17D.6 Objectively Identifying Transverse Cirrus Bands in Tropical Cyclones using a Convolutional Neural Network

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1 INTRODUCTION

Transverse cirrus bands (TCBs) are a phenomenon that occurs in many mesoscale and synoptic weather systems, including tropical cyclones. TCBs are defined as "Bands of clouds oriented perpendicular to the flow in which they are embedded" (NOAA) and can be associated with low static stability and high environmental vertical wind shear in the upper-levels (Kawashima 2021). TCBs in tropical cyclones are of particular interest due to their apparent occurrence and potential linkage to the tropical cyclone diurnal cycle, stronger tropical cyclones, and rapid intensification, where rapid intensification is an intensification rate of 30 knots or more in 24 hours (NHC). To fully understand TCBs and how they relate to tropical cyclones, they must be efficiently identified, which can be achieved through a machine-learning model. Miller et al. (2018) developed such a model, which identified whether TCBs were present anywhere within a satellite image. However, this model does not provide information on the spatial structure of the bands and their location relative to a feature of interest, such as a tropical cyclone. This task is particularly suited for a U-Net Convolutional Neural Network (CNN) model because a U-net contains an upsampling portion that a CNN does not do. While a CNN can be used to identify whether TCBs are in an image, a U-Net allows for the specific location of a TCB and the number of pixels a TCB makes up to be identified.

U-Nets are a type of model that can be used to identify features present in a dataset by comparing manually identified features to features that are predicted using a training dataset, which is composed of arrays. U-Nets require an array to be reduced in size, which means the image becomes blurred and then increased in size back to the array's original size, which means an array must have a row and column length divisible by two for each layer used in the model. U-Nets also utilize a variety of methods to improve learning, such as dropping out certain memory nodes to force the model to utilize different methods of identification and normalizing the outputted data to create a normal distribution (O'Shea and Nash 2015). The condensed architecture of the U-Net model used in this study can be seen in Figure 1.

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2 MODEL TRAINING AND METHODOLOGY

2.1 MODEL CREATION AND TRAINING

The first step of the U-Net model creation was the selection of which GOES-16 Advanced Baseline Imagery (ABI) channel or channels would be used to train the model and identify TCBs. After initial model testing, channels 13 (clean-IR) and 8 (upper-level water vapor) were chosen as they resulted in a model that produced accurate TCB areas with high confidence. These channels were chosen over visible and near-infrared channels, such as channel 4 (Cirrus Band), due to their ability to identify TCBs both at night and during the day. TCBs were manually identified, and the coordinates were saved to train the model. A total of 184 training cases were used, along with 58 verification cases that all came from a variety of times ranging from 2018 to 2023 and included tropical cyclone TCBs, TCBs from other sources, and images with no TCBs. After the manually identified data was collected, the GOES-16 ABI files were downloaded from the National Oceanic and Atmospheric Administration's Amazon Web Services repository and converted to arrays along with the coordinate files, where the coordinate files became arrays of ones and zeroes to indicate the presence or absence of TCBs at a given pixel. The data for channels 13 and 8 were also scaled using Scikit-Learn's Standard Scaler to help the model identify the global minimum in brightness temperatures more easily. Missing data, which wasn't a large factor in the training cases used but could be a factor in images near the GOES-16 Limb, was assigned a large value much higher than the other values so the model would learn to ignore it. The U-Net was then trained over 100 epochs, with the overall best epoch, determined qualitatively by seeing which epoch provided a balance of TCB location confidence and accuracy, being selected. Usually, a model would be trained until the metrics have stabilized and stopped improving. However, a constant number of 100 epochs was used to see how the model would develop if overtrained.

