4-26-2024

Objectively Identifying Transverse Cirrus Bands in Tropical Cyclones using a Convolutional Neural Network

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by

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An Honors Capstone

submitted in partial fulfillment of the requirements

for the Honors Diploma

to

The Honors College

of

The University of Alabama in Huntsville

04/26/2024

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ABSTRACT

Transverse cirrus bands (TCBs) are bands of upper-level clouds that are regularly seen in mesoscale and synoptic-scale weather systems. In tropical cyclones, their appearance has been subjectively linked to intensification and the diurnal cycle, but these hypothesized relationships have not been rigorously tested due to the difficulty of objectively identifying TCBs in satellite images. This project describes a machine learning technique that successfully identifies TCBs in imagery from the GOES-16 Advanced Baseline Imager. The technique uses a convolutional neural network (CNN) U-Net that assigns a probability of each pixel in the image being associated with a TCB. Using the U-Net, a database of TCBs from 2018 to 2022 was developed for the Atlantic basin. Statistics using this database will be presented, including the relationship between TCBs and deep-layer vertical wind shear along with the relationship between TCBs and intensity change.

I INTRODUCTION

Transverse cirrus bands (TCBs) are a phenomenon that occurs in many mesoscale and synoptic weather systems, including tropical cyclones. 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. To fully understand TCBs and how they relate to tropical cyclones, they must be efficiently identified. While it is possible to identify TCBs manually by looking at satellite images, the process is time-consuming. Therefore, a more efficient way is needed, 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 model because a U-net contains an upsampling and connecting portion that a CNN does not do. While a CNN image classifier 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 is 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.

The purpose of this study is to relate TCBs and tropical cyclones by comparing TCB occurrences to the tropical cyclone's azimuthal shear vector directions, the radius of the tropical cyclone, the strength of the tropical cyclone, the time of day (tropical cyclone diurnal cycle stage), and whether the tropical cyclone is experiencing rapid intensification. These goals will be accomplished by using a previously created U-Net model that is capable of identifying TCB locations in an image in conjunction with a statistically determined cutoff threshold.

II BACKGROUND

Before TCBs can be discussed, some important terms need to be defined. Rapid intensification in tropical cyclones is defined as a 30 knot or greater wind increase in 24 hours or less (NHC). Rapid intensification is important since stronger tropical cyclones generally have a more favorable environment for the development of factors, such as those listed in Kawashima (2021), that can lead to the development of TCBs . TCBs are defined as "bands of clouds oriented perpendicular to the flow in which they are embedded," and at low levels, "often indicate the presence of a temperature inversion (or cap) as well as directional shear in the low- to mid-level winds," (NWS). The diurnal cycle of a tropical cyclone is the maximum and minimums of tropical cyclone intensity, convection, and rainfall associated with the day and night cycle, with peaks coming in the afternoon and evening over land and in the early morning over water (Dunion et al. 2014). It is important since, as previously mentioned, stronger tropical cyclones can produce a more favorable environment for the development of TCBs. The shear vector direction of the tropical cyclone is the direction of the azimuthal shear vector at a given image pixel, which is important for binning TCB data. Finally, for this study, tropical cyclones will be divided into three main categories using the Saffir-Simpson Scale: tropical depressions (TD) and tropical storms (TS, sustained winds of 60 knots or less), category one through two hurricanes (CAT 1-2, sustained winds of 65 to 95 knots), and category three and above hurricanes (CAT 3-5, sustained winds of 100 knots and greater), which is also important for binning TCB data.

In addition to the above definitions, CNNs are an important part of this study. CNNs are a type of computer model and neural network that, at its most basic form, is a series of weights used to give confidence probability values of whether an image pixel, defined by brightness temperatures in this case, is a certain type of feature. However, CNNs do not operate in the same way as a U-Net does. A U-Net is an extension of a CNN where the U-Net provides the ability for the CNN to upsample the image and connect to the original downsampled images, which is the second half of the model's architecture. The U-Net is composed of "multiple interconnected nodes (or neurons)" that are given training data and validation data to learn from (O'Shea and Nash 2015).

The way the U-Net learns is through its architecture, which is composed of a convolutional layer, a pooling layer, and a fully-connected layer. The convolutional layer revolves around kernels, which are matrices that move around the image to determine the activation map that shows which kernels fire at certain inputs. The pooling layer reduces the size and blurs the input data, meaning that the input data size must be divisible by two. In the case of this study, an image with dimensions of 512 by 512 is used. There are also different kinds of pooling, but max-pooling will be used, which minimizes a part of an image by converting it to one pixel using the max value of that part as the value of the pixel. The fully-connected layer contains neurons connected to neurons in the other two layers. This general architecture can be reiterated multiple times depending on the size of the data images, which are inputted into the model as arrays. The model can also handle multiple data inputs by concatenating the data into a single four-dimensional array. It may seem unusual to use a four-dimensional array since the data is two-dimensional, but the model uses a four-dimensional array regardless of the number of inputs, where the first dimension is a None value. However, the model converts inputted two-dimensional arrays into the correct format. However, the probabilities produced by the model are in a four-dimensional format, where the second and third dimensions are the actual probabilities. There can also be other factors added, such as batch normalization, which smooths and centers the output, and dropout, which randomly removes nodes (or neurons) to force the model to come to new outcomes. This structure is iterated over multiple times until a sufficiently accurate model, or one that can no longer improve, is produced (O'Shea and Nash 2015).

