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RESEARCH ARTICLE

Enhancing Flood Risk Assessment Through Machine Learning and Open Data

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Abstract
Urban flooding causes billions of dollars in damages annually, with severe flood events becoming more frequent and destructive as our climate changes. While extreme weather is a primary driver of flooding, its consequences depend on the interconnectedness of urban systems - referred to as the Urban Multiplex, which includes the power grid, transportation network, natural surface water and groundwater systems, sewerage and drinking water systems, intertwined with the socioeconomic and public health sectors. One component of this multiplex - a reliable building inventory - is critical for assessing the number of people affected by flooding, the propagation of shocks throughout the economy, and for forecasting detailed socioeconomic risk from flooding. Yet, a major discrepancy exists in the way data about buildings are collected across the U.S. There is no harmonization in what data are recorded by city, county, or state governments, let alone at the national scale. We demonstrate how existing open source datasets can be spatially integrated and subsequently used as training for machine learning models. These machine learning models can then predict building occupancy type, a currently lacking component of flood risk assessment. Multiple machine learning algorithms are compared and an application to the 100-year flood in North Carolina is provided. Results indicate that a 100-year flood will disproportionately impact Mecklenburg, Wake, Dare, and Brunswick counties

Preprint Statement

This manuscript has been submitted to Environmental Data Science. At the time of submission to EarthArXiv, the manuscript has not been peer-reviewed.

Impact Statement

In this study, we show how machine learning can be used to enhance flood risk assessments. We identify several features from open datasets capable of predicting building occupany type while also evaluating multiple machine learning approaches. Our results suggests strategies for enhancing flood risk assessment across the continental United States.

1. Introduction

As cities become more complex and integrative we have an increasing need to understand where urban features are, and what their primary purpose is. Recognizing the interconnectedness of systems such as buildings, transportation, power, and water is critical to the success, safety, and sustainability of urban regions. Collectively, this system of systems is referred to as an Urban Multiplex. Yet, there is a major discrepancy in the way building and related multiplex data is collected across the United States. There is no harmonization in what data are recorded by city, county, or state governments let alone at a national scale. Most previous efforts to harmonize the urban multiplex are proprietary, owned by groups such as Google, Yelp, and Zillow, and utilized solely in their respective apps. Specifically in the area of urban flooding, which causes billions of dollars in damages annually, a reliable building inventory is critical for assessing the number of people affected, the propagation of shocks throughout the economy, and for forecasting detailed socioeconomic risk from flooding. Publicly available open source building inventory data sets exist; yet, they are not spatially aligned nor do many of them contain a critical element necessary for flood assessment - building occupancy type. Knowing a building's occupancy type plays a critical role in analyzing risk, assessing damage, performing mitigation efforts, and coordinating search and rescue.

In this work, we identify available open datasets and compare multiple machine learning (ML) algorithms in an attempt to accurately predict building occupancy type. We demonstrate how multiple ML models are needed for the myriad use cases involved in flood risk assessment. Moreover, we demonstrate the socio-economic utility of these ML models in a real-world application in the state of North Carolina. We aim to assess the accuracy of building occupancy classification techniques using only open data that is available on the scale of the continental United States (CONUS). Related research has shown the predictive power of various data in determining building occupancy type. Yet, many highly predictive data sources (e.g. LIDAR [8]) are not freely and publicly available at the continental scale. This dramatically limits their utility in any open CONUS-scale applications.

