biotic and abiotic stressors across various spatial and temporal scales (Wang et al., 2017). Satellite remote imagery, especially the utilization of shortwave infrared (SWIR), near infrared (NIR) and red spectral band, have been widely used to map and identify large-scale defoliation events (Astola et al., 2019; Lima et al., 2019; Pasquarella et al., 2017, 2021). Supervised classification techniques have proven effective in identifying areas of forest disturbance and defoliation (Otsu et al., 2018). Utilizing remote sensing to identify areas of Eastern Hemlock mortality over two periods can help predict and model how different environmental factors affect Hemlocks.

2.4 Risk Assessment Mapping: Utilizing GIS and Logistic Models

Incorporating GIS applications can be beneficial in creating risk assessment models. GIS is a valuable tool to help analyze and map spatial environmental variables (Liang et al., 2014; Pontius et al., 2010; Young et al., 2000). GIS can be used to process raw data, such as remote sensing imagery, into quantifiable data, such as terrain slope— that can be utilized in the model to understand spatial patterns in Eastern Hemlock vulnerability.

To quantify the influence of these variables and predict areas of high susceptibility, a bivariate logistic regression model can be employed (Koch et al., 2006; Zheng et al., 2021). Logistic regression has been widely used in ecological modeling due to its accuracy and interpretability. (Koch et al., 2006). When combined with GIS, logistic regression enables the creation of risk assessment models— allowing visual mapping of potential areas with higher hemlock mortality.

3.0 Study Area

This project was conducted in Franklin Gulf County Park, located in North Collins, New York. The park spans approximately 631 acres and is managed by the Erie County Parks and Recreation Department (Erie County Parks). Franklin Gulf has a unique terrain, with landscape features such as ravines, streams, and waterfalls, creating various suitable Eastern hemlock habitats. The geographic diversity allows for adequate assessments on how various environmental factors could influence hemlock mortality.

The site was visited between May 18-19, 2023, in cooperation with Erie County Parks and Western New York PRISM, to observe the presence of Eastern Hemlock and HWA. The region of interests consisted of both deciduous and evergreen stands. The evergreen species observed included Eastern Hemlocks and white pines (*P. strobus*)— with Eastern Hemlocks being the dominant species. HWA infestation was found to be spread throughout both young and mature Eastern Hemlock stands.

Eastern hemlock stands in Franklin Gulf provide critical ecological functions, including shading, water regulation, and habitat structure. These stands support a variety of native wildlife, including unique amphibians and reptiles (iNaturalist, 2025). With HWA presence within the study site, a risk assessment model would help effectively manage limited county resources and effectively reduce hemlock mortality to conserve the local wildlife habitat.

4.0 Data and Methodology

4.1 Data and Sources

The environmental data that was used to conduct this study includes the study area's slope, soil types and their respective drainage characteristics, and stream locations. Slope and stream data were derived from the 2011 digital elevation model dataset (DEM) provided by New York State GIS Clearinghouse (NYSGC) (Fig. 1). The soil maps and drainage classifications were obtained from USDA Web Soil Survey (Fig. 2; Table 1). It was required for these original datasets to be preprocessed before they were implemented to predict areas of low and high risk of Eastern Hemlock mortality.