TCBs, while well documented, still play a not fully understood role in tropical cyclones. TCBs are well documented to occur within tropical cyclones, including the eye wall, central dense overcast (CDO), and the outer rainbands (Knox et al. 2010). When TCBs occur in tropical cyclones, they are often embedded within the upper-tropospheric outflow associated with the tropical cyclone's upper-tropospheric anticyclonic high, which means they often flow clockwise away from the storm. TCBs also seem to be related to low static stability and high vertical wind shear in the upper levels (Kawashima 2021). However, it is important to note that TCBs are not limited to the outflow and can occur due to jet streak interactions and non-tropical related interactions and in tropical cyclone infrared eyewall imagery.

In addition to tropical cyclone-related TCBs, MCS-related TCBs are also important for understanding TCBs. It has been shown in previous research that TCBs favor upper-level divergence and relative vorticity gradients in MCSs (Lenz et al. 2009). This research agrees with observed tropical cyclone TCB characteristics as the outflow they form in is a strong region of upper-level divergence, and tropical cyclones do have relative vorticity gradients. However, the correlation of TCBs, upper-level divergence, and relative vorticity gradients does not mean there is a causality relationship. Relative vorticity gradients are associated with high environmental wind shear, meaning that both are occurring concurrently. Therefore, the relation of TCBs to relative vorticity gradients may be due to correlation instead of causality. A more direct relationship is between TCBs and the previously mentioned turbulence, low static stability, high vertical wind shear in the upper levels, and small Richardson's Numbers (Kawashima 2021).

III HYPOTHESIS AND RESEARCH QUESTIONS

Since TCBs are a phenomenon that is not completely understood, the goal of this study is to improve understanding of TCBs and their relationship to tropical cyclones, which may then be extended to other TCB sources in future research. In particular, TCBs will be related to the time of day at which they occur, the radius at which they occur relative to a tropical cyclone's center, the direction of relative azimuthal shear the tropical cyclone is experiencing, the strength of the tropical cyclone, and if the tropical cyclone is experiencing rapid intensification. To find these relationships, a previously created U-Net will be utilized to identify TCBs in GOES-16 tropical cyclone imagery from 2018 to 2022 in the Atlantic Ocean basin. Tropical cyclone data will also be interpolated to create hourly data, which will increase diurnal cycle understanding and strengthen the other data's reliability.

There are six main hypotheses in this study. First, TCBs are more likely to occur in the afternoon part of the diurnal cycle. Second, TCBs occur most often away from the tropical cyclone's eye. Third, TCBs occur most often in the downshear quadrants of a tropical cyclone. Fourth, stronger tropical cyclones will produce more TCBs than weaker ones. Fifth, TCBs occur more often in rapid intensification. Sixth and finally, stronger and rapidly intensifying tropical cyclones and the downshear quadrants experience more TCBs due, at least partially, to low static stability, high vertical upper-level wind shear, and stronger updrafts.

IV DATA AND RESEARCH METHODS

4.1 TRANSVERSE CIRRUS BAND CASE IDENTIFICATION

TCB cases had to be first identified before the U-Net could be created. A modified Jupyter Notebook based on the NASA SPoRT Dust Training AI was created to identify the cases. The modified notebook used GOES-16 Advanced Baseline Imagery (ABI) Channel 13 to display images so TCB features could be identified and outlined. The selection of dates and times was random. TCBs in both tropical and non-tropical settings were identified. Other similar features, such as cloud streets, were also identified but listed as null cases. Unrelated features such as empty skies and other non-TCB clouds were also identified as null cases. The presence of null cases allowed the model to learn what to look for and what not to look for and to prevent the model from misidentifying features in cases where no TCBs were present. More information about this process is provided in the next section.

4.2 MODEL CREATION AND TRAINING

The first step of the U-Net model creation was the selection of which GOES-16 ABI channel or channels would be used to train the model and identify TCBs. After initial model testing, channels 13 (clean-IR, 10.35 micrometers) and 8 (upper-level water vapor, 6.2 micrometers) 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.

4.3 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. Vertical wind shear over the 850-200 mb layer was obtained from the Statistical Hurricane Intensity Prediction Scheme (SHIPS) dataset's shear magntiude (SHDC) and the vector of the shear magnitude (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 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.

V RESULTS

5.1 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. This result was expected from prior observations and is possible due to the relation between TCBs and upper-level vertical wind shear. Additionally, updrafts in tropical cyclones occur most frequently and are stronger and larger in the downshear quadrants (Barron et al. 2022), which aligns where TCB are most frequently located. There are also slightly more updrafts in the downshear left quadrant (Barron et al. 2022), which also aligns with the downshear left quadrant having slightly more TCBs than the downshear right quadrant.

5.2 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 was created to help confirm the validity of the results in Figure 4. Figure 5 uses a minimum pixel threshold of roughly 20% of the total pixels in a 512 by 512 to limit the number of images involved. If the results are valid, then the overall bar chart distribution should remain the same, which it does. Overall, both figures show the same thing, but Figure 5 excludes cases that do not have many TCB pixels to show if there would be any change with the data distribution, which there is not. Figure 6 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 7 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. One reason for these results may be related to the previously mentioned association between TCBs, upper-level vertical wind shear, and updrafts. Tropical cyclones undergoing rapid intensification and category 3-5 hurricanes have a better potential to support stronger updrafts. Storms occurring in the evening are usually stronger due to the diurnal cycle maximum that occurs, which also increases the potential for stronger updrafts.