2.2 CREATION OF TRANSVERSE CIRRUS BAND STATISTICS

After the creation of the model, error statistics were performed to determine an ideal probability threshold that would minimize false positives while still identifying TCBs. The reason a probability threshold is needed is that the model outputs a percentage for each pixel, showing how confident the model is that the pixel is part of a TCB. The Jaccard Score, which is the intersection over the union of the true and predicted arrays, was determined to be the best choice since it maximizes intersection while minimizing the union of the true and predicted data, where the truth arrays were determined by manual identification of TCBs in 43 tropical cyclone cases. The Jaccard Score provided a probability threshold of 48.09 percent. An example of the model identifying TCBs using the Jaccard Score probability threshold can be seen in Figure 2, which clearly demonstrates the ability of the model to not only identify TCBs but also to identify them with high confidence. Figure 2 is only one example of the model, which performs similarly in other tropical cyclone and non-tropical cyclone imagery.

Two datasets were then used to relate the presence of TCBs to tropical cyclone structure and intensity. The HURDAT2 dataset (Landsea and Franklin 2013) was used to identify the tropical cyclone best track. Environmental vertical wind shear over the 850-200 mb layer was obtained from the Statistical Hurricane Intensity Prediction Scheme (SHIPS) dataset's SHDC and SDDC variables (DeMaria and Kaplan 1994). Once the data for all North Atlantic tropical cyclone advisories from 2018 to 2022 was downloaded, converted to arrays, and scaled, the model was run on the data. Using the TCB probabilities, statistics were generated, including a polar density map of TCB locations for the environmental shear vector and radius, along with bar charts of the number of TCB pixels per time of day, rapid intensification status, and tropical cyclone intensities. The tropical cyclone intensity bar is based on the Saffir–Simpson scale with tropical storms and depressions, category one and two hurricanes, and category three through five hurricanes were grouped together. The bar charts were created by first sorting images and their associated amount of TCB pixels into bins. This was done multiple times to sort based on the time of day, intensity, and whether rapid intensification was occurring. Data for the bar charts were sorted into bins of TCB pixels based on the time of day, intensity, and whether rapid intensification was occurring. The total number of TCB pixels in each bin was then divided by the total number of all pixels (TCB plus non-TCB) in each bin to get a percentage.

3 RESULTS

3.1 TRANSVERSE CIRRUS BANDS RELATION TO SHEAR RELATIVE VECTORS AND RADIUS

After calculating the necessary TCB statistics, a polar density map of the number of TCB pixels per 50-kilometer radius and 0.5 degrees was created (Figure 3). From the figure, it is evident that TCBs occur most frequently in the downshear quadrants of tropical cyclones between 200 and 400 kilometers and less frequently close to a tropical cyclone's center, in the upshear quadrants, and at greater distances away from the tropical cyclone center.

3.2 TRANSVERSE CIRRUS BANDS RELATION TO TROPICAL CYCLONE STRENGTH AND THE DIURNAL CYCLE

Figure 4 shows the percentage of TCB pixels per image for different tropical cyclone strength intensities that are based on the Saffir–Simpson scale. Overall, category three and higher hurricanes, which have winds greater than 95 knots, had greater than 20% of image pixels be TCBs, while category one and two hurricanes, which have winds of 64 to 95 knots, had a value of 20%, and tropical storms and depressions combined, which have winds less than 64 knots, had a value of 15%. Figure 5 shows the percentage of TCB pixels per image for a tropical cyclone's rapid intensification status. Overall, TCBs were more common in tropical cyclones undergoing rapid intensification than in storms not undergoing rapid intensification. Figure 6 compares the probability of TCBs in tropical cyclones at four different times of day using the percentage of TCB pixels per image. Times in the evening, or around 1800 local time, had a percentage of 18%, while 0000, 0600, and 1200 had percentages close to 17%, 15%, and 17%, respectively.

3.3 CONCLUSION

A U-Net CNN was trained to successfully identify TCBs in GOES-16 ABI imagery and was used to relate the presence of TCBs to tropical cyclone structure and intensity. TCBs occur more frequently in the downshear quadrants of a tropical cyclone, in tropical cyclones with greater intensity, in tropical cyclones undergoing rapid intensification, and in the evening hours. In the future, the model will be run every hour rather than every six hours to increase the size of the dataset and provide a more complete picture of the diurnal cycle. More analysis will also be done into the relationship between TCBs and tropical cycle intensity change, along with statistical significance testing to confirm the statistical significance of the results.

