5-2023

A Satellite Imagery Approach to Estimating Migratory Flows in Guatemala Using Convolutional Neural Networks

Sarah Larimer
William & Mary

A Satellite Imagery Approach to Estimating Migratory Flows in Guatemala Using Convolutional Neural Networks

A thesis submitted in partial fulfillment of the requirement
for the degree of Bachelor of Science in Data Science from
William & Mary

by

Sarah Jean Larimer

Accepted for __________________________________

(Honors, High Honors, Highest Honors)

____

Dr. Dan Runfola, Advisor

____

Dr. Anthony Stefanidis

____

Dr. Alex Nwala

Williamsburg, VA
May 11, 2023

WILLIAM & MARY

HONORS THESIS

A Satellite Imagery Approach to Estimating Migratory Flows in Guatemala Using Convolutional Neural Networks

---

Author:
Sarah LARIMER

Advisor:
Dan RUNFOLA

A thesis submitted in fulfillment of the requirements for Interdisciplinary Honors in the degree of Bachelors of Science in the

Data Science Program

Accepted for Honors

Chair: Dr. Dan Runfola

Dr. Anthony Stefanidis

Dr. Alex Nwala

Williamsburg, Virginia May 11, 2023

WILLIAM & MARY

Abstract

Dr. Dan Runfola

Data Science Program

Bachelors of Science

A Satellite Imagery Approach to Estimating Migratory Flows in Guatemala Using Convolutional Neural Networks

by Sarah LARIMER

Being able to predict migratory flows is important in ensuring political, social, and economic stability. In the wake of violence, unrest, natural disasters, and social pressures, millions of migrants have fled Central America in search of a better life. However, due to the infrequent nature and high cost of census data, there is a need for a more remote and up to date approaches. Convolutional Neural Networks offer a computer vision based approach that is cheaper and with significantly less lag. In this study, we seek to evaluate the effectiveness of different convolutional neural networks in predicting migratory patterns in Guatemala. Using a combination of open source satellite images and census data, we implement a variety of network architectures that seek to predict migration both through regression and classification techniques. We find that while regression and classification models do not prove to be an effective tool, there is an opportunity for additional research into the spatial nature of migratory prediction. Our preliminary results affirm the need for continued research and advancement in deep learning algorithms to predict migratory flows.

Contents

List of Figures

List of Tables

List of Abbreviations

ADM1	Administrative Division Level 1
ADM2	Administrative Division Level 2
CDR	Call Detail Records
CNN	Convolutional Neural Network
EU	European Union
IPUMS	Integrated Public Use Microdata Series
MAE	Mean Absolute Error
MAPE	Mean Absolute Percent Error
MSLE	Mean Squared Logarithmic Error
MSE	Mean Squared Error
NIR	Near-infrared
RGB	Red, Green, Blue

Chapter 1

Thesis

1 Introduction

Human migration is an international phenomenon that has important connections to the environment, policy making, diplomacy, conflict resolution, social organization, and the economy (Pellegrino, 2000). Migratory rates to the United States have been remarkably consistent over the last 200 years, with the percent of the population born outside of the country increasing only from 13% in 1860 to 13.6% in 2021 (Batalova and Ward, 2023).

Measuring migration is an important task for governments and policy makers to effectively deal with changes in population and population composition. Unpredicted migration can lead to over-strained cities, limited resources, social tensions, and even violence. It is estimated that by 2040, 80% of urban growth will occur in the countries and cities that are least equipped to handle the influx of in-movers (Office of the Director of National Intelligence, n.d.).

This study explores whether convolutional neural networks (CNNs) are a viable approach to predicting migratory flows using satellite imagery or if more advanced techniques are worth exploring. We specifically test models which use a combination of open source Landsat 5 satellite imagery and data from the 2002 census. This paper explores a variety of regression and classification models that employ transfer learning, data augmentation, and parameter optimization. First, we present a literature review covering current approaches to measure and predict migration, deep learning, and the intersection of neural networks and satellite imagery. In section 3, we discuss the data sets that are use in our analysis. Then, an overview of methods and results is given. Lastly, limitations and future directions are discussed.

2 Literature Review

The phenomenon of migration has been a topic of interest in the social sciences for many years, and it is a complex and multifaceted phenomenon that is driven by a variety of factors. Economic factors have been identified as one of the key drivers of migration, as people seek better job opportunities and higher wages in other countries or regions. This is particularly true for migrants from developing countries who move to developed countries in search of better economic prospects (Brettell and Hollifield, 2023). Political factors are also important drivers of migration, including social unrest, violence, crime, and political instability (Burrows and Kinney, 2016). Environmental factors are another reason why people may migrate, as changes in climate and the environment can affect the availability of resources and the livelihoods of individuals and communities (Black et al., 2011, Abel et al., 2019). Finally, social and cultural reasons are also important drivers of migration, including the pursuit of educational opportunities and the desire to join family members in a new country (Sue, Riosmena, and LePree, 2018). Understanding the various factors that drive migration is critical for policymakers and researchers alike, as it can inform the development of policies and interventions aimed at managing migration flows and addressing the needs of migrants and host communities.

This literature review will first cover current methods used to model migratory flows. Second, it will cover a review of the most current deep learning models and their wide variety of applications. Finally, it will address the ways in which deep learning is being applied to predicting migration which will serve as a foundation for the rest of the work that will be presented in this paper.

2.1 Current Approaches to Measure & Predict Human Migration

Measuring & predicting migratory flows is a difficult task that has been of interest for governments and researchers for decades. Some current survey based approaches to measuring human migration include census data, inter-census surveys, country specific self identification systems, and specialized studies such longitudinal studies (Massey and Capoferro, 2004). Predictive models using demographic, economic, and social variables can help account for migratory flows in between census years (Tarver, 1961).

Census data and other inter-census surveys (surveys done between census years) provide direct measures of migration. In the XI Population Census and VI Housing Census of 2002, the data set of interest in this study (National Institute of Statistics (INE), 2002), a direct question is asked on the number of international migrants that travel through each household in the previous 5 years. Other studies also use direct census data to directly quantify levels of migration (Siraj et al., 2019). Siraj et al. used 5 years worth of census micro-data for Columbia at the ADM-1 level to estimate migration. Using a logistic regression, they used a variety of economic, demographic, and geographic factors to estimate migratory flows. Combined with data from the ADM-2 level, they used ADM-1 migration data to estimate the ADM-2 migratory flows and then re-aggregate to select the best model which comparing the estimation and observations had a correlation coefficient of 0.84. Their approach highlights the difficult that using survey data has to estimate migration. Often information about migration is only directly collected at the ADM-1 level so estimation of more granular spatial units is challenging. Furthermore, census data is only collected every 10 years which makes updating models difficult and limits their application to the current day.

Inter-census surveys gather additional information in between census years at a smaller scale. These can provide additional information that fill in the gaps of census data. One such example is to use the inter-census survey to estimate internal migration within a country such as the 2005 population survey conducted in China (Ebenstein and Zhao, 2015). Ebenstein et al. used migrants place of origin and destination in order to estimate internal urban to rural migration in China. They found that using origin-based counts resulted in an over-count of migrants in comparison to a destination-based approach. They also found that different estimates over and under represented migrants depending on whether their origin (hukou) was urban or rural. While Inter-census surveys can be helpful in providing additional data, they also have limitations. For example, in the Ebenstein study the 2005 survey was conducted with a different sampling method than the regular decennial census that potentially resulted in an oversampling of communities that experienced a large outflow of migrants and an under-sampling of areas that received a large influx of migrants.

Other types of records can also be used to measure migration. This includes proxy variables such as using the Gini index of inequality to measure the spatial focus of migration patterns (Rogers and Sweeney, 1998). Migration from Mexico to the United States has also been approximated using an identification card program called Matricula Consular de Alta Seguridad (Caballero, Cadena, and Kovak, 2018).

There is a large body of literature on quantitative models that seek to use demographic characteristics of different regions and populations in order to measure migration. The most basic of these is a gravity model based the population of regions of origin and destination, as well as the distance between these two regions. Research using gravity models has achieved an R-squared of .624 when estimating migration to the EU from neighboring countries (Ramos, 2016) and an R-squared of .66 when looking at migration into Canada (Karemera, 2000). Other models seek to incorporate environmental factors such as changes in climate or rainfall (Smit, 2002, Ajzen, 1991). For example, the Model of Migration Adaptation to Rainfall Change that when simulated had a mean correlation coefficient of the modelled and observed data sets of 0.8 (Smith and Kniveton, 2010). Basic econometric models can also capture gross migration by calculating the expected returns of balancing the costs of migration with the benefits. These econometric models include variables such as the distance between capital cities in the regions, the wage rate, unemployment rate, educational outcomes, population, urbanization, and "migrant stock" or the current number of people from the origin location living in the destination location. Another type of econometric model used is the Human Capital model (Walsh, 1974) that evaluates the earnings rate and costs of migration under the assumption that the marginal rate of substitution leisure for consumption is equal to the wage rate. While economic and statistical models can provide an interesting perspective on migratory flows and perhaps capture some migratory patterns, many models rely heavily on theoretical assumptions that are not met in real life such as the symmetry assumption in the gravity model that assumes migration from location A to location B is the same quantity as migration from B to A (Hoda Rahmati S, 2017), or the lack of mobility costs in the human capital model (Walsh, 1974).

Markov Chain Models have also been used by researchers to measure and predict migration (Constant, 2012, Lindsay, 1972). One such example is a multistage network equilibrium model (Pan, 1994). The authors implemented MCM in order to capture the path dependency of migratory flows instead of modeling a single step from origin to destination. Their implementation also captured the intermediary locations a migrant may pass through. This is especially relevant in places like Latin America where crime, natural landscapes, and political climates limit the places where border crossings can occur. As discussed later, this appears in Guatemala as many migrants end up stuck in towns near borders as they wait to cross.

As new big data sources become available, innovative approaches to measure migration are being used. Newer techniques like using geo-tagged online search data (Böhme, Gröger, and Stöhr, 2020) and social media data (Unver, 2022) seek to predict real-time migratory flows. In other examples, phone records can be used to track human mobility (Bengtsson, 2017, European Commission et al., 2016). Call Detail records (CDR) provided by telecommunications companies are being used to follow the location of anonymized individuals. This data can be used to track internal and international migration over time. One such study used CDR to evaluate internal displacement after natural disasters (European Commission et al., 2016). Other studies use Google Location History (Kraemer et al., 2020). Kraemer et al. aggregated and mapped Google Location History data to a 5km x 5km grid for locations where significant time was spent. By using 70 million unique location pairs, they were able to map migratory information for nearly 60 percent of the earth's populated areas. Through their analysis and coupled with other data sources, they were able to identify different migration trends across time as well as across income groups.

The utilization of big data approaches, such as call records and Google search locations, provides various benefits for studying migration patterns. One advantage is that these data types are not self-reported, reducing the potential for biased reporting. Additionally, they are available in real-time or near real-time, enabling faster and more up-to-date analysis without the cost of traditional surveying methods. However, these approaches present real challenges. For example, call detail records (CDRs) rely on the assumption that each phone corresponds to a unique individual, but phones can be gifted or shared by multiple people. CDRs can also only track migrants with phones, which excludes many of the poorest migrants. Furthermore, CDR data are usually available at a single country level, and integrating data across phone providers can be difficult. The integration of Google Location History data partially resolves these issues as it is available across countries and at more frequent intervals than call data. However, both techniques can be undermined by migrants who switch SIM cards when leaving the country.