5.3 TRANSVERSE CIRRUS BANDS RELATION TO TROPICAL CYCLONE PREVIOUS AND FUTURE INTENSITY CHANGES

Figures 8 and 9 show the percentage of TCB pixels per image for different tropical cyclone intensity changes over the next and previous six hours, respectively. From the figures, it is apparent that future intensity decreases and previous intensity increases seem to be associated with increased TCB activity. Figure 8, in particular, seems to be counter-intuitive since the previous results show intensity increases result in the formation of TCBs. However, stronger storms are more prone to intensity fluctuations. Therefore, TCBs being associated with future intensity decreases may be due to stronger storms fluctuating in intensity, which will be looked into more in the future. Additional results are provided in Figures 10 through 13, which show the percentage of TCB pixels per image for different tropical cyclone intensity changes over the next 12 and 18 hours and the previous 12 and 18 hours, respectively.

VI CONCLUSION

A U-Net 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. TCBs also seem to occur more frequently with previous intensity increases and future intensity decreases. 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.

VII ACKNOWLEDGMENTS

The author would like to thank Vivian Brasfield for her mentorship and instruction during this project and Ryan Wade, Patrick Duran, and Andrew White for all the help, support, feedback, and instruction during this project. He would also like to thank NASA SPoRT for the support during this project and the UAH Department of Atmospheric and Earth Science and the UAH Honors College for their dedication and for providing an excellent environment

to perform research.

VIII FUTURE STEPS

Several future steps are currently planned. First, interpolation will be performed on the HURDAT and SHIPS datasets to create hourly data. The hourly will then allow for more investigation into the correlation between TCBs and the tropical cyclone diurnal cycle along with tropical cyclone intensity, rapid intensification, and intensity changes. Second, significance testing will be performed on the results. The significance test will not confirm the validity of the results necessarily, but it will confirm if the results are significant. Third, more research into the relationship between TCBs and intensity changes over the previous and next 6, 12, and 18 hours will be done.

IX APPENDIX A

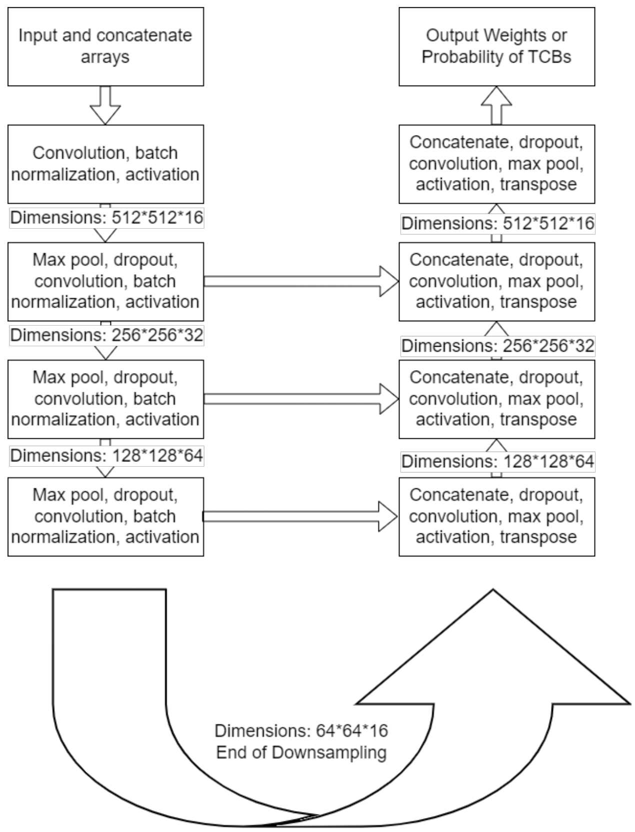

Figure 1.: The U-Net used in this study. The model has three layers and utilizes two inputs. The model also utilizes the dropout, max pooling, and batch normalization methods to improve model learning and confidence. The basic flow of the model is as follows. The ABI channel 13 and channel 8 arrays are 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 upsampling portion 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.