2011 Digital Elevation Model

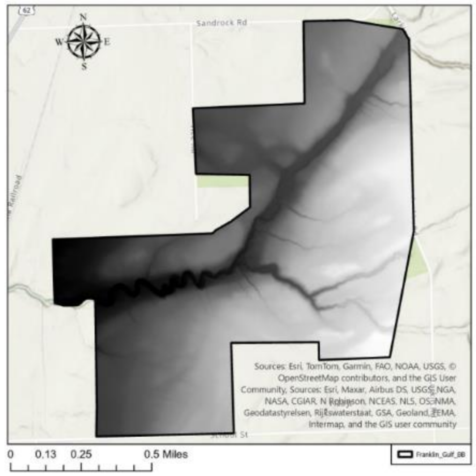


Figure 1. 2011 Digital Elevation Model

Soil Class

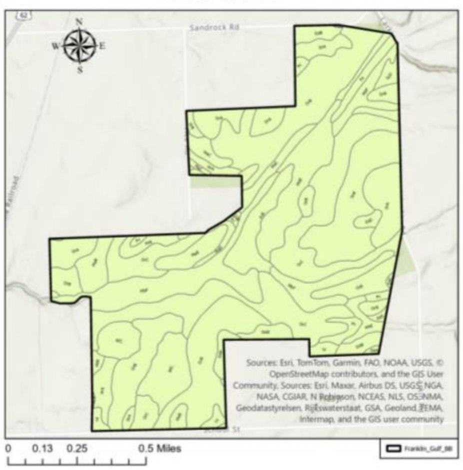


Figure 2. Soil Classification Map

Soil Drainage Classification and Respective Soil Map Unit Codes

Rating	Map_Unit_Symbols
Well drained	BlA, BlC
Moderately well drained	Dp, FbB, FcB, GaA, MfA, MfB, ScD
Somewhat poorly drained	DdA, DdB, DdC, HrA, HrB, HsC, OrA, OrB, OrC, RfC
Poorly drained	Ly, Pc
Somewhat excessively drained	MaB, MaC, MaD, MbE, MbF
Very poorly drained	Fu
Not Rated / Not Soil (miscellaneous)	Pt, Ro

Table 1. Soil Drainage Classification and Soil Map Codes

To locate areas that have already shown Eastern Hemlock mortality, Sentinel-2 SR 10m spatial resolution products were utilized. These remote sensing images, collected on April 22, 2018 and April 28, 2022, were obtained from the Copernicus Browser (Fig. 3). The images were picked due to it the presence of snow cover and limited observations of healthy grasslands and non-evergreen trees in the farmland region. Due to the lack of tree surveying data for the area, orthophotos of 1m spatial resolution were utilized as ground truths to assess the accuracy of the

Sentinel-2 land cover classifications. Orthophotos, from Spring 2022, were obtained from NYSGC (Fig. 4).

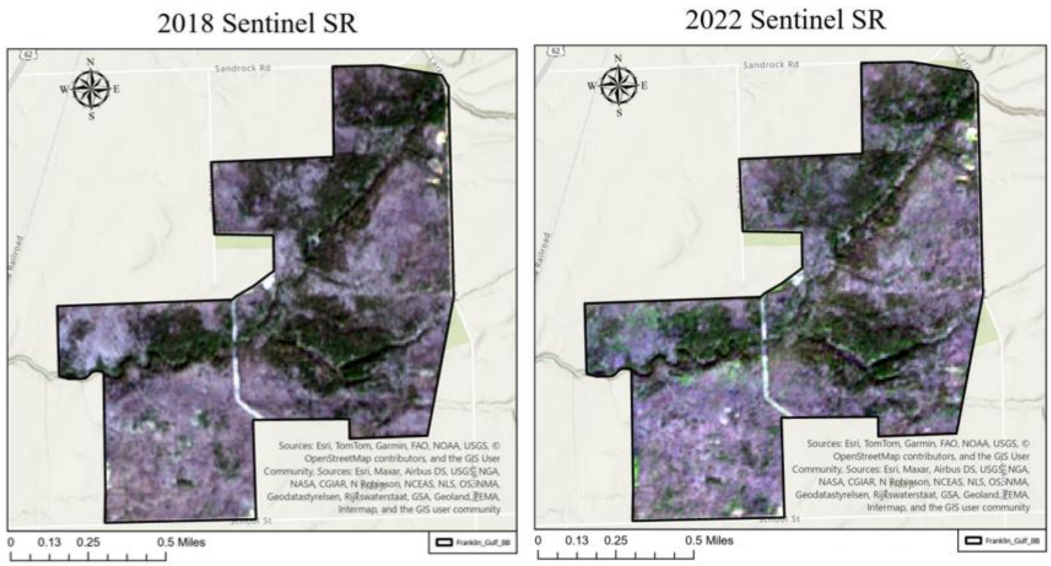


Figure 3. 2018 and 2022 Sentinel Images

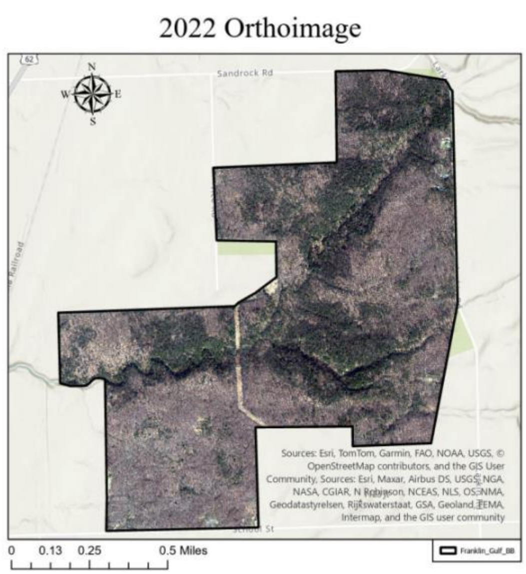


Figure 4. Spring 2022 Orthoimage

4.2 Preprocessing.

All spatial data sets were required to be reprojected to the same coordinate system UTM WGS 1984. Reprojection was required since creating an accuracy assessment model based on spatial environmental factors requires all associated data to be aligned properly. To have the project focused on the study area, all reprojected datasets were then clipped to a manually created polygon— outlining the Franklin Gulf County Park property boundary.