2.2 Deep Learning

Deep learning is a type of machine learning that involves training algorithms called neural networks to recognize patterns in data. Neural networks are composed of layers of interconnected nodes that process and transform data as it passes through the network (Minaee, 2020). Deep learning can be used for tasks such as image recognition (Pak and Kim, 2017, Wu and Chen, 2015) , speech recognition (Deng and Platt, 2018, Noda et al., 2014), and natural language processing (Socher, Bengio, and Manning, 2012). Deep learning algorithms require large amounts of labeled data and computing power to train, but can achieve state-of-the-art performance in many tasks.

Convolutional Neural Networks (CNNs) are a type of neural network that have shown significant success in image analysis tasks. In a CNN, the input image is first passed through a series of convolutional layers, which apply filters to the image and produce a set of feature maps (cite (Sylvain, Drolet, and Brown, 2019). Each filter learns to recognize a specific feature, such as edges or corners, and the combination of filters in the convolutional layer results in the extraction of more complex features (Simulink, n.d.).

In recent years, CNNs have been applied to a wide range of image analysis tasks, including medical image analysis (Li et al., 2014b, Avşar and Salçin, 2019, Reshi et al., 2021), autonomous driving (Kaymak and Uçar, 2019, Fujiyoshi, Hirakawa, and Yamashita, 2019), and remote sensing (Zhang, Tang, and Zhao, 2019, Kattenborn et al., 2021, Shao and Cai, 2018). Using CNNs for image analysis can take a few possible routes: Image classification which assigns a label to the category of an image (Rawat and Wang, 2017), object detection which identifies unique components within an image (Zhiqiang and Jun, 2017), semantic segmentation which can distinguish broader components such as foreground and background (Briot, Viswanath, and Yogamani, 2018), image captioning which describes the content of an image (Gu et al., 2017), and style transfer which learns the visual components of one image to translate to a new image (2016).

Although the use of neural networks to predict migration is limited, there is an extended body of literature on the power of CNNs for other predictive uses. Classification tasks vary from using medical imagery like MRIs to detect brain tumors and Alzheimer's (Ayadi et al., 2021, AbdulAzeem, Bahgat, and Badawy, 2021), ECG and PSGs to measure Arrhythmia and sleep cycles (Chen et al., 2020, Phan et al., 2019), malware detection (Vasan et al., 2020), identifying natural features like plants and landscapes (Lee, Park, and Kim, 2016, Pi et al., 2020, Valarmathi et al., 2021, Lu, Tan, and Jiang, 2021), and text classification (Luan and Lin, 2019). Regression tasks also encompass a diverse body of literature with examples such as using 2D and 3D deep learning models to estimate wave heights (Choi et al., 2020), age estimation (Niu et al., 2016, Ren et al., 2019) , facial reconstruction (Jackson et al., 2017), estimation harmful cyanobacteria in rivers (Pyo et al., 2019), cell counting in laboratory samples(Xue et al., 2016), pain intensity estimation in videos(Zhou et al., 2016), fetal head circumference(Zhang et al., 2020), and even apparent personality traits from people talking on camera.(Ventura, Masip, and Lapedriza, 2017)

2.3 Neural Networks and Satellite Imagery

An emergent use of Neural Networks is their application to satellite imagery. They have been used for a variety of image analysis tasks that involve classification, regression, and object detection. As large, high quality, and open-source data sets are becoming more accessible, the combination of neural networks and satellite imagery has continued to grow.

Neural networks have been used for a variety of satellite image classification tasks. These include classifying building damages (Duarte et al., 2018), unused landscape (Akshay et al., 2020), construction activities (Yeşilmen and Tatar, 2022), crop types (Kussul et al., 2017), land use (Kumar and Gorai, 2022), and cyclone intensity (Zhang et al., 2021a). These models perform with relatively high accuracy such as using Landsat 8 imagery to classify land cover with 92 percent accuracy (Li et al., 2014a).

Satellite imagery in conjunction with neural networks is also used to do a variety of image regression tasks. These include estimation of physical attributes like surface soil moisture (Singh and Gaurav, 2023), inter-city road quality(Cadamuro, Muhebwa, and Taneja, 2019), forest height (Ge et al., 2022), building orientation angle(Shahin and Almotairi, 2021), urban expansion (Boulila et al., 2021) and winter wheat yield(Morales and Sheppard, 2021). Other studies estimate non-visible socioeconomic factors such as estimating housing prices(Bency et al., 2017), predicting poverty levels (Jarry et al., 2021). Many of the limitations and challenges that occur in these studies are points of interest in this paper. For example, when looking at housing prices, a consideration is how much of a neighborhood to include in an image to estimate price. Because the variables of estimation are not explicitly shown in the images, the relevant range of which to include is ambiguous. Part of how Bency et al. addresses this is through training 6 different neural networks, one for each image resolution available. Another strategy employed is to describe what can be seen in the images by tagging places of interest such as post offices and stores.

Lastly, deep learning models have demonstrated high performance with object identification tasks such as detecting clouds (Segal-Rozenhaimer et al., 2020) using both visible RGB bands and NIR bands, water bodies(Zhang et al., 2021b) using a Multi-feature Extraction and Combination Network (MECNet), buildings (Li et al., 2020, Kim et al., 2021) like greenhouses and roofs through Faster R-CNN, SSD, and custom CNNs, physical objects (Liu et al., 2020), earthquake induced ground failure effects(Hacıefendioğlu, Başağa, and Demir, 2020), and oil spills (Seydi et al., 2021). However, one limitation that these studies face is the discovery of a ground truth, especially when the image quality is lower resolution or the object of identification is more ambiguous such as cloud cover. The existence of supplemental data such as tagging locations Google Places (Bency et al., 2017) can validate satellite imagery.

Studying migratory flows has increasingly utilized machine learning approaches due to the accessibility of large and open source data sets. Current satellite imagery based approaches include mapping the distribution and growth of informal settlements (Corbane et al., 2017), and estimating population movement during natural disasters (European Commission et al., 2016). Other examples include using dwelling detecting algorithms on refugee and IDP camps (Wickert, 2019), land cover classification to monitor environmental drivers (Atik and Ipbuker, 2021), and contextualizing urbanization and armed conflict in Goma using Landsat data (Pech and Lakes, 2017). More recently, deep learning models have fused satellite imagery with census data in order to achieve higher performance (Runfola et al., 2022). This approach involves incorporating census data in the form of a social signature as a joint input into the neural network. Using the full social signature with imagery resulted in an r^2 of .72 and around 64% of estimates accurate to within 1000 migrants.

3 Data

3.1 Study Area

This study aims to predict migratory patterns in Guatemala, a country with 197 unique municipalities spanning over 42,000 square miles. Guatemala was chosen as the focus of this research due to its status as the largest country in the Northern Triangle, an area known for its tumultuous political climate and significant migrant population. In 1960, Guatemala entered a 36 year long civil war that drove many people to migrate to other parts of Central America and the United Sates. Following the war's conclusion in 1996, Guatemalans continued to leave in the wake of continued poverty, civil unrest, and natural disasters (Jonas, 2013). The temporal area of focus for this study is from 1997-2002. This time period directly follows the civil war and also includes the 5 years before the 2002 census, the most recent data available.

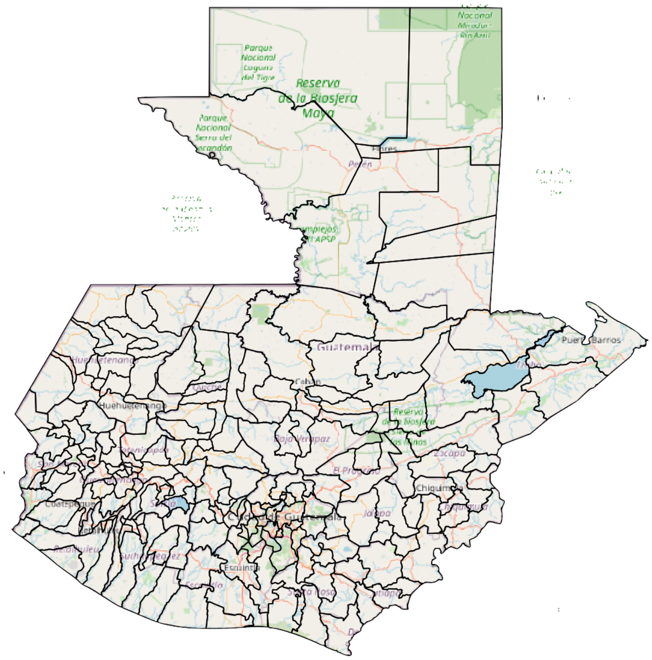


FIGURE 1.1. *2002 Guatemala Municipality Administrative Boundaries.*

3.2 Census Data

Census data is used to determine the number of international migrants in each municipality. Census data was retrieved from IPUMS International (National Institute of Statistics (INE), 2002). The most recent census data available for Guatemala is the 2002 census. This was a 10 percent sample census that asked respondents questions at the individual and household level. The sample had a sample size of 1121946 people located within 222,770 households. The variables of interest in this data set included GEO2GT2002 (the municipality in 2002), INTMIG1 (the number of international migrants), and POPDENSEGEOLEV2 (the population density of the municipality). Census data was downloaded by individual responses, aggregated based on household, and then the number of international migrants was summed for each municipality. To account for variation in population across the different municipalities, an additional column was made that normalized the number of migrants in each municipality by the population density.

TABLE 1.1: Sample Census Data Aggregated by Municipality

Municipality	Pop. Density	International Migrants	Normalized Migrants
Guatemala	4074	61651	1.133
Mixco	4209	4250	1.00
Villa Nueva	4708	1690	.359
...	...	...	...
Atescatempa, El Adelanto	195	68	.465
Quesada, San José Acatempa	105	48	0.457
Santa Catarina llita	111	126	1.135

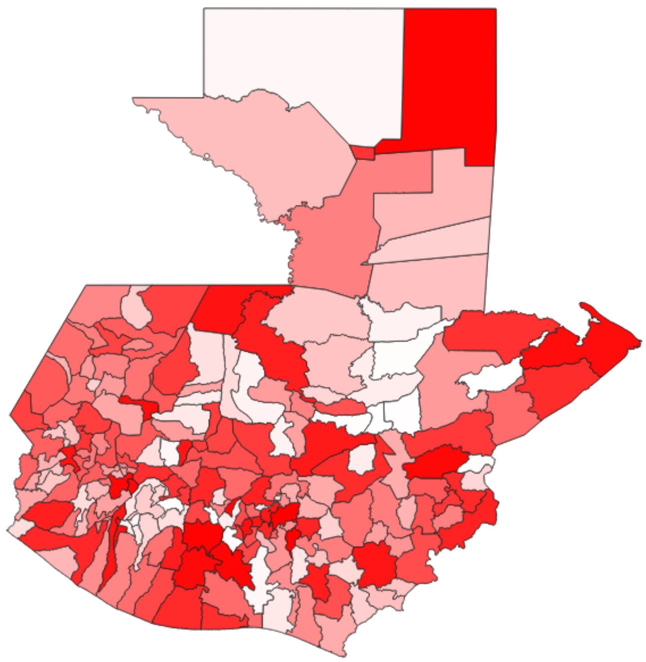
Population density is reported in persons per square kilometer and ranges from 2 to 4746 with a mean of 325.09 and a standard deviation of 647.96. The number of international migrants ranges from 5 to 61,651 with a mean of 1432.74 and a standard deviation of 5069.62. When normalized by population density, the number of migrants ranges from 0.036 to 2,220.71 with a mean of 18.31 and a standard deviation of 158.99. The distribution of both of these variables can be found in Appendix A.

