ARTIFICIAL INTELLIGENCE

COSC 6368 SUMMER 2023

Final Project Report

ESTIMATING TRAFFIC THROUGH SATELLITE IMAGE

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1) ABSTRACT:

Recently, the general public has gained access to high-resolution satellite imagery that can be used to find vehicles. The goal of this project is to construct a model to estimate traffic on roads by analyzing satellite photos. The vehicle information contained in the image can be utilized to predict traffic. Moreover, to use the region's current VMT (Vehicle Miles Traveled) data and compare it to the outcomes of satellite image analysis. We have gathered VMT summary statistics information from regional government departments' "Department of Transportation" and high-resolution satellite pictures from the Hurricane Harvey Imagery website. For the purpose of counting the number of cars in a satellite image, we employed a Detectron-2 and faster R-CNN model. To determine the vehicle count particular to a zip code, we employed this model.

2) LITERATURE REVIEW:

The article "Vehicle Detection in Overhead Satellite Images" is related. In "Using a One-Stage Object Detection Model" (Ref. 4), the use of one-stage object recognition models, such RetinaNet, is used to identify the satellite images. Accurate and effective vehicle detection is made possible by this cutting-edge method, creating new opportunities for environmental studies, urban planning, and traffic monitoring. The RetinaNet architecture, utilized by the researchers, combines the speed of one-stage approaches with the performance of two-stage detectors. Where the solution mixes the COWC and RetinaNet architecture's intricacy. Their major objective, independent of the type of data used, was to determine the best training parameters.

The article " Truck traffic monitoring with satellite image" (Ref. 6) is related. The study provides a framework employing deep learning and satellite data to predict travel demand during the COVID-19 epidemic. The framework consists of a truck detection model and a freight monitoring model. In order to count freight trucks in satellite images, the detection model uses R-CNN with ResNet 50 and 101 layers and SSD Inception V2, and the monitoring model converts these counts into the Annual Average Daily Traffic (AADTT) and other pertinent data.

The research demonstrates that pre-training with COCO and xView data improves model performance, especially when restricted to the road area, using R-CNN ResNet 50 and 101, as well as SSD Inception V2. Prediction accuracy and recall for predictions on the complete image are only slightly enhanced by additional pre-training on xView data.

The article "Reference 6", By utilizing satellite- and air-based images, the study seeks to improve estimates of Vehicle Miles Traveled (VMT) and Annual Average Daily Traffic (AADT). The work focuses on a parallel strategy that is compatible with the current method for estimating ground-based data. The authors investigate the use of traffic pattern deviation factors to estimate average conditions for the full year from a single traffic count collected over a period of time.

The researchers discovered reasonably low errors and unbiased results when comparing AADT estimates obtained from satellite photography and ground-based data. By averaging numerous image-based results for the same section, the short equivalent count intervals employed for satellite-based AADT estimation showed potential advantages for achieving precise estimates.

Potential advantages of AADT and VMT estimates using satellite- and air-based images. Although the current costs might prevent widespread implementation, the positive findings highlight the need for more study to improve techniques and cut costs, making satellite-based estimating an affordable choice for transportation authorities. Utilizing satellite and aerial data can considerably improve transportation planning and decision-making, resulting in more precise and effective traffic management.

3) PREVIOUS WORK:

In order to count cars from satellite photos, many object detection algorithms have been proposed and modified. To detect autos based on handcrafted features, conventional techniques like Haar cascades, HOG (Histogram of Oriented Gradients), and SVM (Support Vector Machine) have been utilized. However, given the variety of vehicle appearances and complicated surroundings, their performance is constrained. Pre-trained CNN models, such as VGG (Visual Geometry Group) and ResNet, are fine-tuned on car-specific datasets to adapt them to the car counting task, and data augmentation techniques, such as rotation, flipping, and scaling, are employed to augment the training dataset and improve the model's robustness.

4) NOVELTY:

Here, in this project we are extracting the **Polygon** for each zipcode and utilizing pre-trained Detectron2 and Faster RCNN to recognize the vehicles in the satellite images gathered from different websites, we are attempting to predict the combination of **(Vehicle Miles Traveled) VMT** of polygon zipcodes based on the concepts raised by the publications mentioned above. So that, it gives the better predictions and possibilities of combining geospatial data with machine learning for planning and managing transportation.