DEM was utilized to create two different environmental variables, slope and stream. The slope layer was generated using the *Slope* tool— quantifying the steepness of the study area. To improve interpretability and reduce noise of each individual pixel, slope pixels were reclassified in 10 value intervals, between 10-70, where 10 indicated areas with less than 10° and 70 represented areas with slopes higher than 70° (Fig. 5). The slope reclassification allows for a better understanding of how different slope ranges may affect the eastern hemlock mortality compared to distinct slope angles. The stream layer was produced using the tools *Fill*, *Flow Direction*, *Flow Accumulation*, and *Stream Order*. Together these tools created a stream network within the study site. Stream orders higher than 4— indicating smaller flow paths were removed from the data to emphasize more apparent streams. The stream data was converted to a raster format using the *Euclidean Distance* tool— quantifying the distance of individual pixels, within the study area, from a classified stream. Each pixel was reclassed to be between 1 and 5, where 1 indicated pixels closest to a stream and 5 furthest from a stream (Fig. 6).

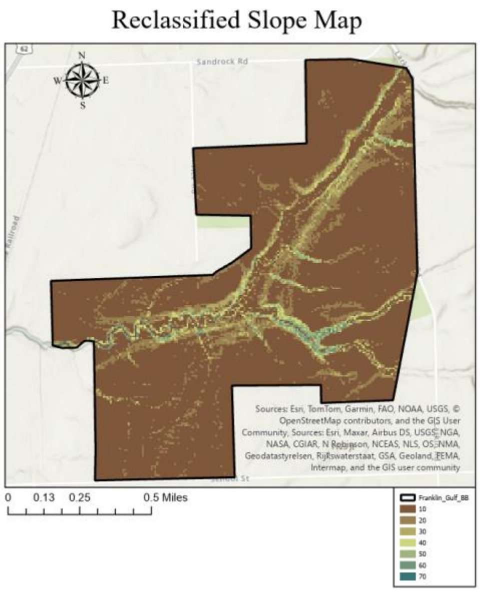


Figure 5. Classified Slope Map

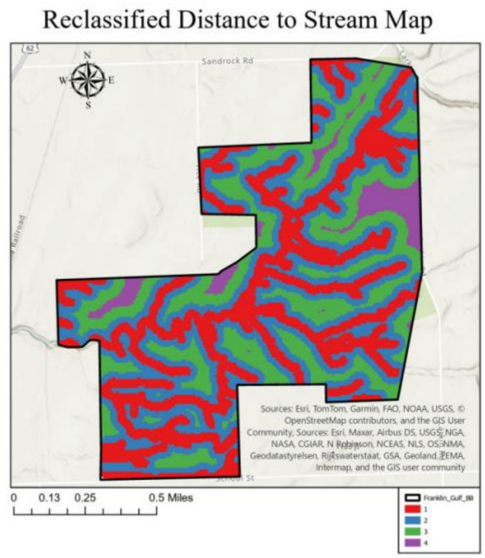


Figure 6. Classified Distance to Stream Map

The soil map and drainage classifications were obtained as separate datasets, one spatial and the other tabular. Due to the difference in the data forms, it was required to use the *Calculate Field* tool to create one singular spatial dataset. Each soil class was coded to specific drainage characteristics and was reclassified to a quantitative value between 0 and 4 using a python script. The drainages were classified as: Very Poor: 1, Poor: 2, Somewhat Poor: 3, Moderately Well: 4, Well: 4, and Somewhat Excessive Drainage: 3. These reclassified values are based on soil habitat suitability for Eastern Hemlocks— where 0 indicates least suitable and 4 indicates most suitable (Fig. 7).