It is important to note that both the raw count of migrants and the normalized migrants both contain one large outlier. However, this outlier is a different municipality in each distribution. In the raw data, Guatemala City has significantly more migrants than the other municipalities. However, when normalized for population density, it has a normalized population density of around 15. The outlier in the normalized data is Flores and Melchor de Mencos. While it has a relatively low number of migrants, it is also has a very low population density. The city of Melchor de Mencos is the only major border crossing from Guatemala to Belize. Hundreds of Guatemalans cross the border into Belize each day either to work or to go to school (Reynolds, 2010) While counted as international migrants, they are not the point of interest in this study.

TABLE 1.2: Outliers in Raw and Normalized Migrant Counts

Municipality	Pop. Density	International Migrants	Normalized Migrants
Guatemala 1	4074	61651	15.133
Flores, Melchor de Mencos	7.0	15545	2220.71

FIGURE 1.2. *Number of international migrants by municipality.*



3.3 Landsat Imagery

In order to compile the imagery for this study, Landsat 5 imagery was obtained using GeoPandas and Google Earth Engine. Of the seven bands available, only the three visible bands (B1: Blue (0.45 - 0.52 μm), B2: Green (0.52 - 0.60 μm), B3: Red (0.63 - 0.69 μm)) were used, with a resolution of 30m. The shapefile for Guatemalan municipalities in 2002 was obtained from geoBoundaries. Since Guatemala's administrative boundaries have undergone changes over time, it was crucial to ensure that the correct year for boundaries was being used. The Google Earth Engine API was used to download images of individual municipalities, employing a bounding box method to capture the entire municipality, including parts of surrounding municipalities.

FIGURE 1.3. *Bounding Box Methodology.*

Images for municipalities that were too large to download via the script were manually downloaded via Google Earth Engine. All municipalities were downloaded using a bounding box method where the northern, southern, western, and easternmost points for each municipality were used to form a box around the entirety of the area. As seen in this image, this method includes the entire municipality but also parts of the surrounding regions.

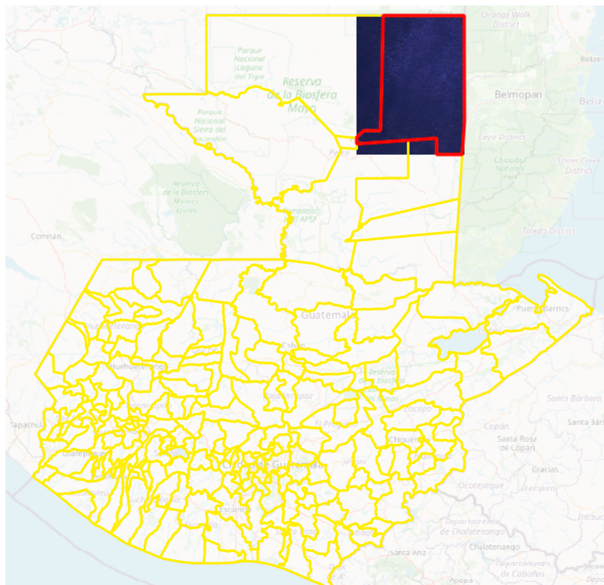
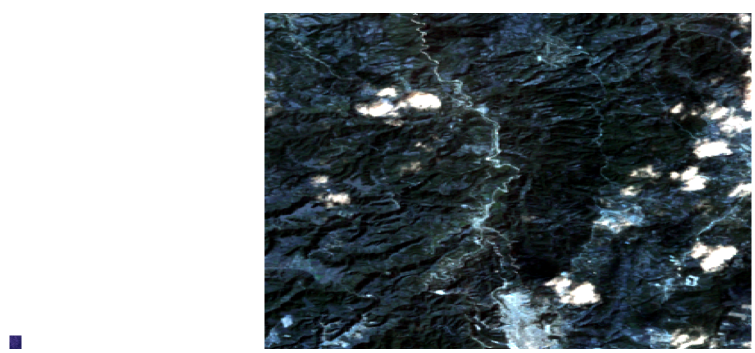


FIGURE 1.4. *Image Size Difference.*

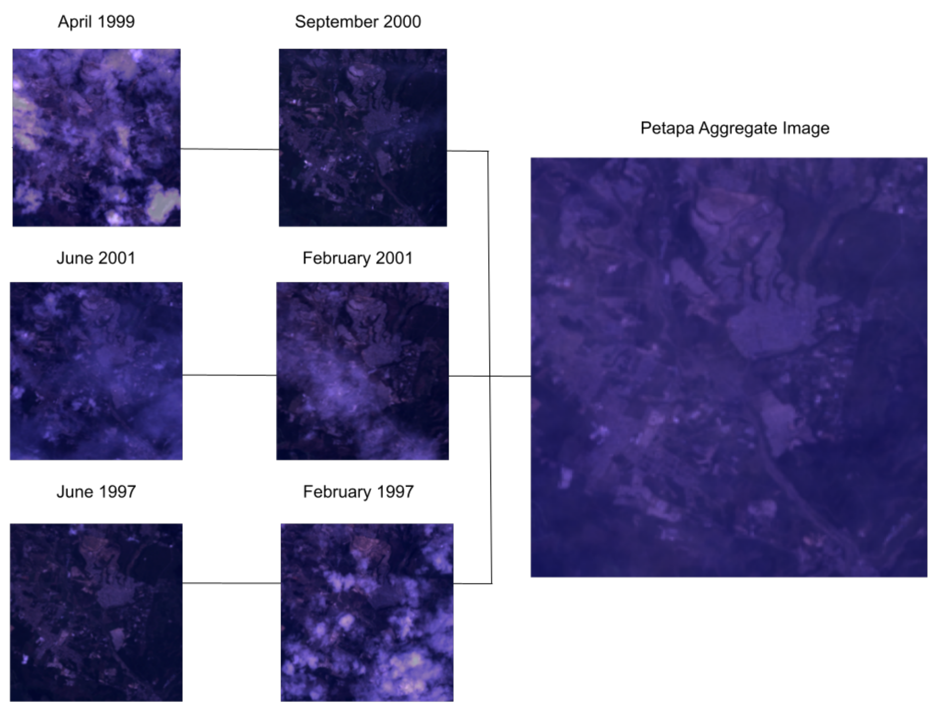
The smallest (Petapa: 218 x 192 pixels) and largest (San Andrés, San José: 3236 x 4687 pixels) municipality images in the data set.



This method was selected over blocking out the surrounding municipalities, as municipal characteristics such as economic, geographic, and social factors are not confined solely to their borders.[1] As municipalities differ in area, the resulting images varied in size, ranging from the largest municipality at 4,678x3,236 to the smallest at 192x218.

Satellite imagery from 1997-2002 was download and aggregated.Because the most recent census data is from 2002, satellite imagery was downloaded from 1997-2002 and aggregated. This included taking the average pixel value for each municipality across all of the available satellite imagery. Municipalities ranged from 43 to 55 in the number of raw images that went into the average pixel value. An average pixel value was taken to account for longer term drivers of migration leading up to the census as well as to account for cloud cover.

FIGURE 1.5. *Average Pixel Value.*



[1]Thirty-four municipalities were too large to be downloaded automatically via the API, and were instead manually downloaded from Google Earth Engine (see Appendix B).

Landsat imagery is a widely used in the field of remote sensing. Having collected data since 1972, Landsat has provided spatial, spectral, and radiometric data across continents, oceans, coastlines, and islands for 50 years. (Wulder et al., 2019) Numerous studies have used Landsat imagery to successfully train deep learning models for a variety of tasks. For example, Landsat 8 imagery was used to successfully identify man-made reservoirs in certain regions with 99 percent accuracy (Fang et al., 2019), active fire detection with 87 percent accuracy (Almeida Pereira et al., 2021), and map/monitor salt storms with 93 percent accuracy (Aghazadeh et al., 2022) Satellite imagery has also been used to study non-geological information such as mapping temporal population density (Zhuang et al., 2021), estimating building heights (Cao and Huang, 2021) and detecting armed conflict damages (Pfeifle, 2022).

TABLE 1.3: Data sources and descriptive statistics

Data Type	Source	Average	Median	Min	Max
Satellite Imagery	Google Earth Engine	(919,986)	(789,751)	(192, 218)	(4678, 3236)
Migration Counts	IPUMS Census Data	1432.7	169	5	61651

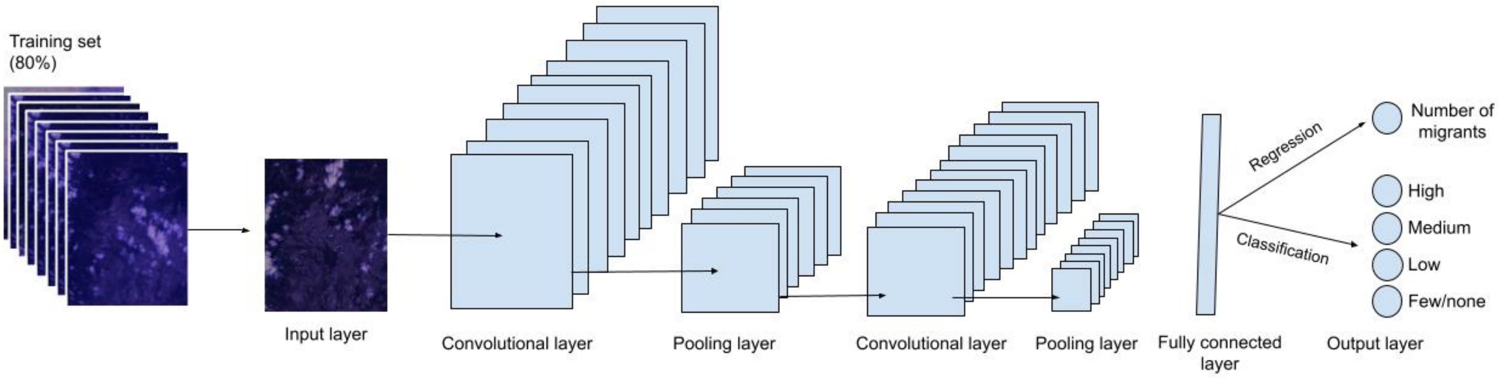
n = 197

4 Methods

This study explores whether convolutional neural networks (CNNs) are a viable approach to predicting migratory flows using satellite imagery. A variety of model architectures were evaluated for both regression and classification tasks.

For all models, data were split using an 80:20 training/testing split with 158 municipalities used for training and 39 for testing for all model types. Then, models were trained to do either a regression or classification task. In either case, these models take in satellite imagery as an input, process it trough a series of network layers, and produce an output, whether that be a value (regression) or a category (classification).