2. Related Work and the Need for Machine Learning

OpenStreetMap[1] (OSM) is a crowd-sourced initiative that aims to provide free and open access to spatial data on a global scale. OSM's representations of streets, natural landmarks, and building outlines are often more comprehensive and accurate than traditional data sources such as the CIA World Factbook and United States Census Topologically Integrated Geographic Encoding and Referencing (TIGER)/Line data [3, 2, 6, 10]. Yet, even in areas with abundant data, the free-form and optional nature of OSM's building type attribute results in most mapped buildings having no reliable occupancy type. The lack of reliable building occupancy type has led several researchers to explore using machine learning to predict this value. For instance, [1] achieved 98% accuracy in the binary classification task of predicting residential vs. non-residential occupancy type. To achieve this, the authors used other features within the OSM dataset to train a decision tree. While the accuracy result is impressive, one of the required inputs to the decision tree is the so-called OSM building tag. There are two major challenges with this requirement. First, OSM building tags are rarely available and when they are they can be ambiguous. As noted by [5] "It is important to note that, apart from the vocabulary difference and spelling error in the building tag, OSM also faces ambiguities in their finer classification scheme that is defined in the OSM Wiki". Such a decision tree could not be applied to tens of millions of buildings when used at CONUS scale. Second, having access to a highly informative tag such as "house" or "apartment" would seem to negate the need for machine learning. [5] used a deep learning approach that predicted building type from a combination of aerial and street view images. They designed a multiclass prediction system in which the available categories were: commercial, residential, public, and industrial. [5] concludes that with a multiclass setup and the challenges of OSM, a classification accuracy of about 60% to 80% on average would be a realistic expectation. Our goals in this research are threefold. First, to demonstrate the need for both binary and multiclass classification in flood risk assessment. Second, to see if the classification accuracy laid out by [5] can be achieved using publicly available data and without the need for deep learning and large-scale image collections. And, third, to determine which building related features openly available at CONUS-scale have the most predictive power.

[1]OpenStreetMap, https://www.openstreetmap.org/

3. Machine Learning Dataset

No CONUS-scale ML-ready dataset for building occupancy type currently exists. It is not even apparent which building level features available openly at CONUS-scale have the most predictive power. We do not claim that the features utilized in this study are the most predictive. Rather, we gather a wide sampling of different types of open data available at the building level and perform exploratory analysis. Our goal is to predict a building's type (e.g. Residential/Commercial/Industrial) based on known features of the building (area, location, etc.). To accomplish this, we gather a number of building features from open datasets. Our sources of building features are Open Street Map (OSM), the Multi-Resolution Land Characteristics Consortium (MRLC)[2], United States Census' County Business Patterns (CBP)[3], and the United States Census' American Community Survey (ACS)[4]. We've preprocessed the data to spatially align all features. We used building longitude and latitude provided by OSM to determine which county the building resides in. We've then gone to the ACS and looked up socio-econimic county data such as median income and housing density. The imperviosness values are taken from a 30 meter data set that is part of the MRLC from which the mean area weighted average of the imperviousness underneath the building footprint was computed. The resulting machine learning ready data has the features listed in Table 1.

Assessing the accuracy of building occupancy type predictions involves a source of "ground-truth" data. We utilize the USA Structures[5] dataset maintained by FEMA and created in conjunction with DHS Science and Technology and Oak Ridge National Laboratory. USA Structures was created by extracting building outlines via commercially available satellite imagery. Building occupancy type (e.g. residential, commercial, industrial) was then determined from a combination of local governments who agreed to share it, open data from the National Geospatial-Intelligence Agency (NGA), Census housing data, and parcel data. These USA Structures building types are what we are trying to predict. The USA Structures 'OccupancyType' is the final column in our training data and our source of "ground-truth" values. We note that the USA Structures dataset is smaller than OSM and currently only available in Alabama, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Texas, and Virginia. Thus, while a good source of ground-truth data, USA Structures does not preclude the need for machine learning. Utilizing North Carolina as a test site, we've created an ML-ready dataset of 1,078,144 buildings with known building occupancy type. USA Structures recognizes eight building occupancy types and the occurrence of these types in North Carolina is shown in Table 2.

Evident from Table 2 is that we have a significant class imbalance. The residential buildings, for example, outnumber the commercial buildings 15 to 1. The residential buildings outnumber the agricultural buildings nearly 600 to 1. This can be a challenge for machine learning classification algorithms. The algorithm may not "learn", but rather obtain high accuracy simply by picking the majority class. We will look at techniques for dealing with such imbalance.