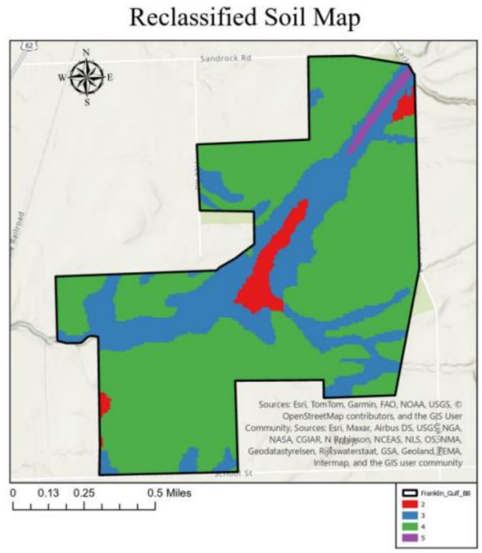


Figure 7. Classified Soil Drainage Map

Sentinel-2 products and orthophotos were classified into five land cover classes: Evergreen, Deciduous, Grass, Urban, and Water, using a supervised classification method (Fig. 8). For each image, a minimum of 3,000 training pixels were manually selected to increase classification accuracy. A binary accuracy assessment was performed on the 2021 Sentinel and 2022 Orthophoto classification using approximately 400 randomly selected validation points. The accuracy assessment analyzed the accuracy of classifying evergreens and non-evergreens. To detect potential Eastern Hemlock mortality, a change detection analysis was conducted between the 2018 and 2021 Sentinel-2 classifications, identifying areas where pixels originally classified as evergreen had transitioned to other land cover types. The resulting change map was reclassified into a binary format, where a pixel value of 1 represented areas of vegetation change—interpreted as potential hemlock mortality—and a pixel value of 0 indicated no change. Later, pixels that were not initially classified as evergreens in the 2018 classifications were removed from the change map (Fig. 9)

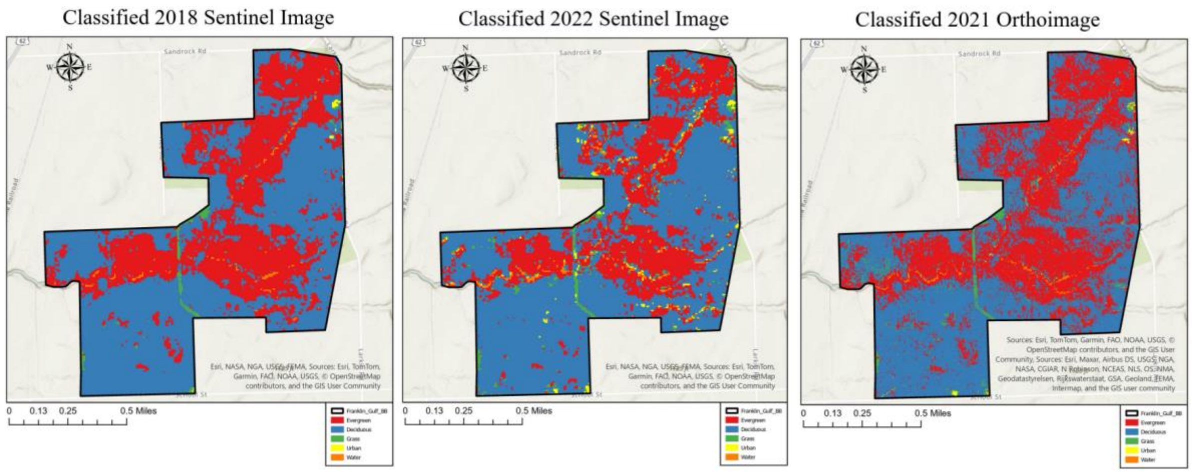


Figure 8. Classified 2018 and 2022 Sentinel-2 and 2021 Orthoimage, Respectively

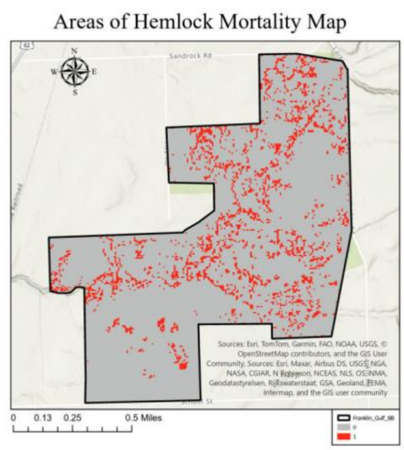


Figure 9. Areas of Hemlock Mortality Map

4.3 Post Processing

To create a risk assessment model of Eastern Hemlock mortality based on different potential environmental stressors, a logistic regression model was utilized. The logistic regression model was conducted using the *Generalized Linear Regression* tool along with the independent variables: reclassified slope, reclassified soil drainage, and reclassified distance to streams raster datasets. These independent variables were joined into one dataset using the *Zonal Statistics* tool. Roughly 5,000 random points (70% of the total pixels) were sampled from the binary change map to train the logistic model based on pixels classified as areas with no evergreen mortality and areas with evergreen mortality.