FIGURE 1.6. *Model Workflow.*



For regression tasks, a variety of model architectures were trained and a series of tests were conducted to select associated hyper-parameters. Five model architectures were tested: ResNet50, EfficientNetB7, InceptionV3, VGG16, and a custom 14-layer sequential model. These models were iteratively run with a combination of select hyper-parameters such as image size, batch size, optimizer, loss function, and whether or not data augmentation was employed. As neural networks can only accept standard image sizes, the images had to be standardized to the same size, given their initial differing dimensions due to different sizes in municipalities. Batch size refers to the number of images before updating the weights. Adam and Stochastic Gradient descent (SGD) were the 2 optimizers tested. The 4 different loss functions evaluated were Mean Absolute Error (MAE), Mean Squared Logarithmic Error (MSLE), Mean Absolute Percent Error (MAPE), and Mean Squared Error (MSE). Lastly, because the data set is small, data augmentation techniques were tested in some of the models to see if they improved accuracy. Through these tests, final metrics were recorded including the final learning rate and number of completed epochs. These varied between models because callbacks for early stopping and decreasing learning rate on plateaus were employed. Models with the highest performance were then explored further, including further testing including techniques such as unfreezing some of the inner base model layers.

Classification tasks were also run to answer the same predictive question but just at a less granular level. In this case, both the raw count of migrants and the normalized migrant count were classified into 1 of 4 categories: very few, few, moderate, and high number of migrants. The same architectures as the regression models (ResNet50, VGG16, EfficientNetB7, InceptionV3, simple sequential) were repeated. Models were then trained in a way similar to the regression task by testing a variety of model parameters such as image size, batch size, and optimizer. However, instead of testing different loss functions, different activation functions for the final layer were tested instead. Because it is a classification task, Categorical Cross-entropy was the loss function in all models. Like the regression models, the highest performing models were then selected for further testing and iterations. Due to large class imbalances, class weights were added to all of the classification models.

TABLE 1.4: Raw Count Data Classifications

Category	Range	Count
Very Few	<1	87
Few	[1-10)	83
Mid	[10-80)	23
High	>80	4

TABLE 1.5: Normalized Data Classifications

Category	Range	Count
Very Few	[0-100)	61
Few	[100-900)	98
Mid	[900-11000)	34
High	>11000	4

The pre-trained networks (ResNet50, EfficientNetB7, InceptionV3, and VGG16) all employ a transfer learning technique. These models start from with the pre-trained weights from ImageNet. ImageNet is a large (14 million observations) data set of images that cover over 80,000 unique objects (ImageNet, n.d.). The top layer is then removed and a new fully connected layer is added which the model retrains to fit the task at hand. The inner layers remain frozen in order to preserve the pre-trained weights. Pre-trained models build off the progress of computationally expensive models without having to re-train the entire network, and generally perform well. In this case, all models used weights that were a result of training on the imagenet data set. For models that performed well with standard transfer learning, some of the inner layers of the base model were systematically unfrozen and re-trained at a low learning rate to free up more trainable parameters and facilitate increased performance. First, just the last frozen layer before the top layer was unfrozen followed by the second and third to last. Then, a custom sequential model was also developed. This original sequential model has 14 layers with a repeated convolutional-pooling-dropout structure.

5 Results

In these results we present the performance for both the regression and classification modeling approaches. In general, all model architectures performed similarly and we found that techniques such as normalizing the data by population, unfreezing inner layers of pre-trained networks, and switching from a regression task to a classification task, did not lead to significant performance gains. Highest performing regression models had a MAPE of 80% and highest performing classification models had an accuracy of 50%. However, because of outliers, summary statistics have limitations in interpretability.

5.1 Regression Results

For the regression task, models trained on the raw data performed significantly better than models performed on the normalized data. As presented in the table below, the models trained on the non-normalized data had a highest MAPE of 80% and across architectures only varied by 10%. This is different from the same models trained on the normalized data where the best performing model was 80% and the worst performing model at 854%. Also, neither unfreezing inner layers nor adding data augmentation resulted in gains in accuracy for the regression models.

The table of results below show a summary of the highest performing models of each architecture. Although MAE is very large relative to the mean number of migrants, the variance of both the MAE and MAPE is large across municipalities and also subject to extreme outliers. In a sample of predictions done on the highest performing VGG16 model, absolute error ranged from 61,000 to 3 and percent errors ranged from 3% to 565%.

TABLE 1.6: Model Performance: Non-Normalized Data, Regression

Architecture	Image Size	Batch Size	Epochs	Optimizer	Learning Rate	Loss	MAPE	MAE
InceptionV3	360	15	23	Adam	.001	MSLE	87.23	3842.71
VGG16	360	15	5	Adam	.001	MAPE	82.20	3877.99
ResNet50	360	15	4	SGD	.01	MAPE	81.80	3882.50
EfficientNetB7	720	5	8	Adam	.001	MAPE	80.29	3875.47
Sequential	360	10	10	Adam	.01	MAPE	87.66	3906.27

Normalizing the count of international migrants by population density resulted in worse model performance. Only the custom sequential model was able to achieve a MAPE of under 100%. A point of not here is that whereas the highest performing model on the non-normalized data was EfficientNetB7 and the worst was the custom sequential model, this was nearly reversed for the normalized data where the sequential model outperformed the other models by a substantial amount and EfficientNetB7 had the second worst performance.

TABLE 1.7: Model Performance: Normalized Data, Regression

Architecture	Image Size	Batch Size	Epochs	Optimizer	Learning Rate	Loss	MAPE	MAE
InceptionV3	720	10	9	SGD	.01	MSLE	854.72	11.06
VGG16	360	5	5	Adam	.001	MAPE	156.97	9.90
ResNet50	360	15	12	SGD	.01	MAE	155.52	10.00
EfficientNetB7	360	10	4	Adam	.001	MAPE	164.79	9.83
Sequential	720	15	30	Adam	.001	MSE	88.47	10.04

5.2 Classification Results

Unlike the regression results, classification results improved when the data was normalized and all of the top performing models of each architecture that were trained on both normalized and non-normalized data performed similarly with accuracies from 45% to 50%. Similar to the regression models, neither unfreezing the inner layers of the pre-trained models nor adding data augmentation resulted in additional accuracy gains.

TABLE 1.8: Model Performance: Non-Normalized Data, Classification

Architecture	Image Size	Batch Size	Epochs	Optimizer	Learning Rate	Activation Function	Accuracy
InceptionV3	360	5	3	Adam	.001	tanh	44.73%
VGG16	360	10	6	Adam	.001	tanh	47.37%
ResNet50	360	5	4	Adam	.001	tanh	44.73%
EfficientNetB7	360	5	3	Adam	.001	sigmoid	44.73%
Sequential	360	5	13	Adam	.001	sigmoid	44.73%

Normalizing the data had a positive impact on performance and the top performing VGG16 model was able to achieve 50% classification accuracy. Interestingly, many of the top performing models in each architecture switched which activation performed the best when the data was normalized for population.

TABLE 1.9: Model Performance: Normalized Data, Classification

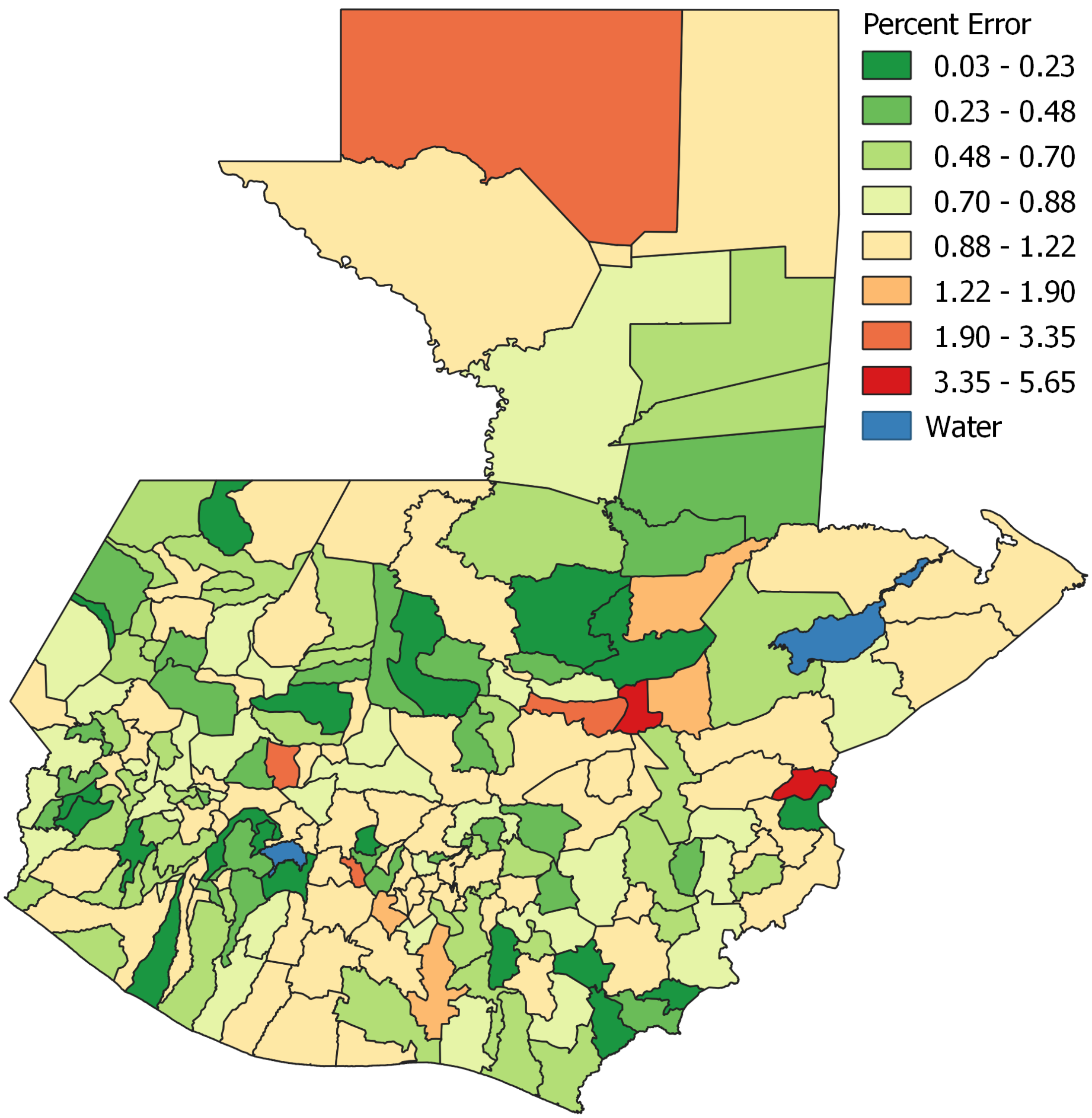
Architecture	Image Size	Batch Size	Epochs	Optimizer	Learning Rate	Activation Function	Accuracy
InceptionV3	360	5	3	Adam	.001	sigmoid	47.37%
VGG16	720	10	5	Adam	.001	tanh	50.00%
ResNet50	360	10	7	Adam	.001	sigmoid	47.37%
EfficientNetB7	360	5	4	Adam	.001	tanh	47.37%
Sequential	360	5	15	Adam	.001	sigmoid	47.37%

5.3 Spatial Distribution of Error

Looking at the spatial distribution of error can help better understand which municipalities are resulting in the highest errors and if there are any commonalities between municipalities that are predicted with significant error.