Such a model needs to be developed initially in order to detect automobiles in real time. The objectives of this essay are as follows:

1. Collecting satellite images.
2. Identifying vehicles from satellite images.

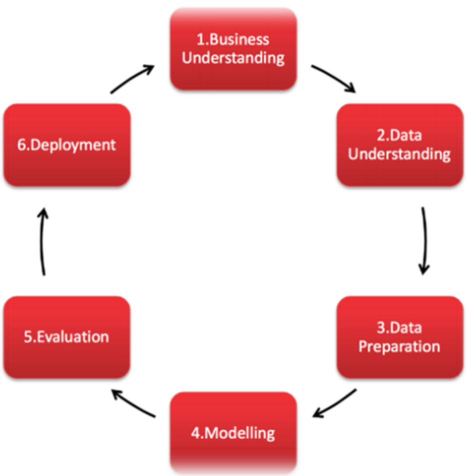
3. Collecting vehicle miles travelled (VMT) data for zip codes of Houston.
4. Extracting coordinates for all the zip codes in Houston along with the polygon for each zip code.

The difficulty in determining the state of the detected automobiles in static images emphasizes the necessity for vehicle identification in satellite photography that is more than merely real-time. The cars have a set direction, can drive themselves into parking spaces, etc. This detection must thus be performed continuously on real-time images captured by drones or sensors since more information is required. The Cars Overhead with Context dataset and the Car-counting model are used in this research to propose and show a system for identifying cars in satellite pictures. This methodology is based on the characteristics mentioned above. This model can identify cars in aerial images captured by drones and satellites. The first of these two important aspects of the model that we focus on is detection accuracy. We provide a progressive method to illustrate how our model evolved via various tweaks and eventually generated successful results. Since real-time vehicle detection is another area of interest for us, we examine and stress the detection time as a further vital metric. This statistic shows that our model is suitable for monitoring in real time.

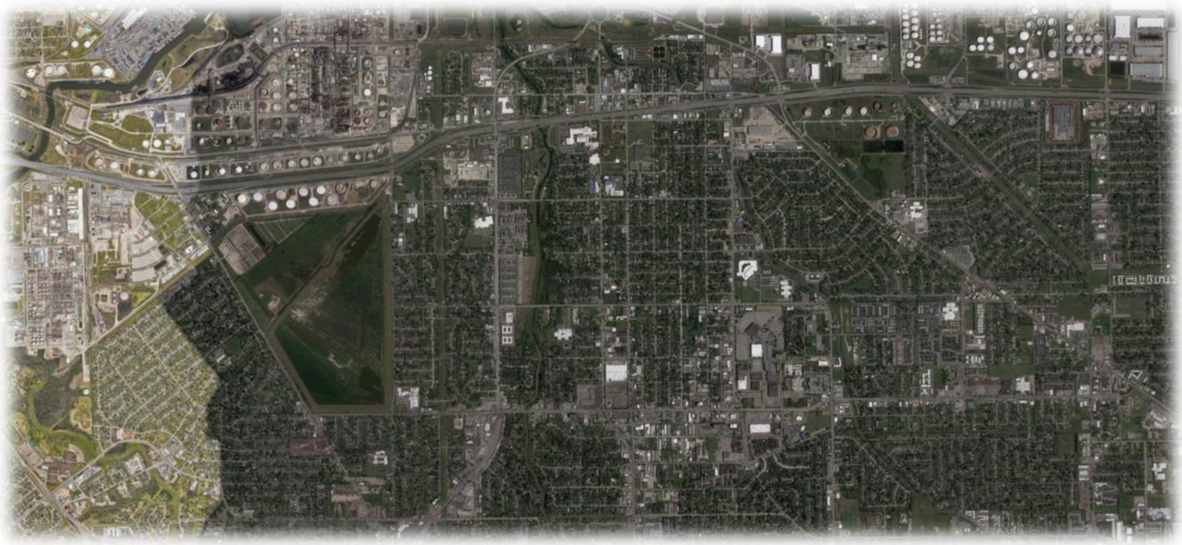
The remainder of this essay is divided into the following sections. In this article, we discuss pertinent studies in vehicle recognition, with a focus on the identification of cars in satellite images. Then, we provide a comprehensive justification for the solution. Following that, the results of our implementation are displayed. Finally, we highlight our results and describe our course of action.