Utilizing the tool *Raster Calculator*, the logistic model equation was used to map each Eastern Hemlock pixel's mortality risk potential. The model classified areas of low and high risk based on the calculated mode of risk percentage distribution. To verify the accuracy of the final risk assessment map, the remaining 30% of the points not used to train the logistic model, were utilized to create a confusion matrix to assess how well the model was at predicting low and high-risk morality areas.

5.0 Results and Discussions

5.1 Remote Sensing Classifications Accuracy Assessment.

The accuracy assessment for the 2022 Sentinel-2 classification produced an overall accuracy (OA) of 83% and a Kappa score of 0.60. For evergreen detection, the user accuracy (UA) was 79%, while the producer accuracy (PA) was lower at 62%. In contrast, the classification of non-evergreen areas—which included deciduous vegetation, bare soil, water, and urban surfaces, showed higher accuracy with a UA of 86% and PA of 94%. The relatively low Kappa score is largely caused by the low producer accuracy from the evergreen class. This is likely due to Sentinel's 10m^2 spatial resolution, which may not adequately capture small evergreen stands compared to the higher resolution orthoimage used for the accuracy assessment (Fig. 10).

Remote Sensing Confusion Matrix Evaluation Metrics

Metric	Value
Evergreen UA	0.790690
Non-Evergreen UA	0.864951
Evergreen PA	0.618180
Non-Evergreen PA	0.937282
Overall Accuacy	0.838866
Kappa Score	0.595530

Figure 10. Sentinel Classification Accuracy Assessment and Metrics

Since the risk assessment model relied on this classification to measure Eastern Hemlock mortality, improving classification accuracy would be beneficial. Utilizing a higher spatial resolution imagery would likely enhance the model's ability to detect smaller evergreen patches and potentially differentiate among conifer species. However, given that Eastern Hemlock is the dominant evergreen species in the study area, distinguishing between conifers such as Silver Pine may not be critical for this specific application.

5.2 Logistic Model

5.2.1 Abiotic Factors Results. The final logistic regression model yielded coefficients of -0.089 for the intercept, 0.061 for soil drainage, 0.007 for slope, and 0.006 for distance to streams. These coefficients indicate the direction and relative strength of each variable's influence on the probability of Eastern Hemlock mortality. Each predictor was calculated to have a VIF close to 1, meaning that there was no multicollinearity among the independent variables (Table 3).

An increase in the soil drainage rating, shifting from poorly or excessively drained soils to well-drained soils, was associated with a 0.06% increase in the probability of hemlock mortality. However, this variable was not statistically significant ($p = 0.794$). This result was unexpected, as the drainage categories were manually ranked based on Eastern Hemlock habitat suitability, with the assumption that poorly drained soils would be associated with higher mortality risk.

For the slope, increasing values, which represent steeper terrain, corresponded to a 0.7% increase in the probability of mortality. This variable was statistically significant ($p = 0.005$), suggesting that steeper areas may be more susceptible to mortality, possibly due to increased soil erosion, harsher microclimates, or greater exposure to sunlight, all factors increasing Eastern Hemlock stress, resulting in HWA infestation effect amplification.

Distance to streams was also positively associated with mortality risk: areas farther from water sources showed a 0.06% increase in the likelihood of hemlock mortality. This suggests that trees in drier or more hydrologically stressed environments may be more vulnerable. Interestingly, this result somewhat contradicts the trend observed with soil drainage, where better-drained soils were also linked to higher mortality. This difference highlights a possible complexity in how soil moisture availability interacts with landscape hydrology. Although distance to streams was not statistically significant ($p = 0.057$), it was close to the 0.05 threshold and may still hold ecological relevance (Table 3).