The map below highlights the spatial nature of error. Unsurprisingly, error in the model does not appear to be random across space. Municipalities with the highest performance tend to be clustered together and surrounded by other higher performing municipalities. The municipalities with higher error appear to be less clustered together in some parts, however, indicating possible municipality-specific reasons for high error.

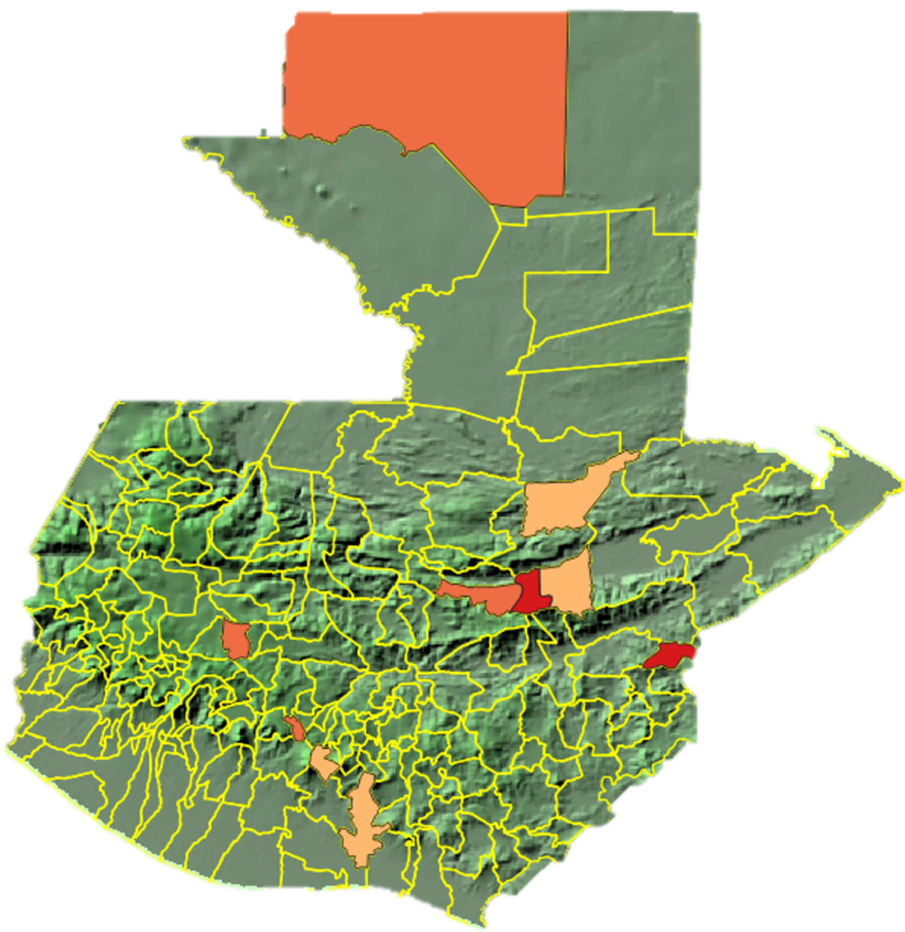
FIGURE 1.7. *Spatial Distribution of Error (VGG16 Regression).*



The dark orange municipality in the top left of the country is San Andres, San Jose. Upon further investigation, much of the municipality is covered by a national park. According to the census, it had reported 21 international migrants. However the model over-estimated the number of migrants to be 83. The large national park means much of the area is undeveloped natural land. Many of the other rural municipalities have higher number of migrants, potentially because of low paying agricultural jobs. Because of this, it would make sense that the model over-predicts the number of migrants in this municipality because the highly undeveloped nature of the national park.

There are also topographical reasons why the model might result in more error in certain municipalities in comparison to others. The map below shows how the highest error municipalities are located in relation to the topographical features of Guatemala.

FIGURE 1.8. *Relationship of Error and Topographical Features.*



The cluster of 4 municipalities in the middle of the country also offer unique circumstances that possibly explain the high error of the model. These municipalities (Panzos, Chahal, Purulhai, and Santa Catalina la Tinta) are all over-predicted by the model. These municipalities sit on the edge of a mountain range. Also, in 1970, the region that contains these municipalities (Northern Transversal Strip) was part of an agricultural development program that looked to improve the agricultural output of the area. This area is more agriculturally productive than the surrounding mountainous areas and may explain why the model over-predicted the number of migrants.

La Unión is the dark red municipality farthest to the right. Upon further investigation, this land is in the shadow of the Sierra de las Minas which produces a climate effect called Chaparral. Chaparral is semi-arid land that is similar to a Mediterranean climate and good for agriculture. This would potentially make the land more profitable than satellite imagery by itself would suggest. Additionally, there is another corridor of municipalities with high error. These model also over-predicts the number of migrants in these areas although besides being along a mountain range, the reasoning is unclear.

In a practical application sense, the top 5 municipalities with the highest percent error shown on the above map all have fewer than 25 observed migrants but absolute errors of between 28 and 83. While this results in a high percent error, for practical application this means only a difference of a few dozen people. Conversely, it is important to keep in mind when looking at percent error that it can also disguise high error. For example, in the data shown here San Pablo Jocopilas and Guatemala City both have approximately 100% error. However in terms of real application that is an absolute error of 25 migrants and 61,566 migrants respectively.

6 Discussion

6.1 Alternative Models

While the models presented in this paper today perform significantly worse than current models of migratory flows, the fact that any information at all is able to be derived from satellite imagery alone has distinct advantages and important implications for future research. Satellites circulate the globe every day and their imagery can be used to make up-to-date predictions that are not bound by multi year survey projects. Furthermore, unlike many statistical modeling methods that rely on difficult to acquire or delayed data, satellite imagery is open source and accessible on Google Earth Engine.

6.2 Socio-political factors

Border crossing towns highlight an important characteristic of international migration in Central America which is that the velocity of migratory flows are not constant. Major border crossing points appear to become locations where individuals aggregate while waiting for migratory opportunities as migration, especially illegally, is a challenging, expensive, and dangerous process. The average Guatemalan waits nearly 5 years to be granted asylum and smugglers charge up to $8,600 to smuggle a single adult (Cordoba, 2019), a debilitation amount of money where nearly half the population lives below the poverty line of $5.5 USD a day. Furthermore, as the US pressures Mexico to limit migratory flows, many migrants are being forcibly turned away at border crossings like Tecun Uman (Carrillo and Ramirez, 2020). For future research, it means that many migrants are likely double counted in both their municipality of origin as well as stuck in border crossing towns. The last phenomenon of relevance to this study are towns like Joyabaj that receive a high number of Guatemalans deported from the US. With a population of less than 85,000 people, it was the second highest destination of deported migrants following Guatemala City.

6.3 Limitations and Future Directions

This study had a number of limitations in which we will discuss: spatial distribution of population, outliers, a temporal aspect, limited scope, and an independence assumption.
Census data reported population density in persons per square kilometer. However, this gives no indication of urban centers or the distribution of a population across space. For example, a municipality that is moderately populated evenly across space could have a very similar population density to a municipality that is primarily rural but with a large urban center. This is an important concept to note as migrants from rural areas are over-represented in migratory flows in relation to their proportional makeup of the Latin American population (Riosmena and Massey, 2012). This potentially means that two municipalities with very different climates and drivers of migration are viewed equally by the model. In future work, this could possibly be corrected for by weighting the population density with an urbanization index.

A second consideration and limitation of the models considered in this paper are that both the raw count data and normalized data had significant outliers. Whereas most of the data was clustered around a single point, the presence of a few large data points skewed the distribution. This is a more significant consideration for the regression models where a few large values can dramatically impact performance metrics. For classification models, this resulted in a very distinct class imbalance. Although class weights were employed to help mitigate the issue, due to how few observations there were for the largest classes, there was still a chance that all of the highest category municipalities were included in the training subset and none in the validation subset of the 80:20 split. Future researchers can seek to minimize this by using block randomization to ensure that half of the under-represented classes always appear in the testing subset.

A large limitation of this study is the removed temporal aspect. Although high quality satellite imagery for Guatemala exists for decades, the study time frame is limited by the census data available to report on the number of international migrants. This limits the relevance of the study to the early millennium and future work would have to be done in order to apply these models to current migratory patterns. This is for two main reasons. First, the political, social, and natural landscape of Guatemala has changed in the last 20 years as a result of regime changes, the rise of organized crime, and climate change. Secondly, the actual administrative boundaries of Guatemala have changed since 2002 so future application of machine learning models will have to account for these changes in municipality boundaries in both the satellite imagery collected and the census data. Lastly, because the data was collected for five years prior to the census, a recurrent neural network (RNN) approach might be beneficial in capturing the temporal patterns. However, this model type was not tested in this study.

Fourth, the scope of this study was small in both the number of models tested as well as the number of samples. Further robustness checks could be done with a variety of architectures including other pre-trained models such as Xcpetion, DenseNet, or Inception. Additionally, ensemble models could be used to employ multiple model architectures at once. In terms of the small sample size, there are fewer than 200 municipalities in Guatemala. Future directions could seek to expand on this by looking at smaller administrative divisions, expanding to multiple countries trained together, or looking at countries that are geographically larger.

Finally, there are inconsistencies in how independently each municipality is evaluated by the model through the nature of the bounding box approach taken to capture the satellite imagery. Some municipalities were represented by images with significant portions containing aerial views of other municipalities while other images were primarily dominated by the municipality in question. This meant that there was inconsistency across the data set of how much information about the surrounding municipalities was contained in an image. The meant that in some cases there was not enough independence from surrounding areas. However, as many migratory drivers impact entire regions at once, the model is also limited in that it evaluates each municipality independent of where it is in space. Combined, this results in a model that is both spatially too independent but also not independent enough. This could be partially addressed through different image processing techniques such as blocking out parts of images that do not correspond the to the primary municipality, or training models on a variety of zoom levels.

7 Conclusion

The study of migratory flows is an important topic yet challenging task when it comes to basic deep learning models. This study seeks to answer the question of to what extent can convolutional neural networks predict migration from satellite imagery alone. Both regression and classification models were able to use satellite imagery to predict at least some variance in migratory flows of Guatemala. Neither regression nor classification models had high measures of accuracy. Highest performing regression models had a MAE of around 81 percent and highest performing classification models achieved an accuracy of around 47 percent.

The model uses public ally available Landsat satellite imagery and 2002 census data. A variety of model architectures were evaluated for both regression and classification tasks. Parameter selection attempted to identify the highest performing models which were then further explored with data augmentation techniques and the unfreezing of inner layers for transfer learning based approaches. Due to a large variance in the data and the presence of significant outliers, models were run on raw and normalized migration counts as well as discreet classification categories.

While model performance in this study is low in comparison to the performance of other migration models, this is a testament to the variety of observable and unobservable factors that drive migration. Future work can seek to supplement these models with other census data through social signatures, include a measure of urbanization in the normalization process, and account for changes in administrative divisions over time.