4. Machine Learning Algorithms

Flood risk assessment applications demand multiple types of classification. For example, during a flood emergency, first responders may only be interested in identifying residential buildings. In this use case, binary classification (Residential vs. non-Residential) is sufficient. However, for economic forecasting applications, a finer grained distinction is needed (i.e. Residential vs. Commercial vs. Industrial). In such a scenario, multiclass classification is needed to determine a comprehensive economic assessment. We provide examples of both scenarios. Specifically, we design a set of supervised learning models in which building features (location, square footage, proximity to other resources, etc.) are used to

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[2]https://www.mrlc.gov/data/type/urban-imperviousness
[3]https://www.census.gov/programs-surveys/cbp/data/tables.html
[4]https://www.census.gov/programs-surveys/acs/data.html
[5]https://gis-fema.hub.arcgis.com/pages/usa-structures

Column	Description	Data Source
X	X coordinate of the building in the EPGS:5070 system	OSM
Y	Y coordinate of the building in the EPGS:5070 system	OSM
Area	Area of building in square meters	OSM
MedianIncomeCounty	Median income of the county in which the building resides	ACS
HousingUnitsCounty	Number of housing units in the county which building resides	ACS
HousingDensityCounty	Number of housing units in the county divided by the number of people residing in the county where the building resides	ACS
Impervious	Percentage of the area surrounding the building that is comprised of impervious surfaces such as roads and other paved surfaces. Value provided is the mean area weighted average of imperviousness underneath the building footprint	MRLC
AgCount	Number of agricultural businesses in the county in which the building resides	CBP
CmCount	Number of commercial businesses in the county in which the building resides	CBP
GvCount	Number of government buildings in the county in which the building resides	CBP
EdCount	Number of educational buildings in the county in which the building resides	CBP
InCount	Number of industrial buildings in the county in which the building resides	CBP
OsmNearestRoad	Type of nearest road to the building	OSM
OccupancyType	Building occupancy classification	USA Structures

Table 1. *Features utilized in our machine learning training data.*

predict building occupancy type. We access the accuracy, precision, and recall of two machine learning algorithms while also investigating techniques for dealing with unbalanced classes.

4.1. Binary Classification

For the binary classification scenario, all non-Residential building types are changed to "Other". The OsmNearestRoad and OccupancyType, which are initially text, are label encoded and we scale the data (for the neural network) based on standard scores. Our ML dataset is split into training and testing portions using the standard 80/20 training/testing splitting. The training data are then applied to multiple variations of random forest and neural network approaches. We include the standard random forest approach as a baseline and then compare variations designed to better handle class imbalance. Trained ML models are then evaluated on the test set. We use the balanced accuracy metric to deal with our imbalanced dataset. Balanced accuracy is defined as the average of recall obtained on each class. Similarly, we use weighted precision, recall, and F1 metrics. Weighted precision, recall, and F1 are computed by calculating metrics for each class, and finding their average weighted by support (the number of true instances for each class). This weighting technique accounts for class imbalance; yet, we note, it can result in an F-score that is not between precision and recall.

Building Occupancy Type	Number of Buildings	Percentage of Dataset
Residential	976,690	90.6%
Commercial	64,029	5.9%
Industrial	16,722	1.6%
Assembly	7,323	0.68%
Education	6,457	0.60%
Government	4,910	0.46%
Agriculture	1,651	0.15%
Utility and Misc.	362	0.03%

Table 2. *Summary statistics of building occupancy types in North Carolina.*

Building Occupancy Type	Number of Buildings	Ratio to Residential
Residential	976,689	-
Other	101,453	1:10