Variable	Coefficient	StdError	z-Statistic	Probability	Odds Ratio	Wald's Low (95%)	Wald's High (95%)	VIF
Intercept	-0.088929	0.136486	-0.651565	0.514682	0.914910	0.700164	1.195521	
Slope	0.007211	0.002577	2.798680	0.005131*	1.007237	0.700164	1.012337	1.129186
Soil Drainage	0.060653	0.031911	1.900710	0.057340	1.062530	0.998110	1.131109	1.055283
Distance to Stream	0.006151	0.023612	0.260511	0.794469	1.006170	0.960667	1.053829	1.097339

Table 2. Logistic Regression Model Summary Table

The finalized logistic regression equation was then used to generate a risk assessment map, identifying areas with low to high risk of Hemlock mortality (Eq. 1). Low risk areas are identified as areas with evergreen absence. These areas are not considered ‘no risk’ without higher remote sensing accuracy. Intermediate and high risk pixels are areas that were identified with evergreen presence that are differentiated by different levels of mortality risk. The map indicates that high-risk sites are distributed throughout the study area, with elevated risk observed near streams. However, this pattern may be more strongly influenced by terrain slope, which was a significant predictor in the model. It is also important to note that slope ultimately influences stream formation, suggesting a potential indirect relationship between proximity to streams and Hemlock mortality risk (Fig 11).

$$\text{"}\boldsymbol{Evergreen}\text{"}*(\mathbf{1}/(\mathbf{1} + \boldsymbol{Exp}(\text{-}(\text{-}\mathbf{0.088929} + (\mathbf{0.060653} * \text{"}\boldsymbol{Soil}\text{"}) + (\mathbf{0.007211} * \text{"}\boldsymbol{Slope}\text{"}) + (\mathbf{0.006151} * \text{"}\boldsymbol{Stream}\text{"})))))$$

<u>Variables</u>
Everegreen—binary raster distguishing non evergreens to evergreens
Soil—Soil raster
Slope —Terrian slope raster
Strea—Distance to stream raster