8 Acknowledgements

We would like to thank the committee Dan Runfola (chair), Anthony Stefanidis, and Alex Nwala. Thanks to Heather Baier for her support in the imagery downloading process and for providing her download script. We acknowledge William & Mary Research Computing for providing computational resources and/or technical support that have contributed to the results reported within this paper.

Appendix A

Appendix

FIGURE A.1. *Distribution of International Migrants (Raw Count).*

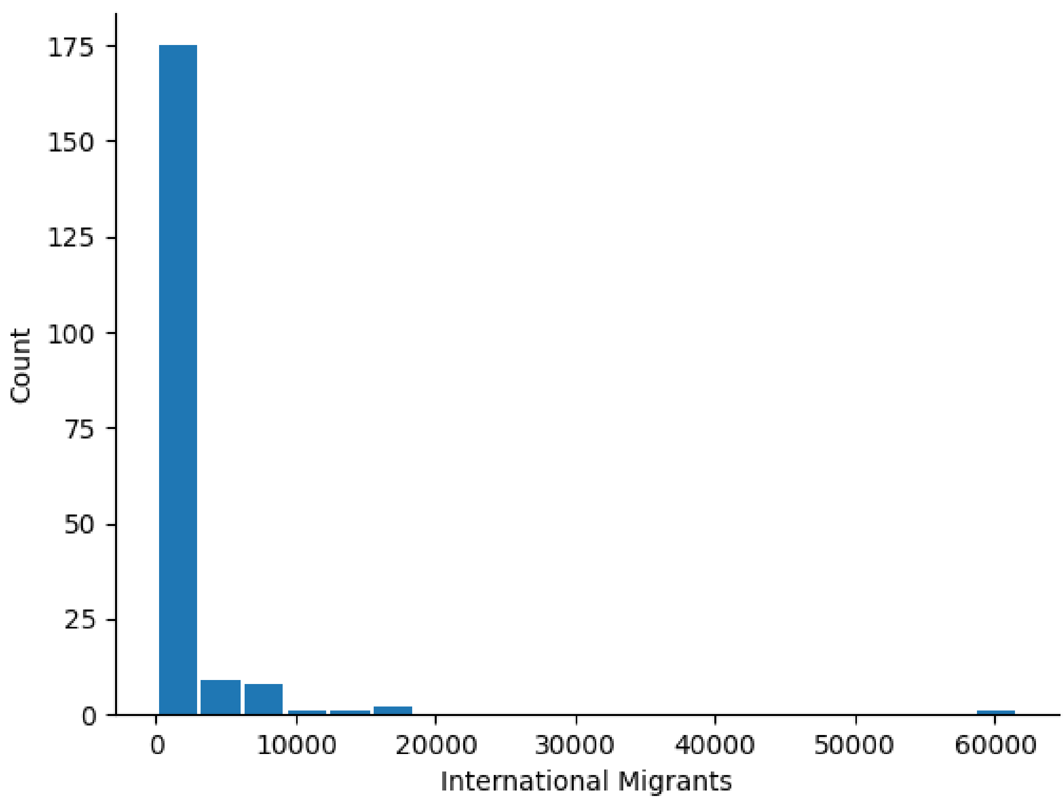
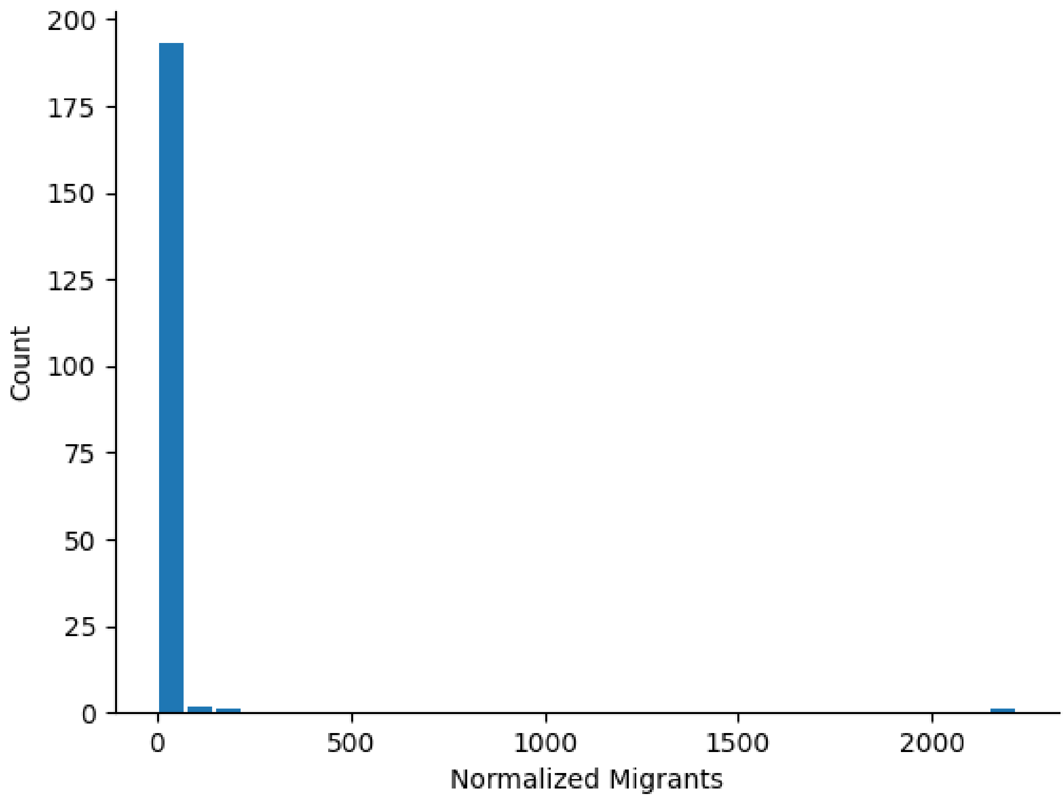


FIGURE A.2. *Distribution of International Migrants (Normalized).*



Manually Downloaded Municipalities

- Guatemala
- El Jícaro, Guastatoya, Morazán, San Cristóbal Acasaguastlán, Sansare
- Iztapa, La Democracia (Escuintla), Masagua
- San Gabriel, San José El Idolo, San Lorenzo (Suchitepéquez), Santo Domingo Suchitepéquez
- Retalhuleu, Santa Cruz Muluá
- Barillas
- San Juan Ixcoy, San Sebastián Coatán, Santa Eulalia
- Concepción (Huehuetenango), San Miguel Acatán, San Rafael La Independencia
- Santiago Chimaltenango, Todos Santos Cuchumatán
- San Pedro Necta
- Ixcán
- Chicamán
- Salamá, San Jerónimo
- Cubulco, Granados, El Chol
- San Pedro Carchá
- Cobán
- Lanquín, Senahú
- Chisec
- Chahal, Cahabón
- Fray Bartolomé de las Casas
- San Francisco, Santa Ana, Sayaxché
- La Libertad (Petén)
- Flores, Melchor de Mencos
- San Luis
- Poptún
- Dolores
- San Andrés, San José
- Morales
- Puerto Barrios
- Los Amates
- Livingstón
- El Estor
- Gualán, Río Hondo
- Concepción Las Minas, Esquipulas

Bibliography

AbdulAzeem, Youssef, Wael Mohamed Bahgat, and Mohamed Badawy (2021). "A CNN based framework for classification of Alzheimer's disease". In: *Neural Computing and Applications* 33.16, pp. 10415–10428. DOI: 10.1007/s00521-021-05799-w. URL: https://doi.org/10.1007/s00521-021-05799-w.

Abel, Guy J et al. (2019). "Climate, conflict and forced migration". In: *Global Environmental Change* 54, pp. 239–249. DOI: 10.1016/j.gloenvcha.2018.12.003.

Aghazadeh, Fatemeh et al. (2022). "An integrated approach of deep learning convolutional neural network and Google Earth engine for Salt Storm Monitoring and mapping". In: *Research Square*. DOI: 10.21203/rs.3.rs-1715901/v1.

Ajzen, I. (1991). "The theory of planned behavior". In: *Organizational Behavior and Human Decision Processes* 50.2, pp. 179–211. DOI: 10.1016/0749-5978(91)90020-t.

Akshay, S. et al. (2020). "Satellite image classification for detecting unused landscape using CNN". In: *2020 International Conference on Electronics and Sustainable Communication Systems (ICESC)*. DOI: 10.1109/icesc48915.2020.9155859.

Almeida Pereira, Gustavo Henrique de et al. (2021). "Active fire detection in landsat-8 imagery: A large-scale dataset and a deep-learning study". In: *ISPRS Journal of Photogrammetry and Remote Sensing* 178, pp. 171–186. DOI: 10.1016/j.isprsjprs.2021.06.002.

Atik, S. O. and C. Ipbuker (2021). "Integrating Convolutional Neural Network and multiresolution segmentation for land cover and land use mapping using satellite imagery". In: *Applied Sciences* 11.12, p. 5551. DOI: 10.3390/app11125551.

Avşar, E. and K. Salçin (2019). "Detection and classification of brain tumours from MRI images using faster R-CNN". In: *Tehnički Glasnik* 13.4, pp. 337–342. DOI: 10.31803/tg-20190712095507.

Ayadi, Wafa et al. (2021). "Deep CNN for Brain Tumor Classification". In: *Neural Processing Letters* 53.1, pp. 671–700. DOI: 10.1007/s11063-020-10398-2. URL: https://doi.org/10.1007/s11063-020-10398-2.

Batalova, Jeanne and Natalie Ward (Mar. 2023). "Frequently requested statistics on immigrants and immigration in the United States". In: *migrationpolicy.org*. URL: https://www.migrationpolicy.org/article/frequently-requested-statistics-immigrants-and-immigration-united-states.

Bency, Ajay J et al. (2017). "Beyond spatial auto-regressive models: Predicting housing prices with satellite imagery". In: *2017 IEEE Winter Conference on Applications of Computer Vision (WACV)*. IEEE, pp. 67–76. DOI: 10.1109/wacv.2017.42.

Bengtsson L., Xin L. Thorson A. Garfield R. (2017). "Improved Response to Disasters and Outbreaks by Tracking Population Movements with Mobile Phone Network Data: A Post-Earthquake Geospatial Study in Haiti". In: *PLoS medicine* 8.8, e1001083.

Black, Richard et al. (2011). "The effect of environmental change on human migration". In: *Global Environmental Change* 21. DOI: 10.1016/j.gloenvcha.2011.10.001.

Böhme, Markus H, André Gröger, and Tobias Stöhr (2020). "Searching for a better life: Predicting international migration with online search keywords". In: *Journal of Development Economics* 142, p. 102347. DOI: 10.1016/j.jdeveco.2019.04.002.

Boulila, Wassim et al. (2021). "A novel CNN-LSTM-based approach to predict urban expansion". In: *Ecological Informatics* 64, p. 101325. DOI: 10.1016/j.ecoinf.2021.101325.

Brettell, Caroline and James F Hollifield (2023). *Migration theory talking across disciplines*. Routledge, Taylor & Francis Group.