Table 3. *Building occupancy type distribution for binary classification.*

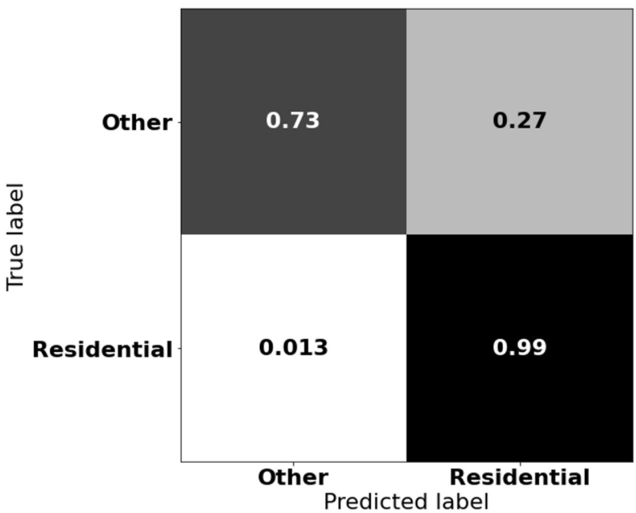

Figure 1. *Confusion Matrix for random forest binary classification. Values are listed as proportions.*

4.1.1. Random Forest

Table 3 shows the distribution of building occupancy types after non-Residential buildings are converted to “Other”. There still exists a significant imbalance in the building occupancy types. We then trained a random forest model using 5-fold cross validation to ensure accuracy was not dependent on how the data was split. We found consistent evaluation values with a balanced accuracy of 85%, a weighted precision of 96%, a weighted recall of 96%, and a weighted F1 of 96%. The confusion matrix for random forest binary classification is shown in Figure 1.

Undersampling refers to a group of techniques designed to balance the class distribution. Undersampling techniques remove examples from the training dataset that belong to the majority class in order to better balance the class distribution. This is in contrast to oversampling, which involves adding examples to the minority class in an effort to reduce the class distribution imbalance. Near Miss [14] refers to a collection of undersampling methods that select examples based on the distance of majority class examples to minority class examples. Distance is determined in feature space using Euclidean distance. NearMiss

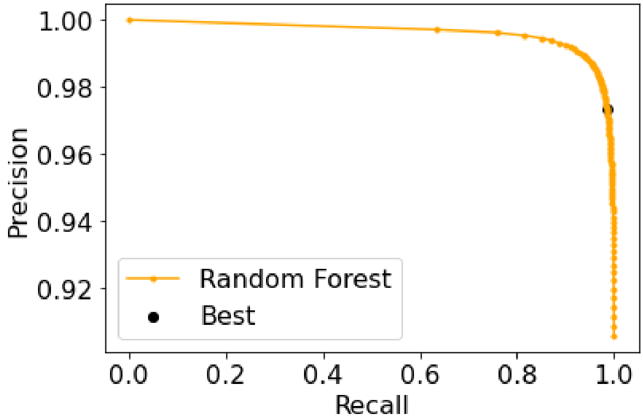

Figure 2. *Precision recall curve for random forest threshold moving.*

allows us to keep majority class examples that are on the decision boundary leaving 101,453 Residential buildings and the same number of non-Residential buildings. The NearMiss approach achieved comparable accuracy at 84%. However, we noticed decreased precision and recall values with this algorithm. Perhaps the simplest approach to handle a severe class imbalance is to change the decision threshold.

Many classification algorithms will return a probability of class membership where all values equal or greater than a threshold are mapped to one class and all other values are mapped to the other class. The default of many algorithms is to set the threshold at 0.5. Threshold moving simply moves the threshold attempting to achieve higher accuracy. Figure 2 illustrates the results of threshold moving applied to our binary classification random forest model. The points connected by a solid line show the change in precision and recall as the threshold is modified. The large solid black dot highlights the location where precision and recall are optimized. This location is determined by finding the threshold with the maximum F1 score, a metric which is the harmonic mean of precision and recall. Our experiments revealed an optimal threshold of 0.55.