5) METHODLOGY:

Using data to solve complicated issues requires an organized process known as data science. This involves using data to solve a problem, which entails grasping the business issue, gathering, and preparing the data, modelling, and assessing the data, implementing the model, and observing and maintaining its performance.

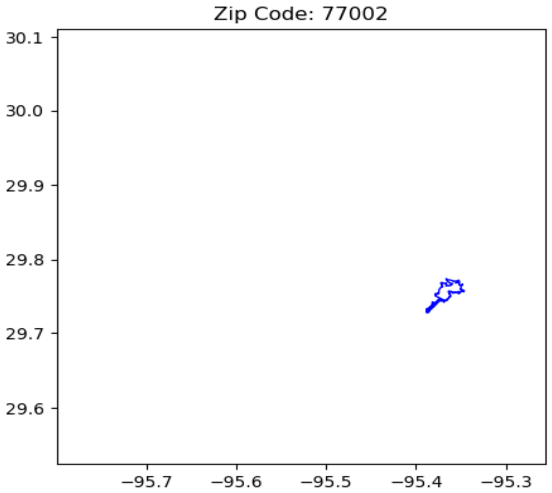


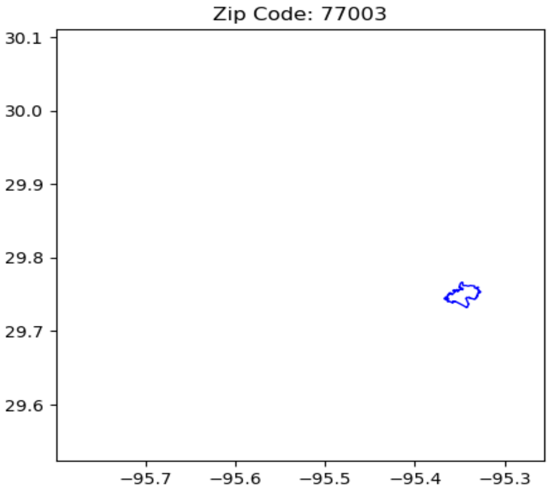
We started by gathering information and working to grasp the issue at hand. To estimate the number of automobiles in a picture, the data uses satellite imagery and VMT. For the portion of VMT data, a measurement of total vehicular traffic that considers both the quantity and duration of vehicle trips, obtained from local government organizations particular to each zip code in Houston and Dallas. When first creating the photos for the automobile counting model, we utilized QGIS and retrieved georeferenced satellite images in TIF format. The whole area between Houston and Dallas is covered by the photographs.



Sample image of an area in Houston from QGIS.

Then, using a faster R-CNN model and the Detectron-2 automobile identification model, we utilized these photos to count the number of cars. Because the TIF picture that was obtained from QGIS is of insufficient resolution, the findings of the detection are erroneous. To solve this problem, we have subsequently gathered high-resolution satellite photographs from Hurricane Harvey Imagery for the Houston region. The automobiles in the photographs are recognized and named after the model has been run. To find the photos associated with each zip code in Houston, we have retrieved coordinates for each zip code as well as the polygon for that zip code.