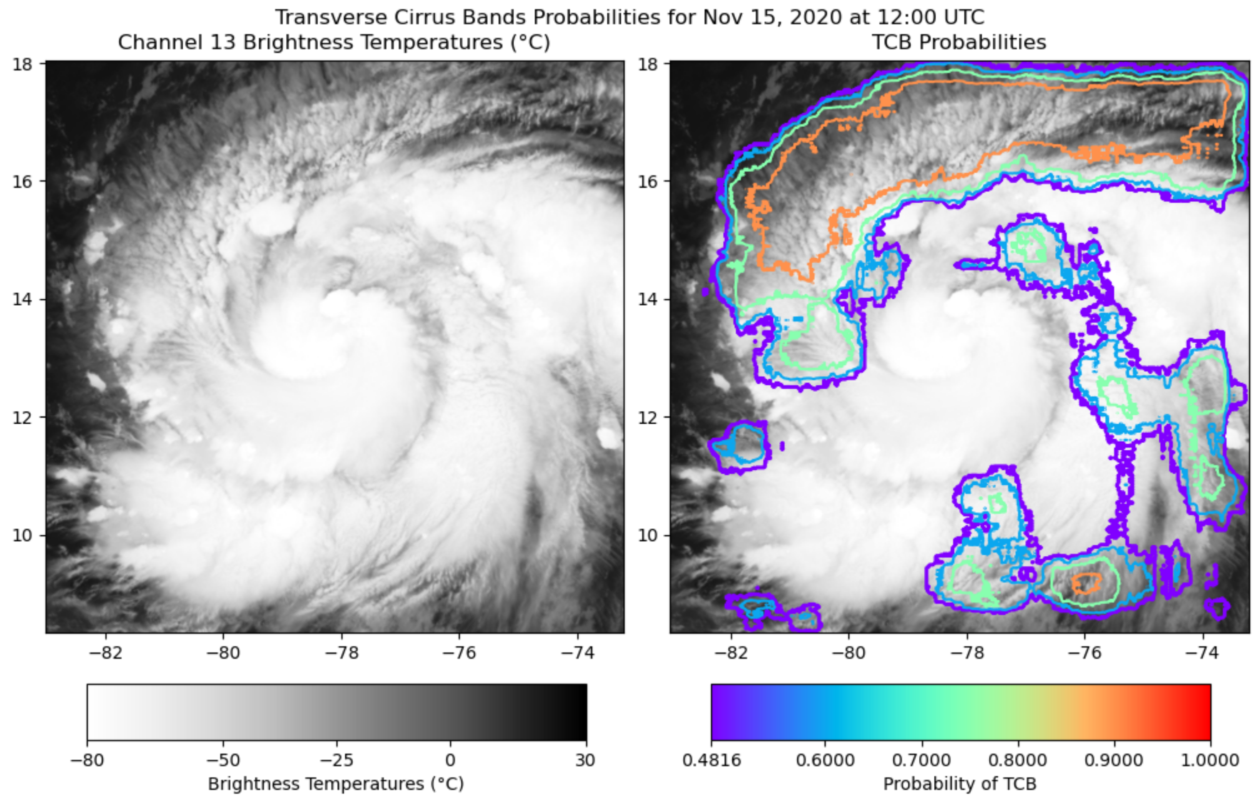

Figure 2.: An example of the model using the Jaccard Score probability threshold. The left panel shows GOES-16 ABI Channel 13 brightness temperatures (degrees Celsius) in tropical cyclone Iota, and the right panel is the same image with the probabilities of transverse bands at each pixel depicted in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

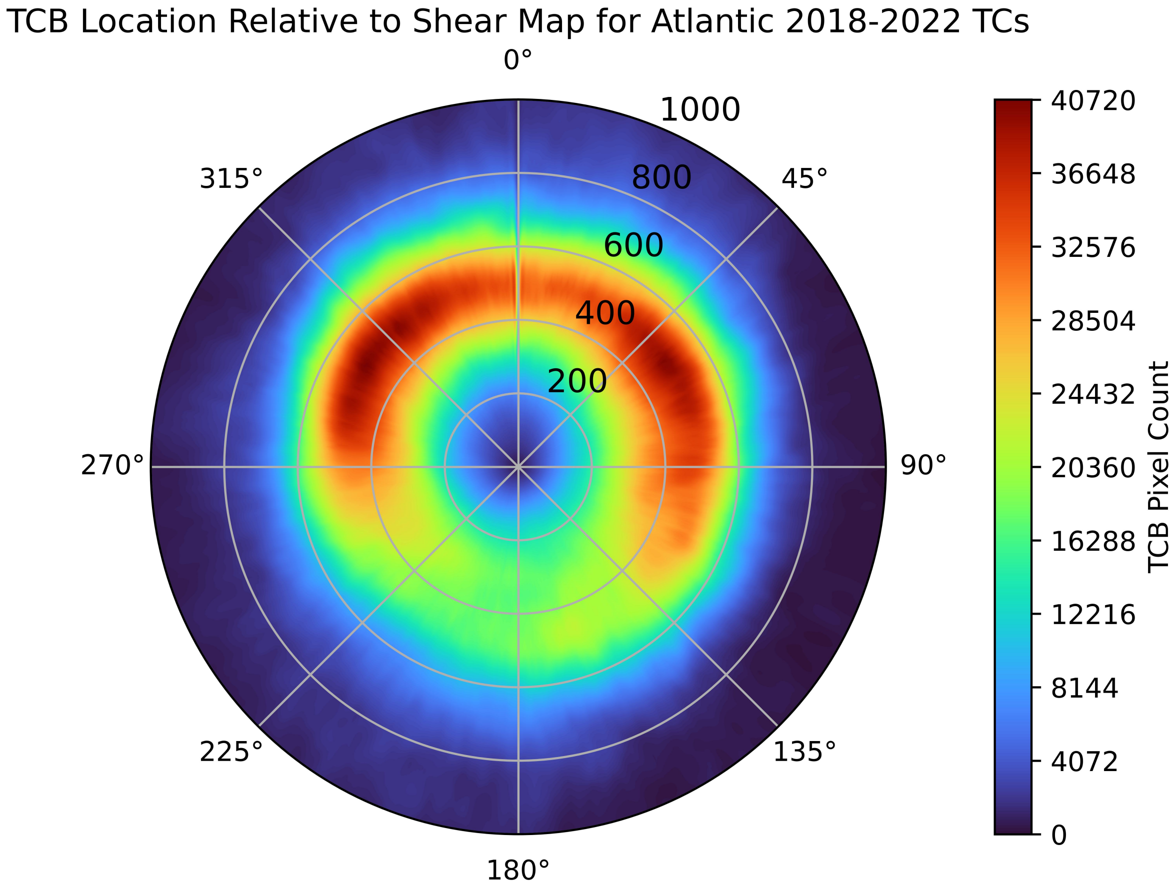

Figure 3.: Storm-centered plot of the number of GOES-16 ABI pixels that contain TCBs at a given radius and shear relative azimuth. Zero degrees is downshear, 180 degrees is upshear, 90 degrees is right of shear, and 270 degrees is left of shear. Range rings are plotted every 200 km out to 1000 km.