Briot, Adrien, Prithvijit Viswanath, and Senthil Yogamani (2018). "Analysis of efficient CNN design techniques for semantic segmentation". In: *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*. DOI: 10.1109/cvprw.2018.00109.

Burrows, Kate and Patrick Kinney (2016). "Exploring the climate change, migration and conflict nexus". In: *International Journal of Environmental Research and Public Health* 13.4, p. 443. DOI: 10.3390/ijerph13040443.

Caballero, M. Fernanda, Brian C. Cadena, and Brian K. Kovak (2018). "Measuring geographic migration patterns using matrículas consulares". In: *Demography* 55.3, pp. 1119–1145. DOI: 10.1007/s13524-018-0675-6.

Cadamuro, Gabriel, Andrew Muhebwa, and Jay Taneja (2019). "Street smarts". In: *Proceedings of the 2nd ACM SIGCAS Conference on Computing and Sustainable Societies*. ACM, pp. 1–10. DOI: 10.1145/3314344.3332493.

Cao, Yang and Xin Huang (2021). "A deep learning method for building height estimation using high-resolution multi-view imagery over urban areas: A case study of 42 Chinese cities". In: *Remote Sensing of Environment* 264, p. 112590. DOI: 10.1016/j.rse.2021.112590.

Carrillo, C. and R. Ramirez (2020). "'Mexico Doesn't Want Us': Migrants Get Stuck at Mexico-Guatemala Border". In: *Reuters*. URL: https://www.reuters.com/article/us-usa-immigration-caravan-mexico/mexico-doesnt-want-us-migrants-get-stuck-at-mexico-guatemala-border-idUSKBN1ZM09V (visited on 04/25/2023).

Chen, Chen et al. (2020). "Automated arrhythmia classification based on a combination network of CNN and LSTM". In: *Biomedical Signal Processing and Control* 57, p. 101819. DOI: 10.1016/j.bspc.2019.101819. URL: https://doi.org/10.1016/j.bspc.2019.101819.

Choi, H et al. (2020). "Real-time significant wave height estimation from raw ocean images based on 2D and 3D Deep Neural Networks". In: *Ocean Engineering* 201, p. 107129. DOI: 10.1016/j.oceaneng.2020.107129.

Constant A. F., Zimmermann K. F. (2012). "The dynamics of repeat migration: A markov chain analysis". In: *International Migration Review* 46.2, pp. 362–388. DOI: 10.1111/j.1747-7379.2012.00890.x.

Corbane, Christina et al. (2017). "Big earth data analytics on Sentinel-1 and Landsat imagery in support to global human settlements mapping". In: *Big Earth Data* 1.1-2, pp. 118–144. DOI: 10.1080/20964471.2017.1397899.

Cordoba, Jose (2019). "The Guatemalan City Fueling the Migrant Exodus to America". In: *The Wall Street Journal*. URL: https://www.wsj.com/articles/the-guatemalan-city-fueling-the-migrant-exodus-to-america-11563738141 (visited on 04/25/2023).

Deng, Li and John Platt (Oct. 2018). "Ensemble deep learning for speech recognition". In: *Microsoft Research*. URL: https://www.microsoft.com/en-us/research/publication/ensemble-deep-learning-for-speech-recognition/.

Duarte, D. et al. (2018). "Satellite image classification of building damages using airborne and satellite image samples in a deep learning approach". In: *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences* IV-2, pp. 89–96. DOI: 10.5194/isprs-annals-iv-2-89-2018.

Ebenstein, Avraham and Yaohui Zhao (2015). "Tracking rural-to-urban migration in China: Lessons from the 2005 inter-census population survey". In: *Population Studies* 69.3, pp. 337–353. DOI: 10.1080/00324728.2015.1065342. URL: https://doi.org/10.1080/00324728.2015.1065342.

European Commission Directorate-General for Employment, Social Affairs et al. (2016). *Inferring migrations, traditional methods and new approaches based on mobile phone, social media, and other big data: Feasibility study on inferring (labour) mobility and migration in the European Union from big data and social media data*. Technical report. Publications Office. DOI: 10.2767/61617. URL: https://data.europa.eu/doi/10.2767/61617.

Fang, Wei et al. (2019). "Recognizing global reservoirs from Landsat 8 images: A deep learning approach". In: *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 12.9, pp. 3168–3177. DOI: 10.1109/JSTARS.2019.2929601.

Fujiyoshi, H., T. Hirakawa, and T. Yamashita (2019). "Deep learning-based image recognition for autonomous driving". In: *IATSS Research* 43.4, pp. 244–252. DOI: 10.1016/j.iatssr.2019.11.008.

Ge, Shaojing et al. (2022). "Improved semisupervised unet deep learning model for forest height mapping with satellite SAR and optical data". In: *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 15, pp. 5776–5787. DOI: 10.1109/jstars.2022.3188201.

Gu, Jiuxiang et al. (2017). “An empirical study of language CNN for image captioning”. In: *2017 IEEE International Conference on Computer Vision (ICCV)*. DOI: 10.1109/iccv.2017.138.

Hacıefendioğlu, K., H. B. Başağa, and G. Demir (2020). “Automatic detection of earthquake-induced ground failure effects through faster R-CNN deep learning-based object detection using satellite images”. In: *Natural Hazards* 105.1, pp. 383–403. DOI: 10.1007/s11069-020-04315-y.

Hoda Rahmati S, Gurudeo Anand Tularam (2017). “A critical review of human migration models”. In: *Climate Change* 3.12, pp. 924–952.

ImageNet (n.d.). *About ImageNet*. https://www.image-net.org/about.php. Accessed May 2, 2023.

Jackson, Aaron S. et al. (2017). “Large Pose 3D Face Reconstruction from a Single Image via Direct Volumetric CNN Regression”. In: *2017 IEEE International Conference on Computer Vision (ICCV)*. DOI: 10.1109/iccv.2017.117.

Jarry, Raphael et al. (2021). “Assessment of CNN-based methods for Poverty Estimation from satellite images”. In: *Pattern Recognition. ICPR International Workshops and Challenges*. Springer, pp. 550–565. DOI: 10.1007/978-3-030-68787-8_40.

Jonas, Susanne (2013). *Guatemalan Migration in Times of Civil War and Post-War Challenges*. Washington, DC: Migration Policy Institute. URL: https://domide.colmex.mx/Archivos/Doc_5338.pdf.

Karemera D., Oguledo V. I. Davis B. (2000). “A gravity model analysis of international migration to North America”. In: *Applied Economics* 32.13, pp. 1745–1755. DOI: 10.1080/000368400421093.

Kattenborn, T. et al. (2021). “Review on Convolutional Neural Networks (CNN) in Vegetation Remote Sensing”. In: *ISPRS Journal of Photogrammetry and Remote Sensing* 173, pp. 24–49. DOI: 10.1016/j.isprsjprs.2020.12.010.

Kaymak, Ç. and A. Uçar (2019). “A Brief Survey and an Application of Semantic Image Segmentation for Autonomous Driving”. In: *Handbook of Deep Learning Applications*, pp. 161–200. DOI: 10.1007/978-3-030-11479-4_9.

Kim, J. et al. (2021). “CNN algorithm for roof detection and material classification in satellite images”. In: *Electronics* 10.13, p. 1592. DOI: 10.3390/electronics10131592.

Kraemer, Moritz U et al. (2020). “Mapping global variation in human mobility”. In: *Nature Human Behaviour* 4.8, pp. 800–810. DOI: 10.1038/s41562-020-0875-0.

Kumar, A. and A. K. Gorai (2022). “Application of transfer learning of deep CNN model for classification of Time-series satellite images to assess the long-term impacts of coal mining activities on land-use patterns”. In: *Geocarto International* 37.26, pp. 11420–11440. DOI: 10.1080/10106049.2022.2057595.

Kussul, Nataliia et al. (2017). "Deep Learning Classification of land cover and crop types using remote sensing data". In: *IEEE Geoscience and Remote Sensing Letters* 14.5, pp. 778–782. DOI: 10.1109/lgrs.2017.2681128.

Lee, Hyungtae, Minje Park, and Jinkyu Kim (2016). "Plankton classification on imbalanced large scale database via convolutional neural networks with transfer learning". In: *2016 IEEE International Conference on Image Processing (ICIP)*, pp. 1359–1363. DOI: 10.1109/icip.2016.7533053. URL: https://doi.org/10.1109/icip.2016.7533053.

Li, Congcong et al. (2014a). "Comparison of Classification Algorithms and Training Sample Sizes in Urban Land Classification with Landsat Thematic Mapper Imagery". In: *Remote Sensing* 6.2, pp. 964–983. DOI: 10.3390/rs6020964.

Li, M. et al. (2020). "Agricultural greenhouses detection in high-resolution satellite images based on convolutional neural networks: Comparison of faster R-CNN, Yolo V3 and SSD". In: *Sensors* 20.17, p. 4938. DOI: 10.3390/s20174938.

Li, Qing et al. (2014b). "Medical image classification with convolutional neural network". In: *2014 13th International Conference on Control Automation Robotics Vision (ICARCV)*, pp. 844–848. DOI: 10.1109/ICARCV.2014.7064414.

Lindsay I., Barr B. M. (1972). "Two stochastic approaches to migration: Comparison of Monte Carlo Simulation and Markov chain models". In: *Geografiska Annaler: Series B, Human Geography* 54.1, pp. 56–67. DOI: 10.1080/04353684.1972.11879364.

Liu, K.-Z. et al. (2020). "SIFT-enhanced CNN based objects recognition for satellite image". In: *2020 IEEE International Conference on Consumer Electronics-Taiwan (ICCE-Taiwan)*. IEEE, pp. 1–2. DOI: 10.1109/icce-taiwan49838.2020.9258037.

Lu, Jinhui, Lihua Tan, and Hao Jiang (2021). "Review on Convolutional Neural Network (CNN) applied to plant leaf disease classification". In: *Agriculture* 11.8, p. 707. DOI: 10.3390/agriculture11080707.

Luan, Yuyao and Shihui Lin (2019). "Research on text classification based on CNN and LSTM". In: *2019 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA)*. IEEE, pp. 234–237. DOI: 10.1109/icaica.2019.8873454.

Massey, Douglas S. and Chiara Capoferro (2004). "Measuring undocumented migration". In: *International Migration Review* 38.3, pp. 1075–1102. DOI: 10.1111/j.1747-7379.2004.tb00229.x.

Minaee S., Boykov Y. Plaza A. Kehtarnavaz N. Terzopoulos D. (2020). "Image Segmentation Using Deep Learning: A Survey". In.

Morales, Gustavo and John W. Sheppard (2021). "Two-dimensional deep regression for early yield prediction of winter wheat". In: *SPIE Future Sensing Technologies 2021*. DOI: 10.1117/12.2612209.

National Institute of Statistics (INE) (2002). *XI Population Census and VI Housing Census of 2002 [Guatemala]*. Retrieved from https://international.ipums.org/international-action/sample_details/country/gt#tab_gt2002a.

Niu, Zhenxing et al. (2016). "Ordinal regression with multiple output CNN for age estimation". In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, pp. 4920–4928. DOI: 10.1109/CVPR.2016.532.