4.1.2. Neural Network

We also trained a binary classification neural network to compare to the random forest approaches. Because of the class imbalance, we want the neural network to pay more attention to the fewer examples of non-residential buildings. A common technique for achieving this is to weight the classes using:

$$weight = (1/n_c) * (N/2) \tag{4.1}$$

where $\mathrm{n_c}$ is the number of buildings in the class and N is the total number of buildings

We arrive at a residential weighting of 0.55 and a non-residential weighting of 5.31. The neural network itself has two hidden layers of size 30 and 15, respectively. The network was set to train for 150 epochs. However, early stopping was applied with the training set to stop if accuracy did not improve for 7 consecutive epochs. After 36 epochs, training stopped with a balanced accuracy of 87%, a weighted precision of 93%, a weighted recall of 89% and a weighted F1 of 91%. Figure 3 shows the confusion matrix resulting from the neural network. Figure 4 shows the results of all binary classification approaches.

4.1.3. Feature Importance in Binary Classification

Feature importance is a technique for assessing how important each of our input features are to making accurate predictions. Features with low importance do not contribute much (do not have much weight) to prediction accuracy. Low importance features can be ignored creating simpler more scalable machine

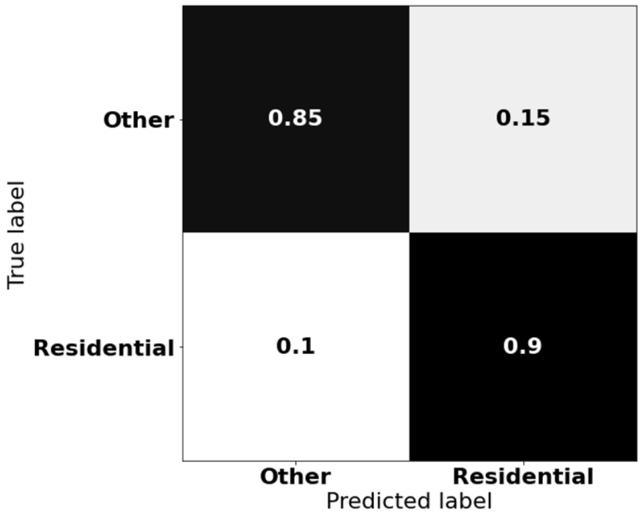

Figure 3. *Neural network confusion matrix. Values are given as proportions.*

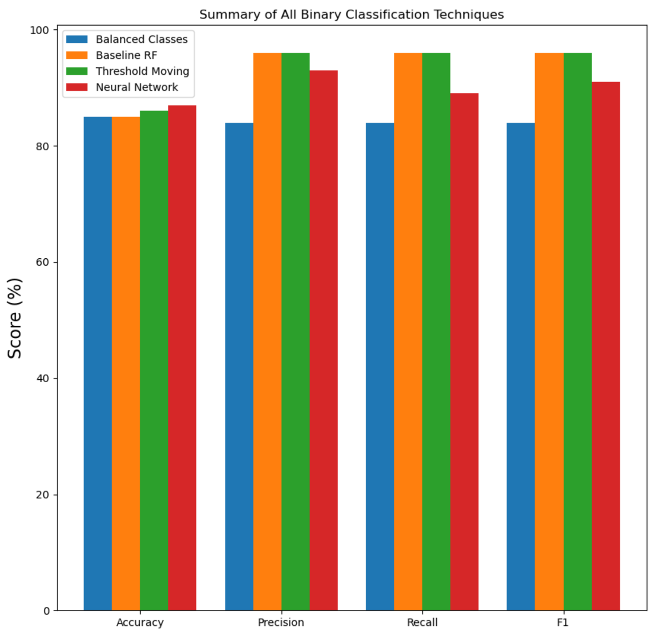

Figure 4. *Summary of results for binary classification approaches.*

learning models. We use a technique called Permutation Importance in which feature values are randomly shuffled. The resulting Mean Accuracy Decrease plot expresses how much accuracy the model losses through feature permutation. The more the accuracy suffers, the more important the variable is for successful classification. Feature importance was carried out using our highest accuracy and F1 score random forest model with the results shown in Figure 5.