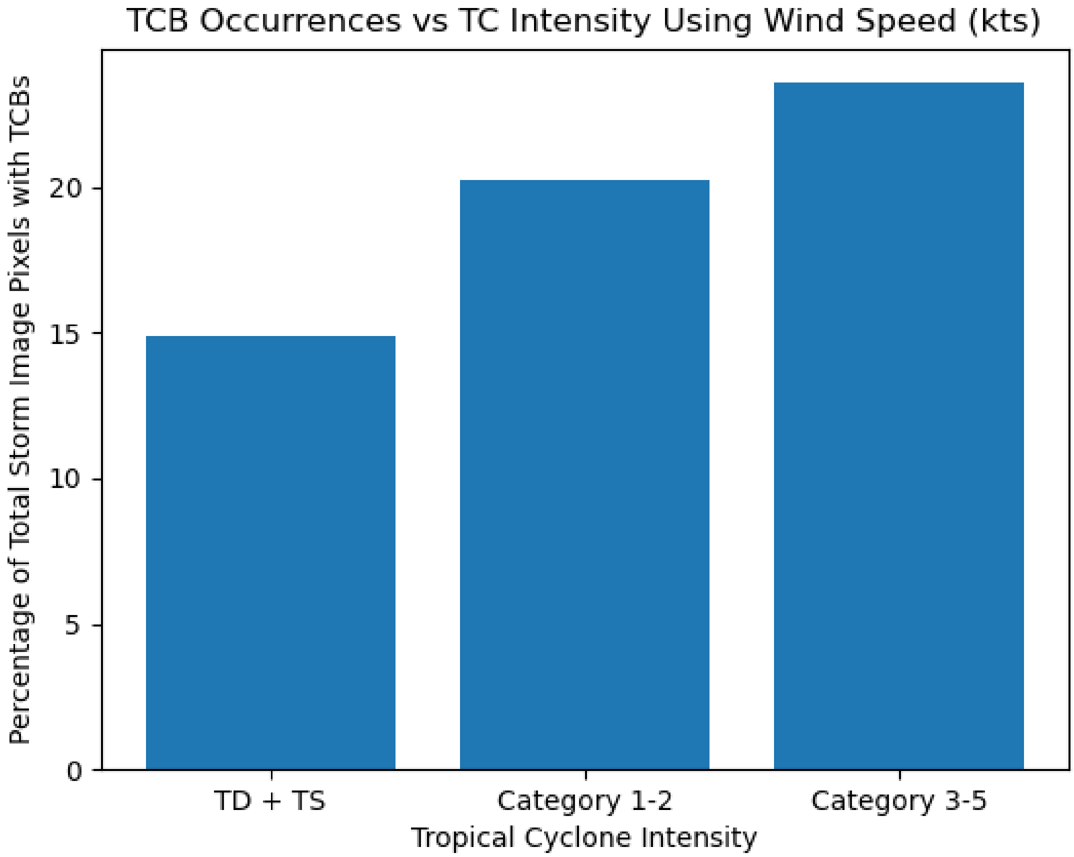

Figure 4.: The percentage of pixels in an image that are TCBs for three different intensity bins. The y-axis shows the percentage of TCB pixels while the x-axis shows the tropical cyclone intensity, which is either a tropical depression or storm, category 1 and 2 hurricane, or category 3 through five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