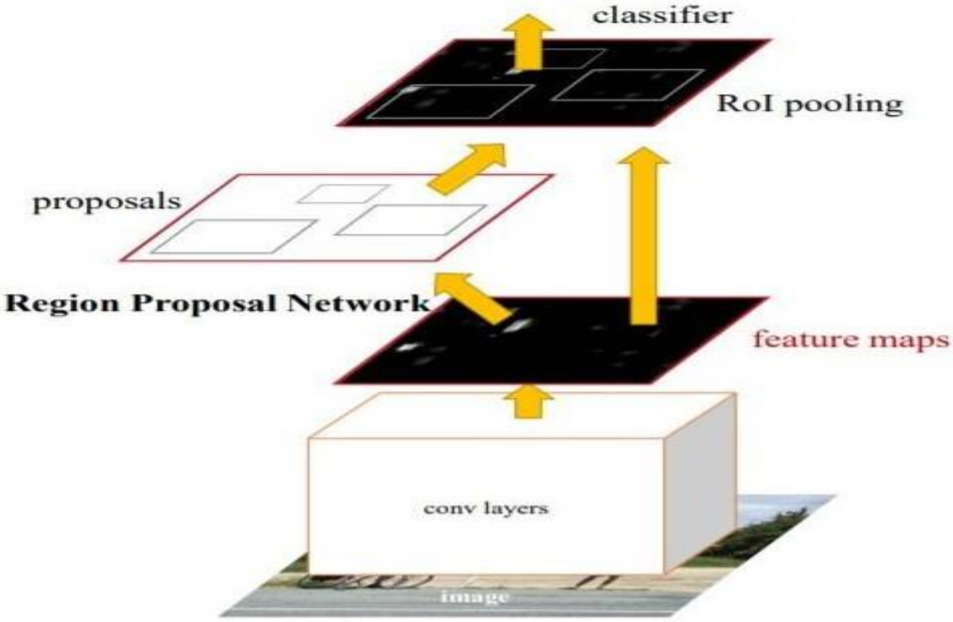




6) IMPLEMENTATION:

6.1) CAR DETECTION MODEL:

We can recognize and localize items in images or movies using computer vision algorithms, such as object detection. This approach allows us to count and categorize the objects in the image as well as pinpoint their precise locations. The unified object detection library used in the model is called Detectron2. A collection of labelled automobiles from satellite images is used to train this model.



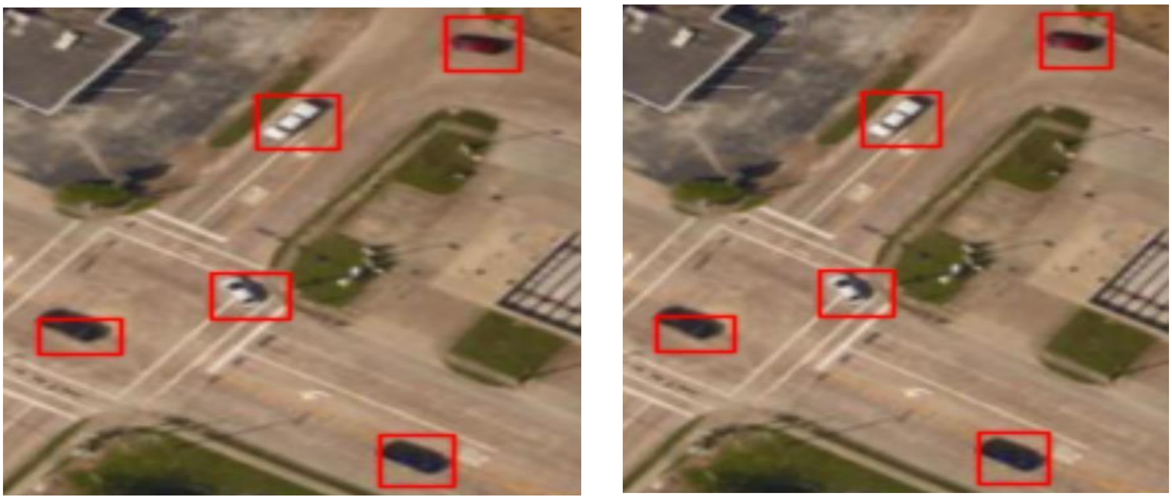
The technique of locating and categorizing items in a picture is called object detection. Rectangular region suggestions and convolutional neural network characteristics are combined in the deep learning method known as regions with convolutional neural networks (R-CNN). R-CNN is used in this model to find objects in satellite photos. This typically involves three steps. It starts by looking for areas of the picture that potentially include an item. Then, these areas are referred to as region proposals. Utilize CNN characteristics to categorize the items by extracting them from the area suggestions.

6.2) IMPLEMENTING ON HOUSTON DATASET:

Using the QGIS website, we ran the code on several the gathered photos. The results are not what was anticipated because of their inadequate resolution. A few automobiles were not fully recognized, and other items were also detected as cars in addition to cars. The code is around 50% efficient.