We find that nearest OSM road type has the most predictive power followed by counts of various business types in the county. Area and geographic location have minimal predictive power as each of the building occupancy types occur across the state and can be found in a variety of square footage.

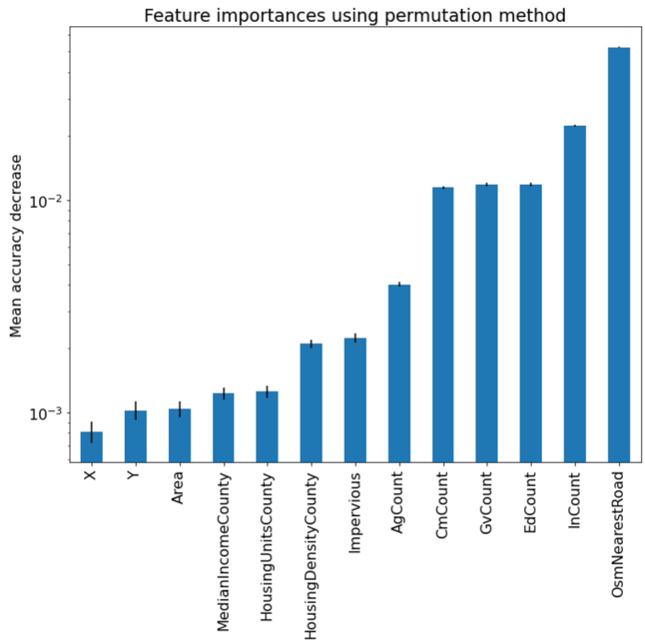

Figure 5. *Permutation feature importance for binary classification. Features are shown in ascending order of importance. The bars show the mean accuracy decrease after 10 repetitions with error bars displaying the standard deviation of the 10 repetitions.*

4.2. Multiclass Classification

4.2.1. Random Forest Multiclass Classification

USA Structures recognizes eight building occupancy types. We first repeated the machine learning process using all eight classes in a multiclass classification scenario. We found class imbalance to be so severe we could not reliably predict more than the three most frequently occurring building types. The classification accuracy for all eight occupancy types was around 30%. When Assembly, Education, Government, Agriculture, and Utility and Misc. were combined into a single 'Other' class, the accuracy only improved to about 50%. We limit our discussion here to machine learning models designed to predict "Residential", "Commercial", or "Other". The distribution of these three classes in our dataset can be found in Table 2.

When a random forest model is applied to this three class classification problem, we achieve a balanced accuracy of 67% and 94% for each of weighted precision, weighted recall, and weighted F1. The confusion matrix for this approach is shown in Figure 6. Feature importance analysis was repeated using the multiclass random forest model. Results did not differ from those shown in Figure 5.

Ensemble methods use multiple learning algorithms to obtain better predictive performance than could be obtained from a single algorithm. One-vs-Rest and One-vs-One have emerged as two popular ensemble techniques for classification. While not specifically designed for addressing class imbalance, decomposing the classification problem into a set of binary classification problems can sometimes help. The one-vs-one and one-vs-rest techniques in particular have led to promising results in empirical studies involving imbalanced classes [4, 7, 15].

The One-vs-One strategy splits a multi-class classification into one binary classification problem per each pair of classes, e.g. Residential vs. Commercial, Residential vs. Other, Commercial vs. Other. The final class assignment is determined by aggregating the results of the binary classifiers. The One-vs-Rest strategy is a related approach, however, fewer models are created. There is one binary classification