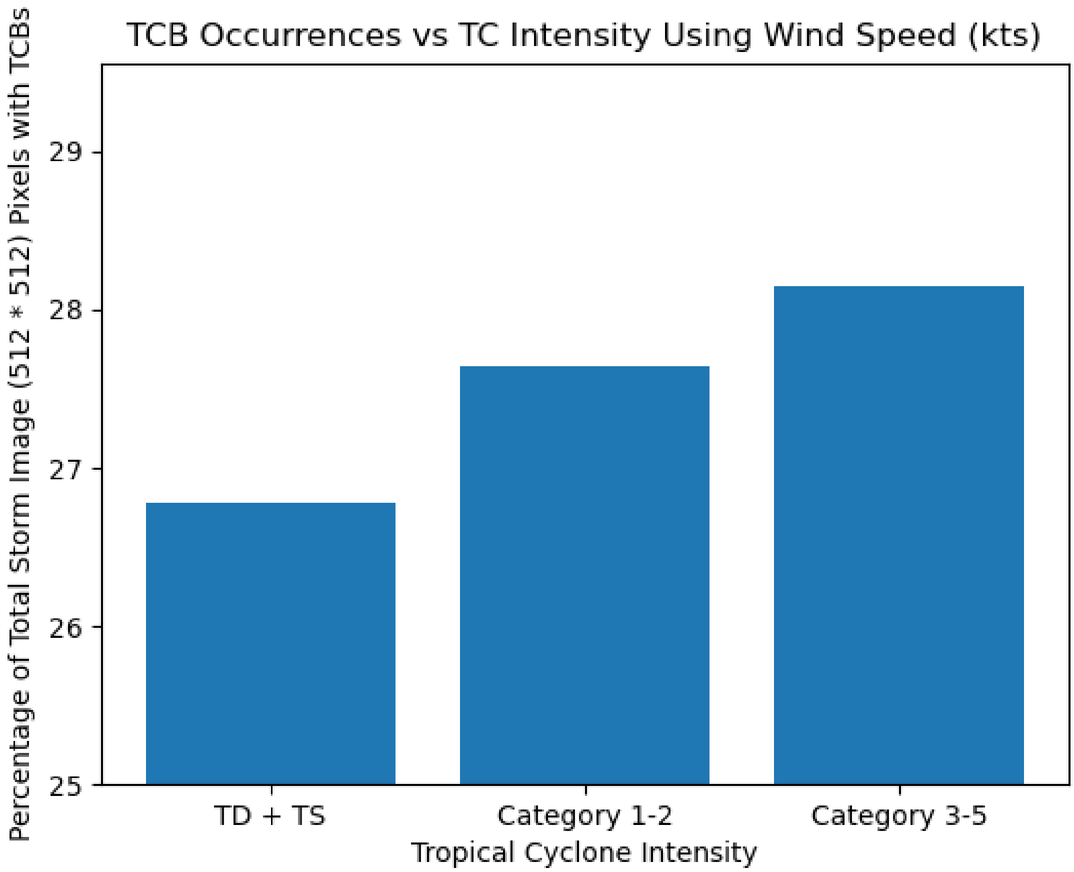

Figure 5.: The percentage of pixels in an image that are TCBs for three different intensity bins. The y-axis shows the percentage of TCB pixels while the x-axis shows the tropical cyclone intensity, which is either a tropical depression or storm, category 1 and 2 hurricane, or category 3 through five hurricane. This figure is different from Figure 4 because it only includes images where 20% of the pixels are TCBs.

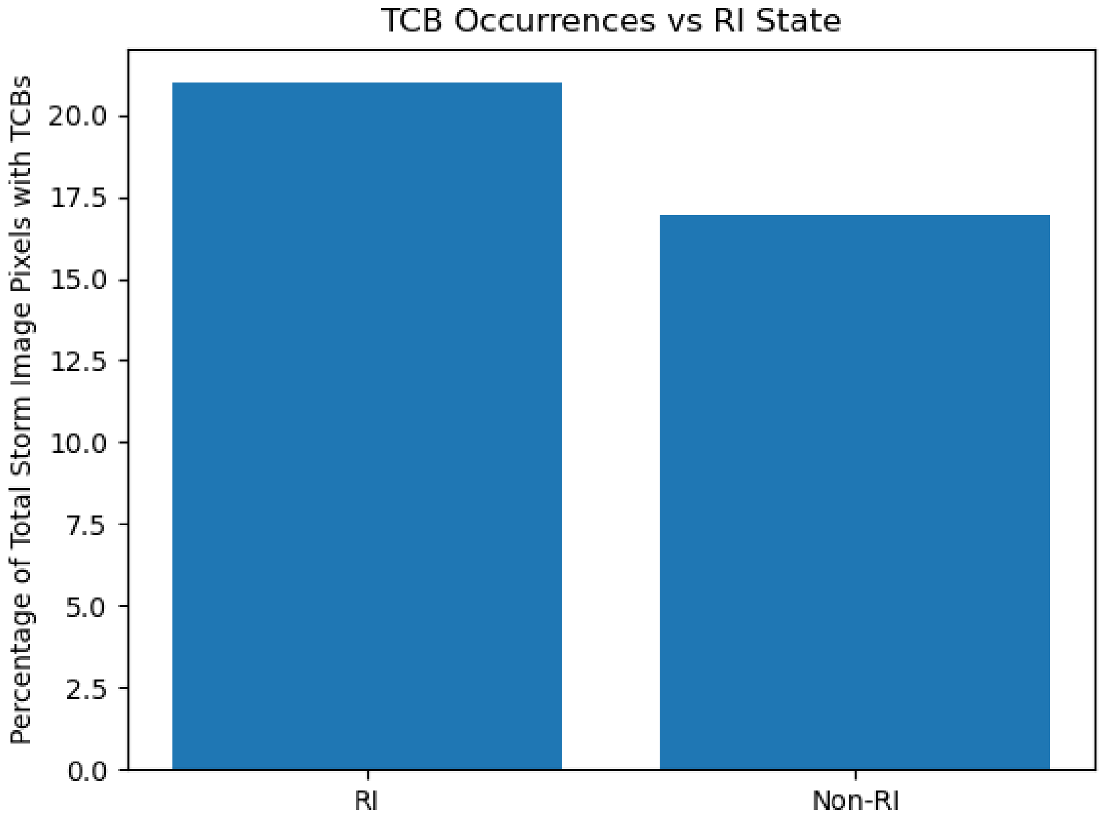

Figure 6.: The percentages of pixels in an image that are TCBs for tropical cyclones undergoing rapid intensification and for tropical cyclones not undergoing rapid intensification. The y-axis shows the percentage of TCB pixels, while the x-axis shows rapid intensification and non-rapid intensification.