4 REFERENCES

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5 Figures

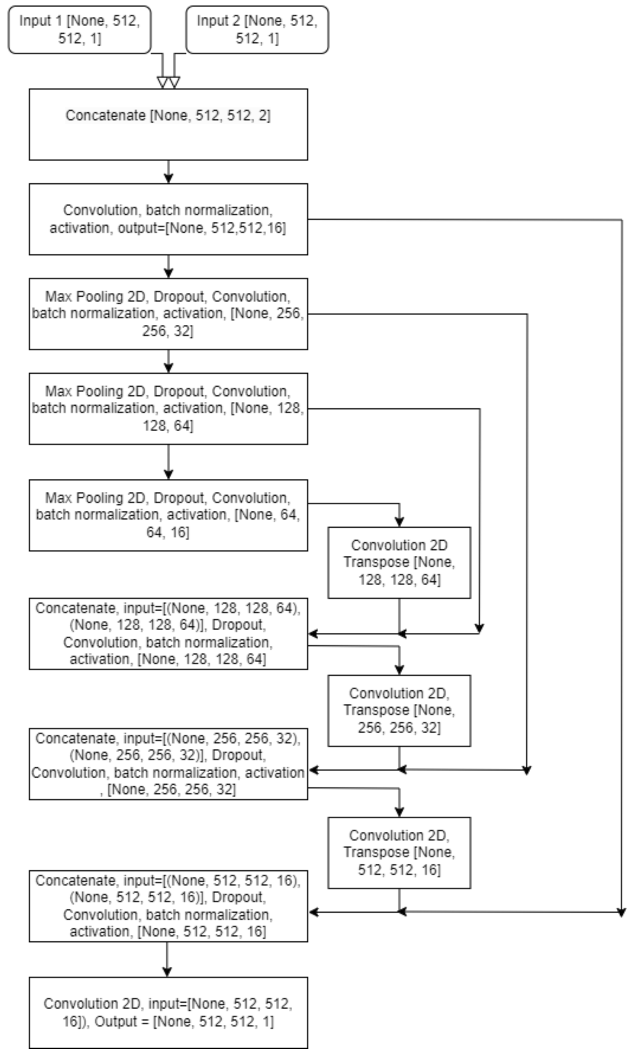

Figure 1: The U-Net CNN used in this study. The model has three layers and utilizes two inputs. The model also utilizes the dropout, max pooling, and batch normalization methods to improve model learning and confidence. The basic flow of the model is as follows. The ABI channel 13 and channel 8 arrays are inputted at the top of the diagram. The two arrays are then concatenated together to make one array. After that, the array is halved in size for each convolution, with an activation, batch normalization, max pooling, and dropout function being used each time except for the first convolution, which does not have a dropout or max pooling function. After the array is reduced to a 64 by 64 array from its initial size of 512 by 512, the U-net portion of the CNN begins. The same general process is applied except that the convolution function is replaced with a 2D convolution function. The array is then increased in size back to its original 512 by 512 dimensions.