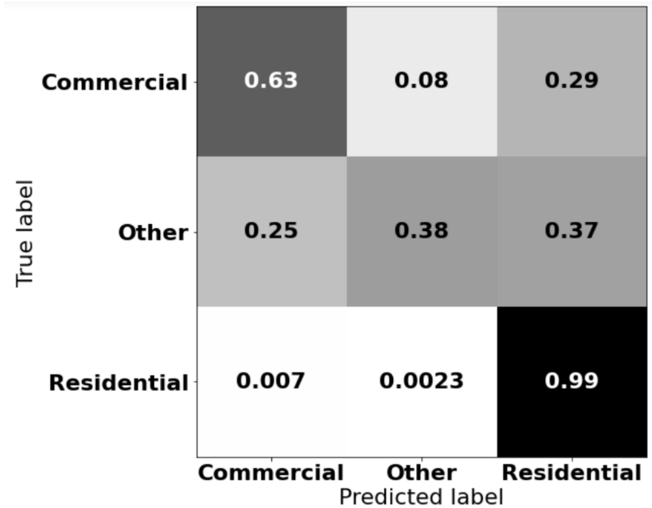

Figure 6. *Confusion matrix for multiclass random forest.*

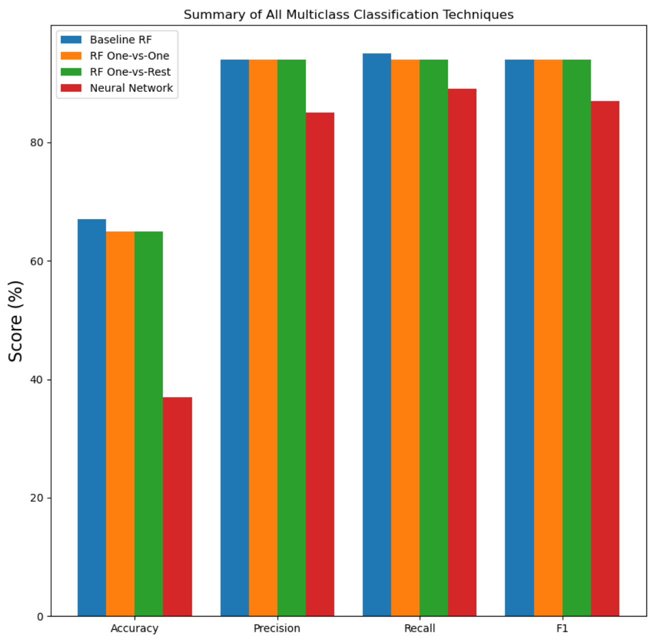

Figure 7. *Summary of results from all multiclass classification techniques.*

problem per class, e.g. Residential vs. Rest, Commercial vs. Rest, Other vs. Rest. Neither approach improved accuracy on our dataset.

4.2.2. Neural Network for Multiclass Classification

A multiclass neural network was implemented with similar characteristics to those utilized in the neural network binary classification. The resulting class weights were 0.55 for residential buildings, 8.42 for commercial buildings, and 14.40 for "other" buildings. The multiclass neural network performed poorly with a balanced accuracy of 37%.

Figure 7 summarizes the results from the various multiclass classification approaches.

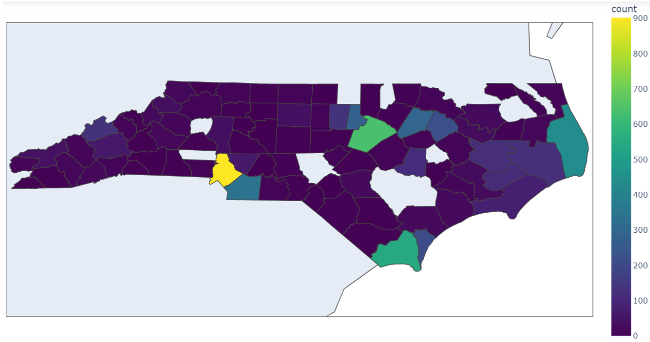

Figure 8. *Predicted residential flooding.*

5. Results

We have identified a features, freely and publicly available at the continental scale, that are useful in building occupancy type classification. These features could become part of a CONUS-scale building classification workflow with accuracy values comparable to existing ML systems (e.g. [5]) and without the reliance on proprietary APIs and large image collections. Specifically, with the current set of features, we achieve 87% accuracy with binary classification and 67% accuracy on the three class (Residential/Commercial/Other) classification problem. As a specific comparison, our technique correctly classifies 63% of commercial buildings compared to [5]'s 64%.