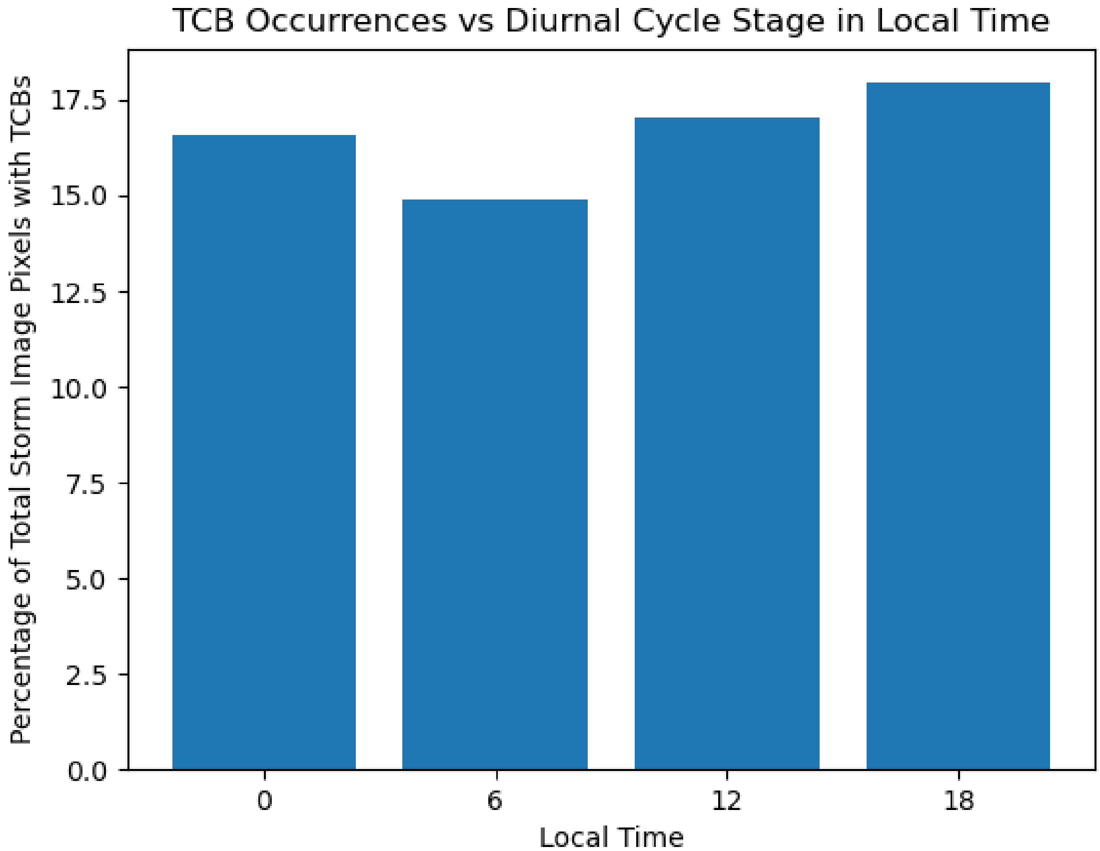

Figure 7.: The percentages of pixels in an image that are TCBs for four different times of day, which are 0000, 0600, 1200, and 1800 local time.