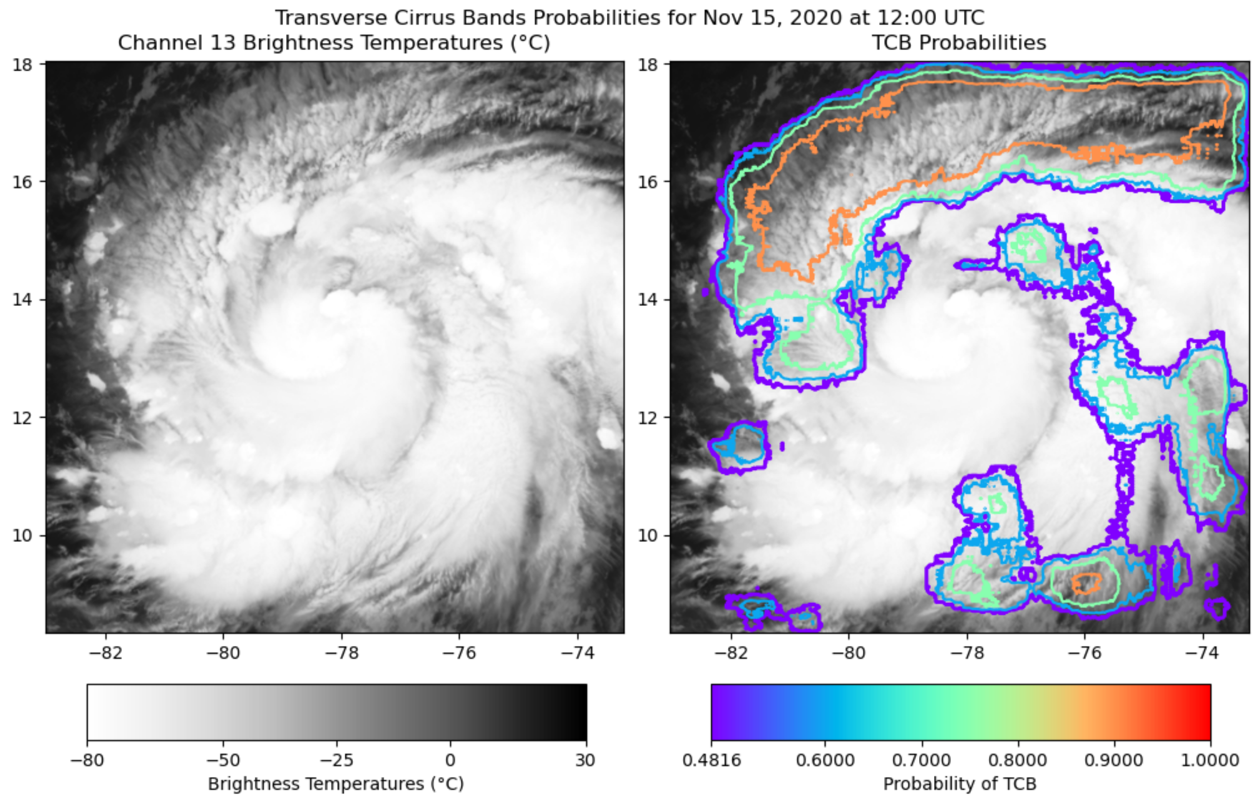

Figure 2: An example of the model using the Jaccard Score probability threshold. The left panel shows GOES-16 ABI Channel 13 brightness temperatures (degrees Celsius) in tropical cyclone Iota, and the right panel is the same image with the probabilities of transverse bands at each pixel depicted in colored contours.