We do note that the severe class imbalance limits practical application of multiclass classification beyond these three classes. Looking deeper into our ML models trained with more classes, we find predictive "confusion" is correlated with the class imbalance. In other words, the less frequently an occupancy type appears in our dataset, the more likely it is to be confused for other occupany types. Industrial buildings, which are outnumbered by residential buildings nearly 60 to 1, are confused for commercial buildings 33% of the time and misclassified as residential buildings 23% of the time. An interesting area of future research is to see if class imbalance can further be addressed via aerial and street view data as in [5]. Additionally, we would like to explore how state level ML models compare to a single CONUS-level ML model.

6. Application of ML Model - Socio-economic Impacts

We identified 219,054 buildings in the OSM North Carolina dataset not used in our train/test data that had unknown building occupancy types. Our best performing multiclass random forest model was applied to these buildings. Further, we obtained the 100-year flood map from the FEMA National Flood Hazards Layer. The phrase "100-year flood" is used to describe the extent of a flood that statistically has a 1-percent chance of occurring in any given year [9]. Here, it is used for illustrative purposes of an overall disaster response application. 5,838 buildings out of the 219,054 unknown North Carolina buildings were impacted by the 100-year flood. Our ML model predicted these to be 5,452 residential, 349 commercial, and 37 "other". The spatial distribution of the predicted residential and commercial buildings is shown in Figures 8 and 9, respectively.

7. Conclusion

Our machine learning models enable us to predict the building type for 219,054 buildings in North Carolina. Combining these predictions with socio-economic data and flood forecast models, we are able to make risk assessments that were not possible without the machine learning. In terms of impacts to residential homes, a 100-year flood will disproportionately impact Mecklenburg, Wake, Dare, and

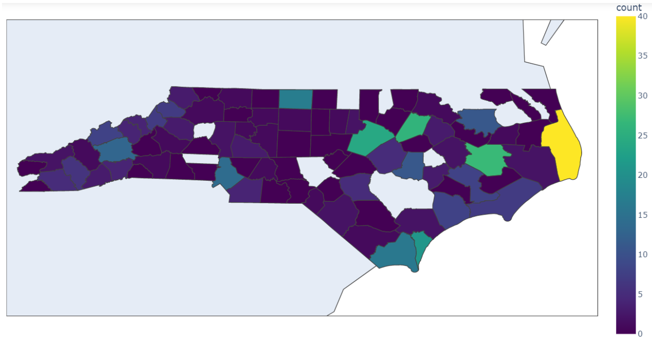

Figure 9. *Predicted commercial flooding.*

Brunswick counties. Nash county, a community with a median household income below the state median income level, and where 11% of the population lives in poverty, is predicted to be especially hard hit. Nash county is predicted to have significant flood impacts to both residential and commercial buildings. Although buildings are just one small part of the urban multiplex, the application of machine learning can help us better understand this interconnected system leading to enhanced risk assessment and forecasting.

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Competing Interests. None

Data Availability Statement. We thank the GeoScience MAchine Learning Resources and Training (GeoSMART) program for their interest in turning our research into a community tutorial. Preprocessing routines, a Jupyter Notebook demonstrating our machine learning training and testing, and our ML-ready data are available via the tutorial at [12]. The integrated spatially aligned data used to create our ML-ready data are freely available via [11].

Ethical Standards. The research meets all ethical guidelines, including adherence to the legal requirements of the study country.

Author Contributions. Conceptualization: T.N.; J.M.J. Methodology: T.N.;J.M.J.;A.M.R. Data curation: T.N.;J.M.J. Data visualisation: T.N. Writing original draft: T.N.;J.M.J.;A.M.R. All authors approved the final submitted draft.

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