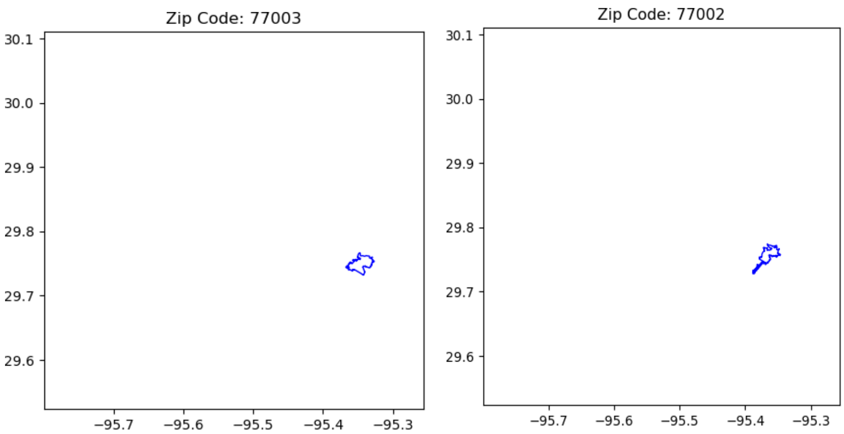
Contains missclassified images as we see.

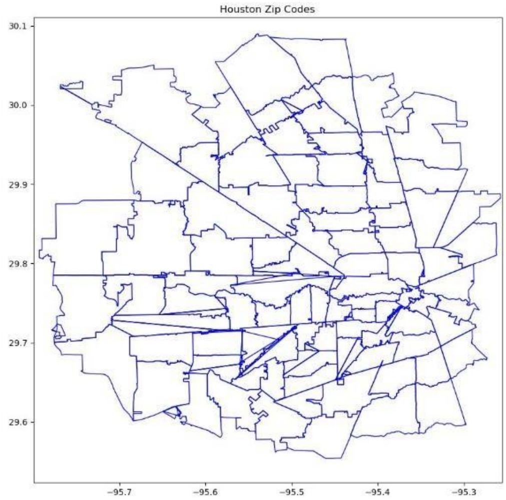
Consequently, we made the decision to use high-resolution pictures from the Hurricane Harvey Imagery website. We obtained about 263 pictures for the year 2017 from the Hurricane website and made an effort to identify the automobiles in them. Now that efficiency is at 75%, we can see that it produced better outcomes than the prior ones.



Cars are identified with the boxes

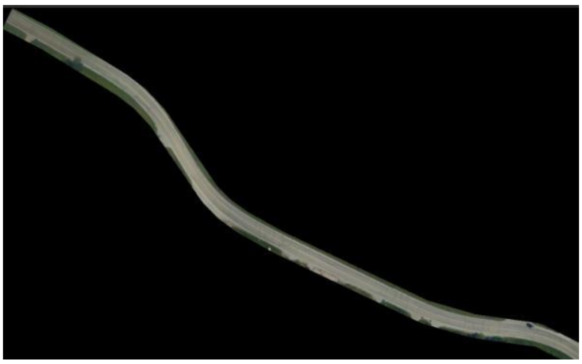
The project's primary goal is to estimate the amount of traffic, thus we just need to count the cars that are really on the road. The majority of the autos in the aforementioned output photographs are from parking lots. In order to obtain the coordinates of roadways, we first attempted to extract the areal coordinates for each zip code in Houston so that it would produce a polygon figure based on the coordinates. The below plots are the outputs for the extracted polygon co ordinates.





The above output shows overall view of all the zip codes of houston.

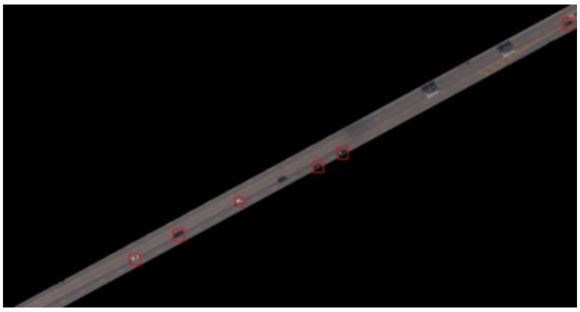
We took 2000 photos that were cropped from the previously obtained photographs in order to determine the number of automobiles in each zip code. Here are some examples of this, which just include the traffic-producing vechiles on the roadways below.

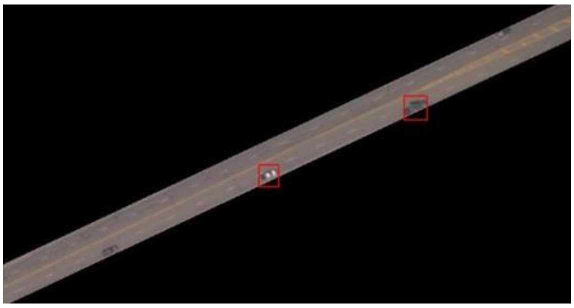


We first determined the zip code of each file based on the coordinates of the road and extracted it to a data frame in order to obtain the total count of traffic in each zip code. After that, we applied the automobile counting model to all 2000 photos stored on the drive. The file names and the number of automobiles in each file were recorded to a data frame. The total count for each zip code was then obtained by combining the two files. The accuracy of the model is around 80%.