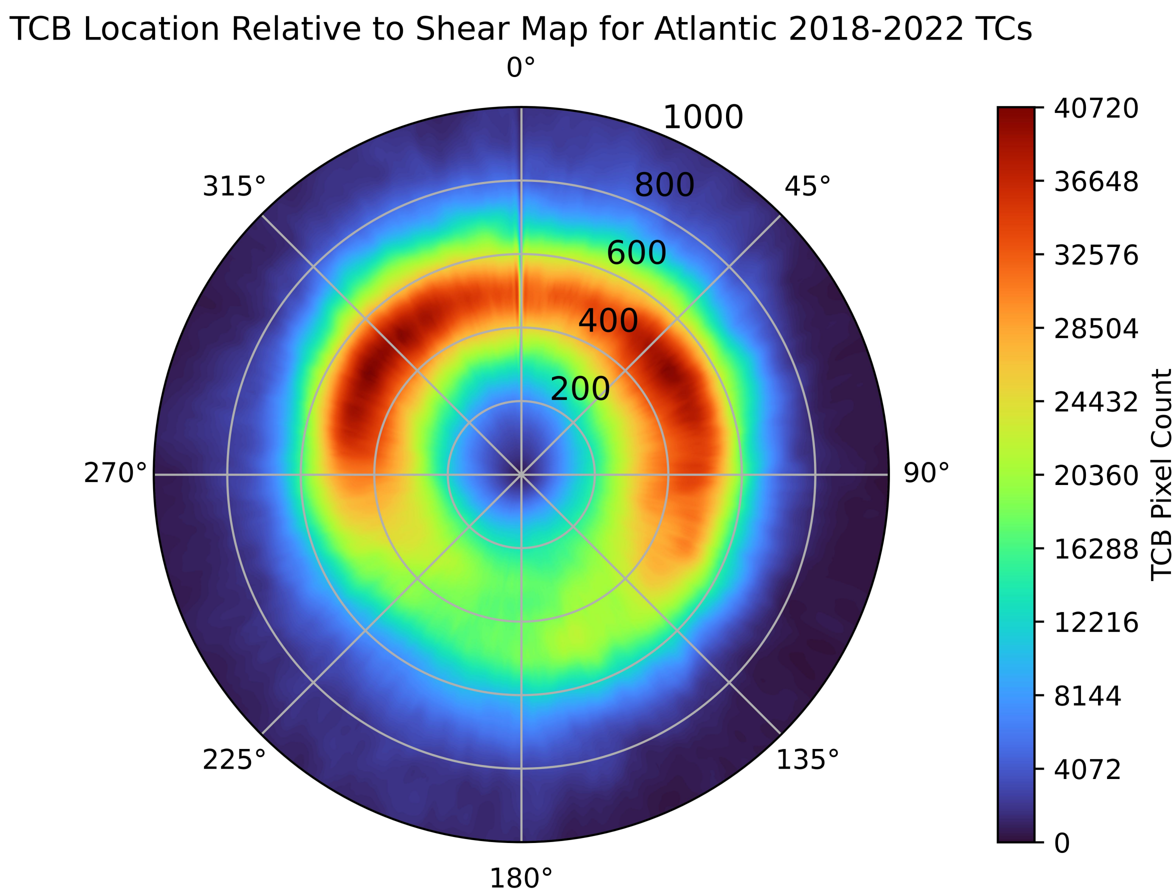

Figure 3: Storm-centered plot of the number of GOES-16 ABI pixels that contain TCBs at a given radius and shear relative azimuth. Zero degrees is downshear, 180 degrees is upshear, 90 degrees is right of shear, and 270 degrees is left of shear. Range rings are plotted every 200 km out to 1000 km.