Equation 1. Logistic Regression Equation to Model Risk Assessment Model

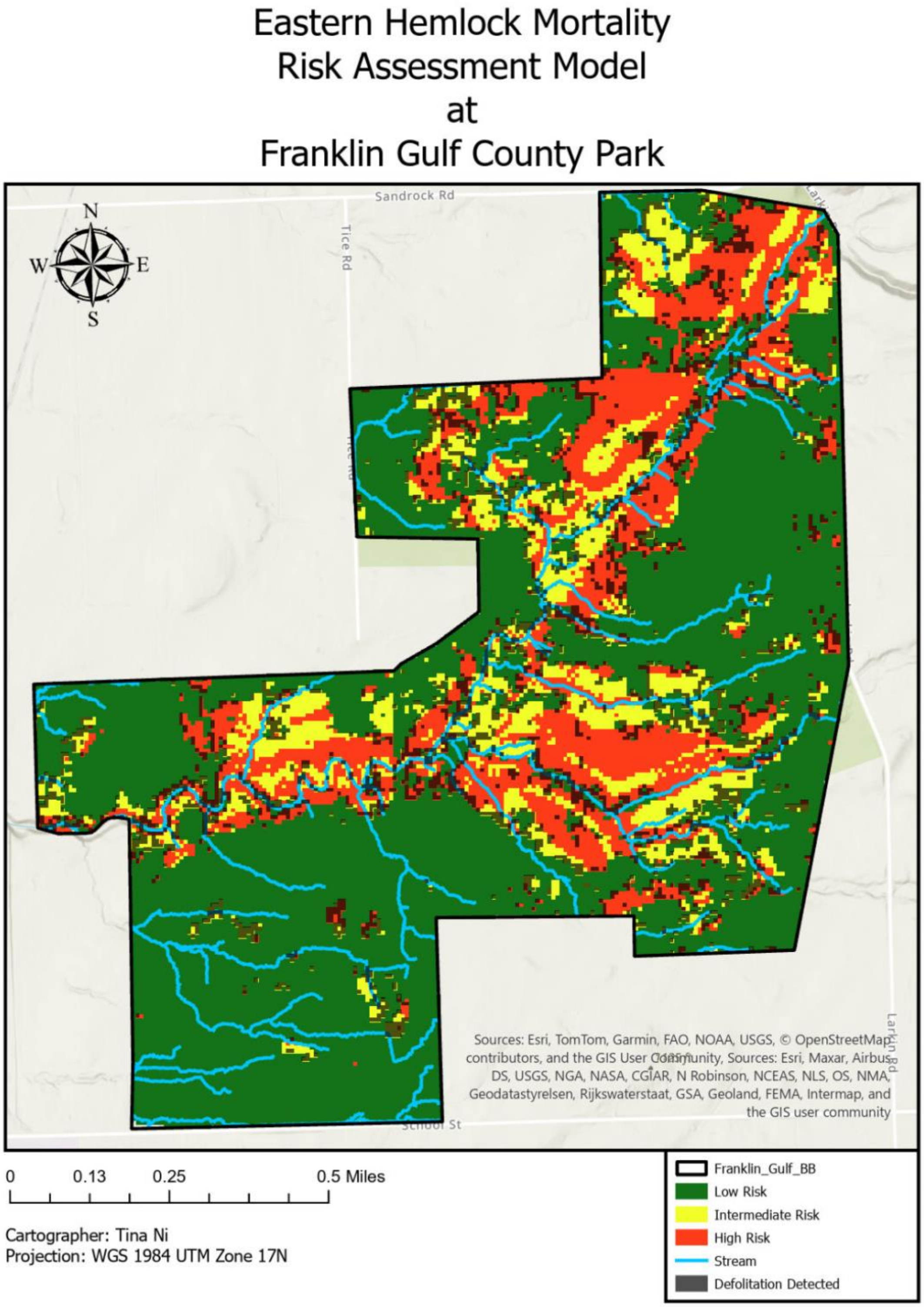


Figure 11. Final Eastern Hemlock Risk Assessment Model at Franklin Gulf County Park

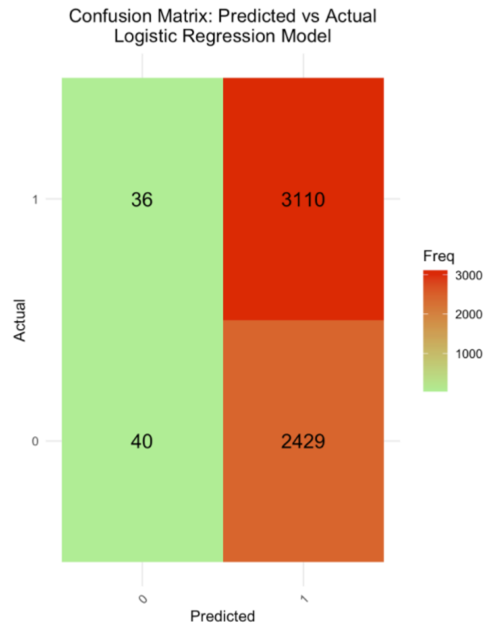
Overall, slope emerged as the most important predictor of Eastern Hemlock mortality in this model, while soil drainage and distance to streams showed less significant effects. These findings suggest further model exploration using other abiotic and possibly biotic factors to help increase the model's predictions.

5.2.2 Overall Model Fit

The logistic regression model explained only 0.13% of the variation in hemlock mortality, indicating that the selected abiotic variables, soil drainage, slope, and distance to streams, do not account for much of the spatial variability in mortality patterns. The Akaike Information Criterion (AIC) was extremely high at 7700.24, suggesting a poor model fit. A lower AIC value would suggest models have more explanatory power. In contrast to the AIC, the Joint Wald Statistic returned a statistically significant result (p = 0.0187), meaning that at least one of the variables contributed meaningfully to the model. This was confirmed by the individual p-values, where terrain slope was the only statistically significant predictor (p = 0.0051), highlighting its potential importance in predicting hemlock mortality (Table 4).

		Dependent Variable	Hemlock Presence/Absence
Number of Observations	5615	Akaike's Information Criterion (AICc)	7700.237875
# of observations equal to 1	3146	Deviance Explained	0.001297
Joint Wald Statistic[h]	9.987341	Prob(>chi-squared), (3) degrees of freedom	0.018674*

Table 4. Logistic Model Accuracy Metrics



Logistic Model Accuracy Metrics

Metric	Value
Accuracy	0.561
Precision	0.526
Recall	0.016
F1 Score	0.031
Specificity	0.989

Figure 12. Logistic Regression Classification Summary

The final model's accuracy assessment, conducted using 30% of the remaining random samples, resulted in an overall accuracy (OA) of 52.33%. While this accuracy is slightly better than random guessing, the low OA further supports the model's limited predictive performance, as indicated by the previously discussed logistic model statistics (Fig. 13).