7) RESULTS:

We started by gathering VMT data for every zip code, then we downloaded georeferenced satellite photos from QGIS. We were able to count the number of cars in the downloaded satellite photos using a car counting model. The coordinates of the roads in the satellite photos were then determined using the road inventory data, and we tallied the number of vehicles on these determined routes. Then we counted the quantity of automobiles in each zip code. A CSV file with the object detection data gives a thorough breakdown of the number of cars found in each image and zip code. This file can be a useful resource for additional research or model enhancements.





Output of labelled images.

Below is the output that represents the number of cars respective to zip code.

file_name	num_labels	zipcode	VMT
IH0010-XG.pkl_781.64_782.14_1046.tif	0	77015	1.71422E+12
IH0069-XG.pkl_25.2_25.7_547.tif	0	77036	1.71422E+12
FM0762-KG.pkl_1.5_2.0_1155.tif	0	77058	1.71422E+12
IH0010-XG.pkl_748.655_749.155_328.tif	4	77084	1.71422E+12
FM3005-RG.pkl_7.983_8.483_762.tif	10	77002	1.71422E+12
PR0066-KG.pkl_0.0_0.5_57.tif	0	77002	1.71422E+12
SH0035-LG.pkl_52.073_52.573_2280.tif	0	77041	1.71422E+12
IH0010-XG.pkl_789.659_790.159_2347.tif	2	77008	1.71422E+12

8) CONCLUSION:

We were able to determine the approximate number of vehicles in each zip code region by using object identification algorithms on satellite pictures. The results are promising, but it's vital to keep in mind that they are only as reliable as the data we have. Better VMT projections will be the direct result of any upgrades or adjustments made to the satellite image or car counting model quality. This research shows the possibilities of combining geospatial data with machine learning for planning and managing transportation. However, there is still a lot of space for advancement in this area. The accuracy of the model can be improved by integrating dynamic variables, like as the time of day, the weather, or special events, which can have a substantial influence on the number of cars on the road.

9) REFERENCES:

1. Wu, Yuxin, Kirillov, Alexander, Massa, Francisco, Lo, Wan-Yen and Girshick, Ross (2019), Detectron2, https://github.com/facebookresearch/detectron2.
2. VMT Dataset is downloaded from https://catalog.data.gov/dataset/select-summary-statistics-dashboard-data.
3. High resolution hurricane images has been taken from hurricane website: https://storms.ngs.noaa.gov/storms/harvey/index.html#7/28.400/-96.690.
4. Article: Vehicle Detection in Overhead Satellite Images Using a One-Stage Object Detection Model.
5. Research paper: Truck Traffic Monitoring with Satellite Image.
6. McCord M., Goel P., Jiang Z., and Bobbit P.. Improving AADT and VMT Estimates with High-Resolution Satellite Imagery: Simulated Analytical Results. Proc., American Society of Civil Engineers Applications of Advanced Technology in Transportation Conference, Cambridge, Mass., 2002.
7. Research paper: Estimating the Impact of COVID-19 on Travel Demand in Houston Area Using Deep Learning and Satellite Imagery.
8. Coifman B., McCord M., and Goel P.. Combining High-Resolution Imagery and Ground-Based Data for Improved AADT and VMT Estimates. Project 01-01. National Consortium on Remote Sensing Transportation-Flows. 2002. http://www.ncrst.org/research/ncrst-f/projects/current.html.
9. QGIS images download process: https://gis.stackexchange.com/questions/278091/exporting-google-basemap-as-tif-non-commercial-w-quickmapservices.
10. High resolution hurricane images has been taken from hurricane website: https://storms.ngs.noaa.gov/storms/harvey/index.html#7/28.400/-96.690.
11. Shape file to get the coordinates specific to zip codes: https://catalog.data.gov/dataset/tiger-line-shapefile-2020-nation-u-s-2010-5-digit-zip-code-tabulation-areas-zcta5.