Noda, Kota et al. (2014). "Audio-visual speech recognition using Deep Learning". In: *Applied Intelligence* 42.4, pp. 722–737. DOI: 10.1007/s10489-014-0629-7.

Office of the Director of National Intelligence (n.d.). *The Future of Migration. Global Trends*. https://www.dni.gov/index.php/gt2040-home/gt2040-deeper-looks/future-of-migration. Retrieved May 4, 2023.

Pak, Myung and Sangwoo Kim (2017). "A review of deep learning in image recognition". In: *2017 4th International Conference on Computer Applications and Information Processing Technology (CAIPT)*. DOI: 10.1109/caipt.2017.8320684.

Pan J., Nagurney A. (1994). "Using markov chains to model human migration in a network equilibrium framework". In: *Mathematical and Computer Modelling* 19.11, pp. 31–39. DOI: 10.1016/0895-7177(94)90014-0.

Pech, Laurent and Tobia Lakes (2017). "The impact of armed conflict and forced migration on urban expansion in Goma: Introduction to a simple method of satellite-imagery analysis as a complement to field research". In: *Applied Geography* 88, pp. 161–173. DOI: 10.1016/j.apgeog.2017.07.008.

Pellegrino, Adela (2000). "Trends in international migration in Latin America and the Caribbean". In: *International Social Science Journal* 52.165, pp. 395–408. DOI: 10.1111/1468-2451.00268.

Pfeifle, Benjamin (2022). "Detecting armed conflict damages in satellite imagery using Deep Learning". PhD thesis. University of Zurich.

Phan, Huy et al. (2019). "Joint Classification and prediction CNN Framework for Automatic Sleep Stage Classification". In: *IEEE Transactions on Biomedical Engineering* 66.5, pp. 1285–1296. DOI: 10.1109/tbme.2018.2872652.

Pi, Wei et al. (2020). "Desertification glassland classification and three-dimensional convolution neural network model for identifying desert grassland landforms with unmanned aerial vehicle hyperspectral remote sensing images". In: *Journal of Applied Spectroscopy* 87.2, pp. 309–318. DOI: 10.1007/s10812-020-01001-6.

Pyo, Jeong Cheol et al. (2019). "A convolutional neural network regression for quantifying cyanobacteria using hyperspectral imagery". In: *Remote Sensing of Environment* 233, p. 111350. DOI: 10.1016/j.rse.2019.111350.

Ramos R., Suriñach J. (2016). "A gravity model of migration between the ENC and the EU". In: *Tijdschrift Voor Economische En Sociale Geografie* 108.1, pp. 21–35. DOI: 10.1111/tesg.12195.

Rawat, Waseem and Zeng Wang (2017). "Deep convolutional neural networks for Image Classification: A Comprehensive Review". In: *Neural Computation* 29.9, pp. 2352–2449. DOI: 10.1162/neco_a_00990.

Ren, X. et al. (2019). "Regression convolutional neural network for Automated Pediatric Bone age assessment from hand radiograph". In: *IEEE Journal of Biomedical and Health Informatics* 23.5, pp. 2030–2038. DOI: 10.1109/jbhi.2018.2876916.

Reshi, A. A. et al. (2021). "An efficient CNN model for COVID-19 disease detection based on X-ray image classification". In: *Complexity* 2021, pp. 1–12. DOI: 10.1155/2021/6621607.

Reynolds, Louisa (2010). *Central America: Living On The Guatemala-Belize Border*. URL: https://digitalrepository.unm.edu/noticen/9781.

Riosmena, Fernando and Douglas S Massey (2012). "Pathways to el norte: Origins, destinations, and characteristics of Mexican migrants to the United States". In: *International Migration Review* 46.1, pp. 3–36. DOI: 10.1111/j.1747-7379.2012.00879.x.

Rogers, Andrei and Stuart Sweeney (1998). "Measuring the spatial focus of migration patterns". In: *The Professional Geographer* 50.2, pp. 232–242. DOI: 10.1111/0033-0124.00117.

Runfola, Daniel et al. (2022). "Deep learning fusion of satellite and social information to estimate human migratory flows". In: *Transactions in GIS* 26.6, pp. 2495–2518. DOI: 10.1111/tgis.12953.

Segal-Rozenhaimer, Michal et al. (2020). "Cloud detection algorithm for multi-modal satellite imagery using Convolutional Neural-networks (CNN)". In: *Remote Sensing of Environment* 237, p. 111446. DOI: 10.1016/j.rse.2019.111446.

Seydi, Seyed Taher et al. (2021). "Oil spill detection based on multiscale multidimensional residual CNN for Optical Remote Sensing imagery". In: *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 14, pp. 10941–10952. DOI: 10.1109/jstars.2021.3123163.

Shahin, Ahmed I. and Saleh Almotairi (2021). "DCRN: An optimized deep convolutional regression network for building orientation angle estimation in high-resolution satellite images". In: *Electronics* 10.23, p. 2970. DOI: 10.3390/electronics10232970.

Shao, Zhenfeng and Jiong Cai (2018). "Remote sensing image fusion with deep convolutional neural network". In: *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 11.5, pp. 1656–1669. DOI: 10.1109/jstars.2018.2805923.

Simulink, MATLAB & (n.d.). *What is a convolutional neural network?: 3 things you need to know*. https://www.mathworks.com/discovery/convolutional-neural-network-matlab.html. Retrieved April 30, 2023.

Singh, Alok and Kailash Gaurav (2023). "Deep learning and data fusion to estimate surface soil moisture from multi-sensor satellite images". In: *Scientific Reports* 13.1. DOI: 10.1038/s41598-023-28939-9.

Siraj, Ahmed et al. (2019). *Modeling human migration across spatial scales in Colombia*. OSF Preprints. DOI: 10.31235/osf.io/avw7z. URL: https://osf.io/avw7z/.

Smit B., Skinner M. W. (2002). "Adaptation options in agriculture to climate change: A typology". In: *Mitigation and Adaptation Strategies for Global Change* 7.1, pp. 85–114. DOI: 10.1023/a:1015862228270.

Smith Christopher, Wood Sharon and Dominic Kniveton (2010). "Agent Based Modelling of Migration Decision-Making". In: *European Workshop on Multi-Agent Systems (EUMAS-2010)*. EUMAS.

Socher, Richard, Yoshua Bengio, and Christopher D. Manning (2012). "Deep Learning for NLP (without Magic)". In: *Tutorial Abstracts of ACL 2012*. ACL '12. Jeju Island, Korea: Association for Computational Linguistics, p. 5.

Sue, Christina A, Fernando Riosmena, and Joshua LePree (2018). "The influence of social networks, social capital, and the ethnic community on the U.S. destination choices of Mexican migrant men". In: *Journal of Ethnic and Migration Studies* 45.13, pp. 2468–2488. DOI: 10.1080/1369183x.2018.1447364.

Sylvain, Jean-Daniel, Guillaume Drolet, and Nicolas Brown (2019). "Mapping dead forest cover using a deep convolutional neural network and digital aerial photography". In: *ISPRS Journal of Photogrammetry and Remote Sensing* 156, pp. 14–26. ISSN: 0924-2716. DOI: 10.1016/j.isprsjprs.2019.07.010. URL: https://www.sciencedirect.com/science/article/pii/S0924271619301777.

Tarver, James D (1961). "Predicting migration". In: *Social Forces* 39.3, pp. 207–213. DOI: 10.2307/2573210.

Unver, H. Ali (2022). "Using social media to monitor conflict-related migration: A review of implications for A.I. forecasting". In: *Social Sciences* 11.9, p. 395. DOI: 10.3390/socsci11090395.

Valarmathi, G et al. (2021). "CNN algorithm for plant classification in Deep Learning". In: *Materials Today: Proceedings* 46, pp. 3684–3689. DOI: 10.1016/j.matpr.2021.01.847.

Vasan, D et al. (2020). "Image-based malware classification using ensemble of CNN Architectures (IMCEC)". In: *Computers & Security* 92, p. 101748. DOI: 10.1016/j.cose.2020.101748.

Ventura, C., D. Masip, and A. Lapedriza (2017). "Interpreting CNN models for apparent personality trait regression". In: *2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*. IEEE, pp. 217–226. DOI: 10.1109/cvprw.2017.217.

Walsh, B.M. (1974). "Expectations, Information, and Human Migration: Specifying an Econometric Model of Irish Migration to Britain". In: *Journal of Regional Science* 14, pp. 107–120.

Wickert, Lorenz (2019). *Dwelling Detection on VHR satellite imagery of Refugee/ IDP Camps using Faster R-CNN*. DOI: 10.24406/publica-fhg-282810. URL: https://publica.fraunhofer.de/handle/publica/282810.

Wu, Meiyin and Li Chen (2015). "Image recognition based on Deep Learning". In: *2015 Chinese Automation Congress (CAC)*. DOI: 10.1109/cac.2015.7382560.

Wulder, Michael A et al. (2019). “Current status of landsat program, science, and applications”. In: *Remote Sensing of Environment* 225, pp. 127–147. DOI: 10.1016/j.rse.2019.02.015.

Xue, Yuliang et al. (2016). “Cell counting by regression using convolutional neural network”. In: *Lecture Notes in Computer Science*. Springer, pp. 274–290. DOI: 10.1007/978-3-319-46604-0_20.

Yeşilmen, Serkan and Burcu Tatar (2022). “Efficiency of Convolutional Neural Networks (CNN) based image classification for monitoring construction related activities: A case study on aggregate mining for concrete production”. In: *Case Studies in Construction Materials* 17. DOI: 10.1016/j.cscm.2022.e01372.

Zhang, Chen-Jun et al. (2021a). “Tropical cyclone intensity classification and estimation using infrared satellite images with Deep Learning”. In: *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 14, pp. 2070–2086. DOI: 10.1109/jstars.2021.3050767.

Zhang, Jing et al. (2020). “Direct estimation of fetal head circumference from ultrasound images based on regression CNN”. In: *Proceedings of the Third Conference on Medical Imaging with Deep Learning*. Ed. by Tal Arbel et al. Vol. 121. Proceedings of Machine Learning Research. PMLR, pp. 914–922. URL: https://proceedings.mlr.press/v121/zhang20a.html.

Zhang, W., P. Tang, and L. Zhao (2019). “Remote Sensing Image Scene Classification using CNN-capsnet”. In: *Remote Sensing* 11.5, p. 494. DOI: 10.3390/rs11050494.

Zhang, Zhiqiang et al. (2021b). “Rich CNN features for water-body segmentation from very high resolution aerial and satellite imagery”. In: *Remote Sensing* 13.10, p. 1912. DOI: 10.3390/rs13101912.

Zhiqiang, Wang and Li Jun (2017). “A review of object detection based on Convolutional Neural Network”. In: *2017 36th Chinese Control Conference (CCC)*. DOI: 10.23919/chicc.2017.8029130.

Zhou, Jizhou et al. (2016). “Recurrent convolutional neural network regression for continuous pain intensity estimation in video”. In: *2016 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*. IEEE, pp. 1015–1023. DOI: 10.1109/cvprw.2016.191.

Zhuang, H. et al. (2021). “Mapping multi-temporal population distribution in China from 1985 to 2010 using landsat images via Deep Learning”. In: *Remote Sensing* 13.17, p. 3533. DOI: 10.3390/rs13173533.