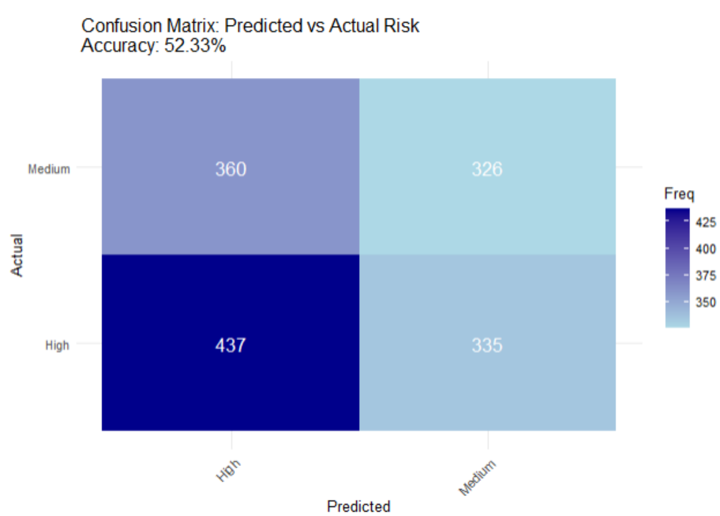


Figure 4. Overall Logistic Model Accuracy Based on 30% Remaining Samples

5.3 Model Discussion and Improvements

One of the primary concerns of this model is its low explanatory power, with only 0.13% of deviance explained. This suggests that the selected abiotic factors: soil drainage, slope, and distance to streams do not sufficiently capture the full range of drivers influencing Eastern Hemlock mortality. Some primary limitations could potentially be the small number of predictor variables used and the overlap in hydrological variables between soil drainage and distance to streams. Utilizing three predictor variables with two of them representing hydrological themes could significantly influence the model's accuracy and performance.

To enhance model performance, future analyses should incorporate a broader range of both abiotic and biotic variables. These might include ecological stressors such as pest presence intensity (e.g., Hemlock Woolly Adelgid), forest canopy dynamics, light intensity, localized temperature variations, and proximity to trails as a proxy for human disturbance. The use of climate-related data such as precipitation, drought indices, or seasonal temperature fluctuations could also provide valuable explanatory power.

Additionally, the limitations from the high spatial resolution likely affected classification accuracy. The $10m^2$ spatial resolution of Sentinel-2 imagery is determined to have challenges to detect small patches of Eastern Hemlock, leading to underrepresentation in the evergreen class and contributing to a lower producer accuracy. Using higher-resolution imagery, such as $1m^2$ orthophotos or LIDAR images, would likely improve classification results and better support mortality detection in finer spatial resolutions.

Finally, alternative statistical modeling approaches may better account for the complex and nonlinear nature of ecological influence and the spatial relationship between HWA reproduction and movement. Unlike the binary logistic regression used in this project, incorporating spatial regression models could also improve predictive accuracy for identifying high-risk areas, particularly for HWA reproduction and movement, which exhibit strong spatial dependencies. The current model, based on pre-existing variables and binary classifications of HWA presence and absence, did not account for spatial relationships between observations. By integrating spatial influences, a spatial regression approach could provide a more accurate representation of neighboring pixels that are classified as infested. Understanding how infested pixels relate to surrounding Eastern Hemlock stands would allow for more precise predictions of potential spread in neighboring areas.

The variables used in this model primarily relied on abiotic factors to predict risk potential across the study area. For future studies, incorporating biotic factors could further improve model accuracy and ecological influence. HWA have the potential to spread both independently and through interactions with other biotic agents, such as human and wildlife interaction as well as wind dispersal. Incorporating variables that represent HWA movement and biological interactions could provide a more accurate prediction for Eastern Hemlock mortality risk.

Overall, expanding the model’s framework to include both spatial and ecological complexity, along with the abiotic conditions that influence Eastern Hemlock tree mortality, can further improve the risk model’s predictive accuracy. By incorporating various aspects that result in HWA spread and infestation on Eastern Hemlocks, future models will have more scientific confidence to be utilized Eastern hemlock and HWA management.

6.0 Conclusion

The use of a logistic regression model to assess environmental predictors—such as terrain slope, distance to streams, and soil drainage, for mapping Eastern Hemlock mortality risk proved to be limited. The model demonstrated poor performance, explaining only 0.13% of the variation in the data, with an overall accuracy of approximately 51% based on 30% of the total pixels used as the validation dataset. These results indicate that the model, in its current form, lacks the predictive power to serve as a reliable risk assessment tool for Eastern Hemlock mortality.

Before this model can be considered for official use in guiding HWA management or conservation planning, substantial improvements are necessary. These include incorporating higher spatial resolution remote sensing data— to more accurately detect Eastern Hemlock populations and associated mortality, expanding the range of environmental variables used to train the model, and integrating biological factors that contribute to tree decline, such as pest and other wildlife dynamics.

Effective risk assessment models for species mortality typically integrate a combination of abiotic and biotic factors. This study relied on only three environmental variables, and the model's poor performance reflects this three-factor limitation. Future modeling efforts should adopt a broader approach to better capture the complexity of factors influencing Eastern hemlock vulnerability.

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