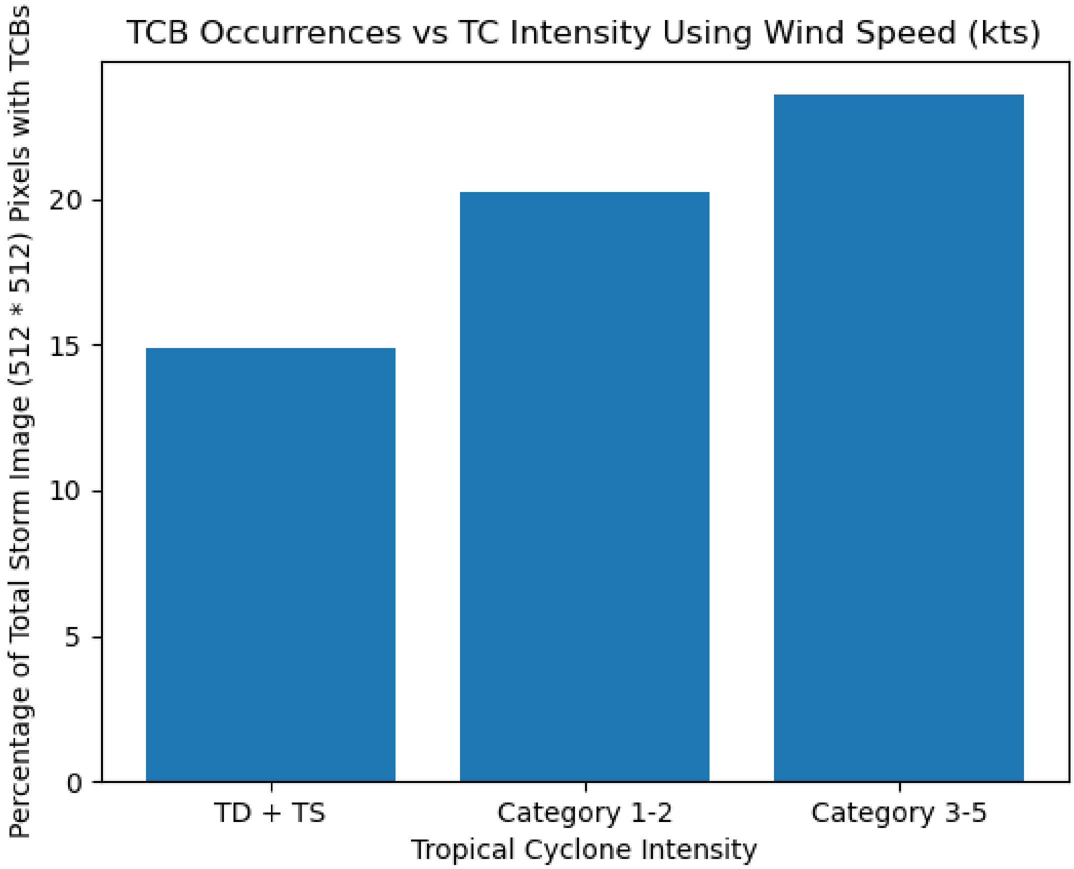

Figure 4: The percentage of pixels in an image that are TCBs for three different intensity bins. The y-axis shows the percentage of TCB pixels while the x-axis shows the tropical cyclone intensity, which is either a tropical depression or storm, category 1 and 2 hurricane, or category 3 through five hurricane.

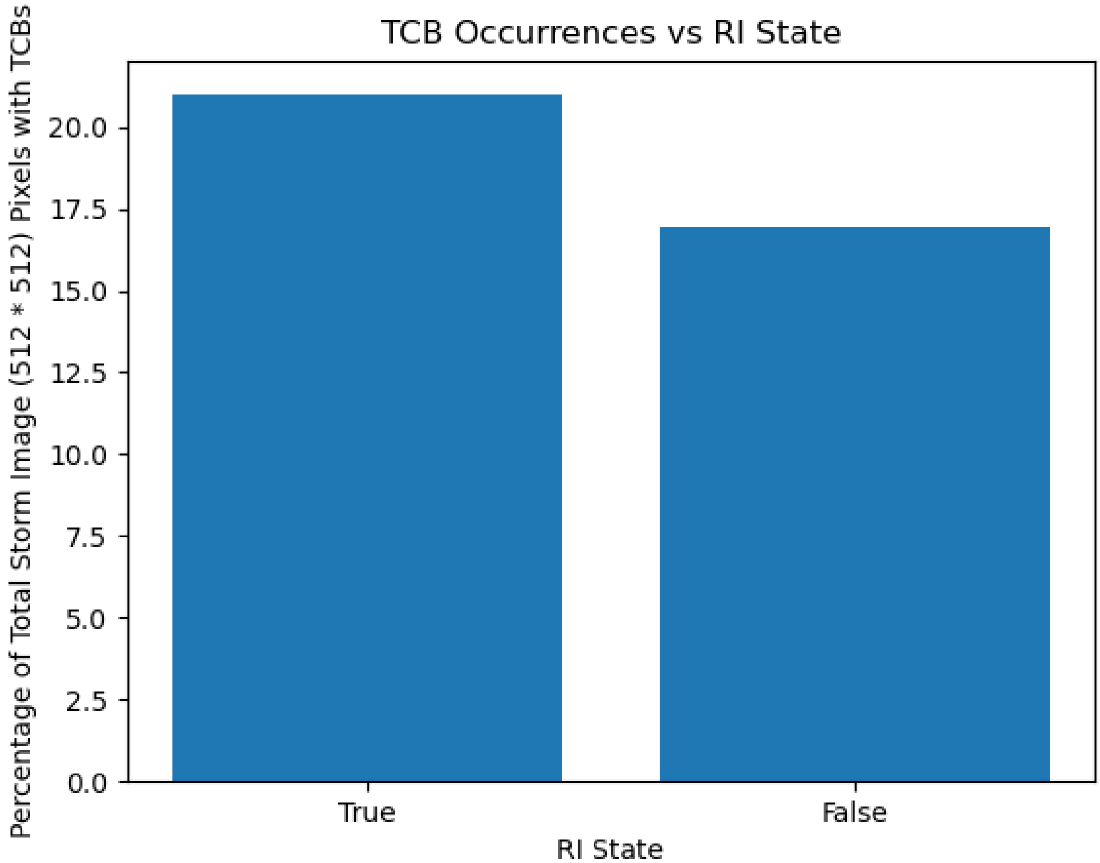

Figure 5: The percentages of pixels in an image that are TCBs for tropical cyclones undergoing rapid intensification and for tropical cyclones not undergoing rapid intensification. The y-axis shows the percentage of TCB pixels, while the x-axis shows rapid intensification and non-rapid intensification.

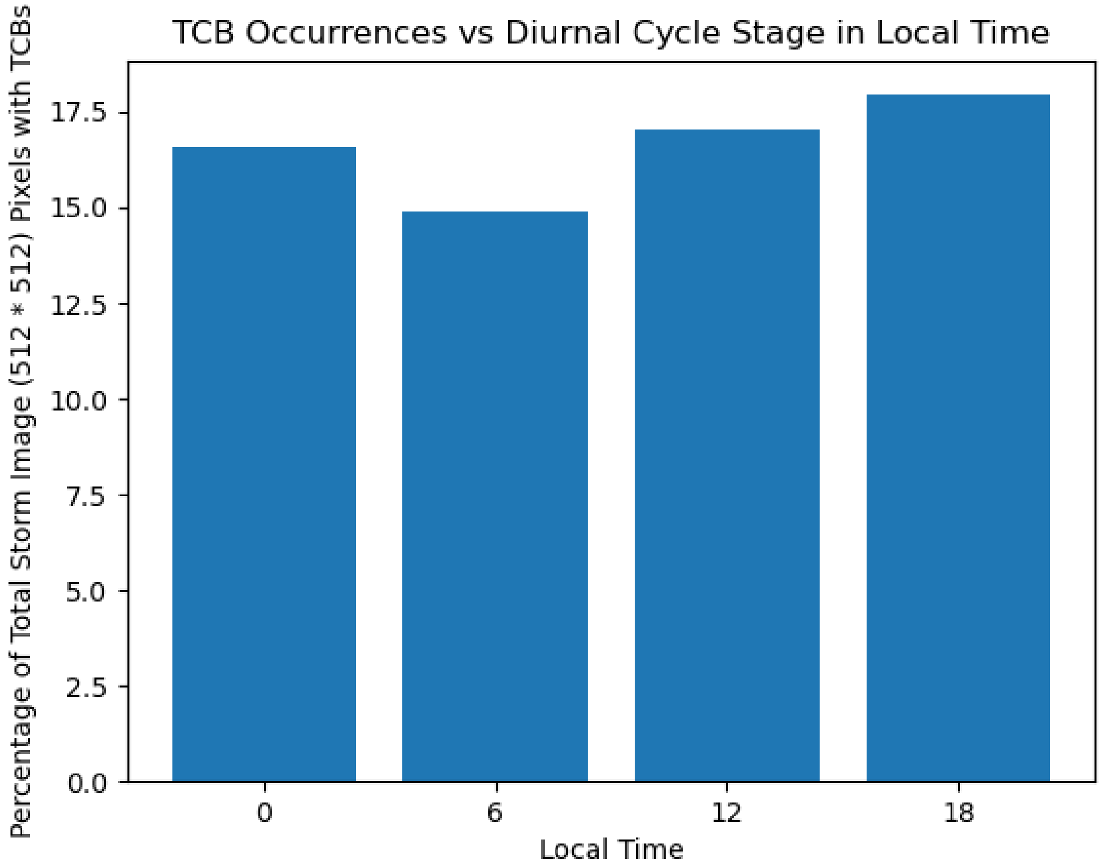

Figure 6: The percentages of pixels in an image that are TCBs for four different times of day, which are 0000, 0600, 1200, and 1800 local time.