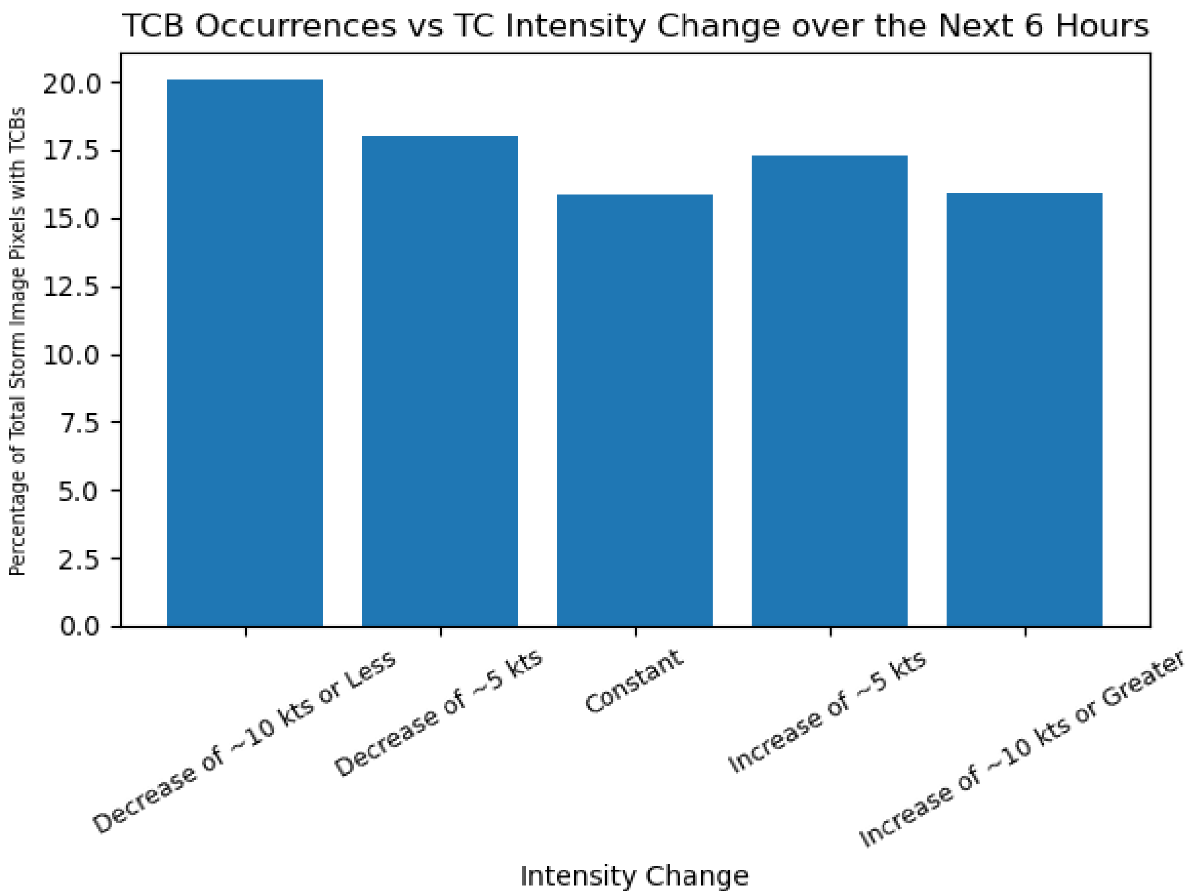

Figure 8.: The percentages of pixels in an image that are TCBs for five different intensity states, which are a decrease of 10kts, a decrease of 5kts, a constant intensity, an increase of 5kts, and an increase of 10kts. The intensity changes are for the next 6 hours.

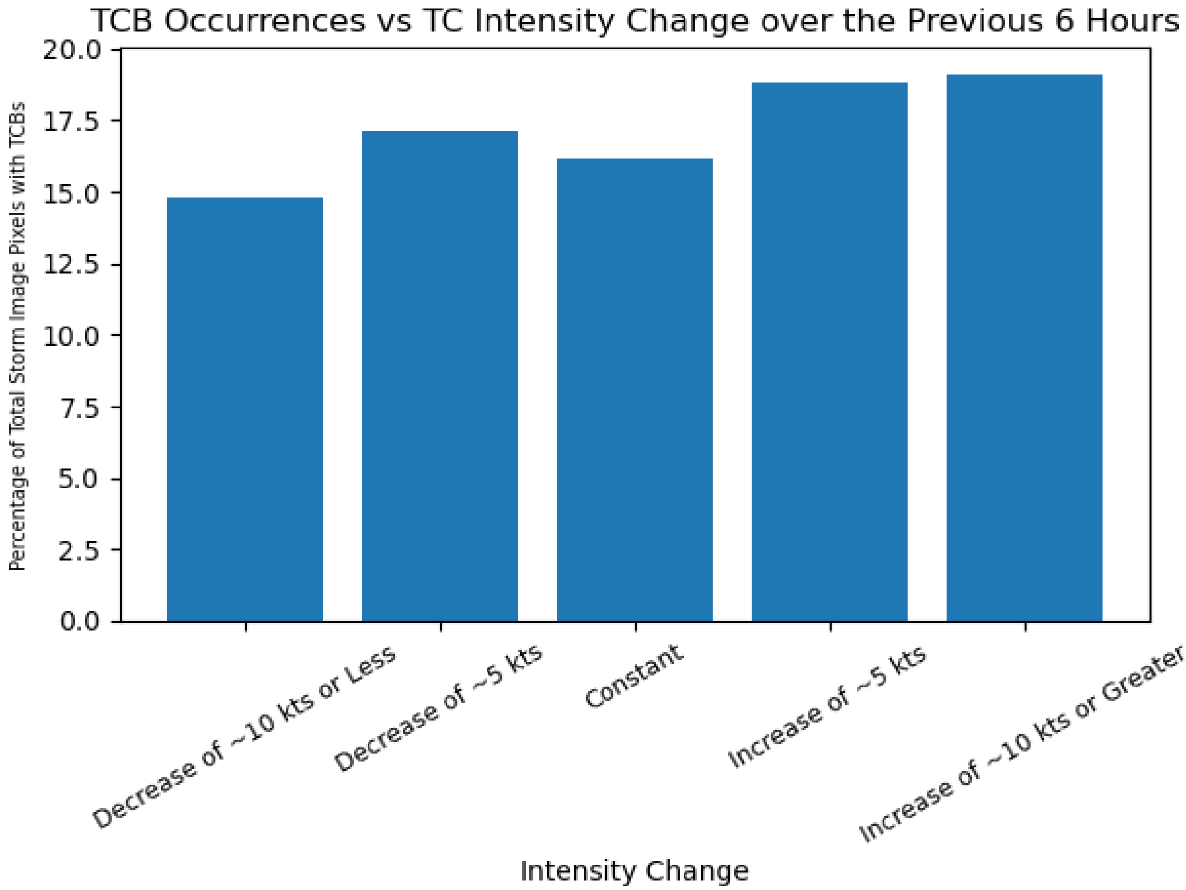

Figure 9.: The percentages of pixels in an image that are TCBs for five different intensity states, which are a decrease of 10kts, a decrease of 5kts, a constant intensity, an increase of 5kts, and an increase of 10kts. The intensity changes are for the previous 6 hours.

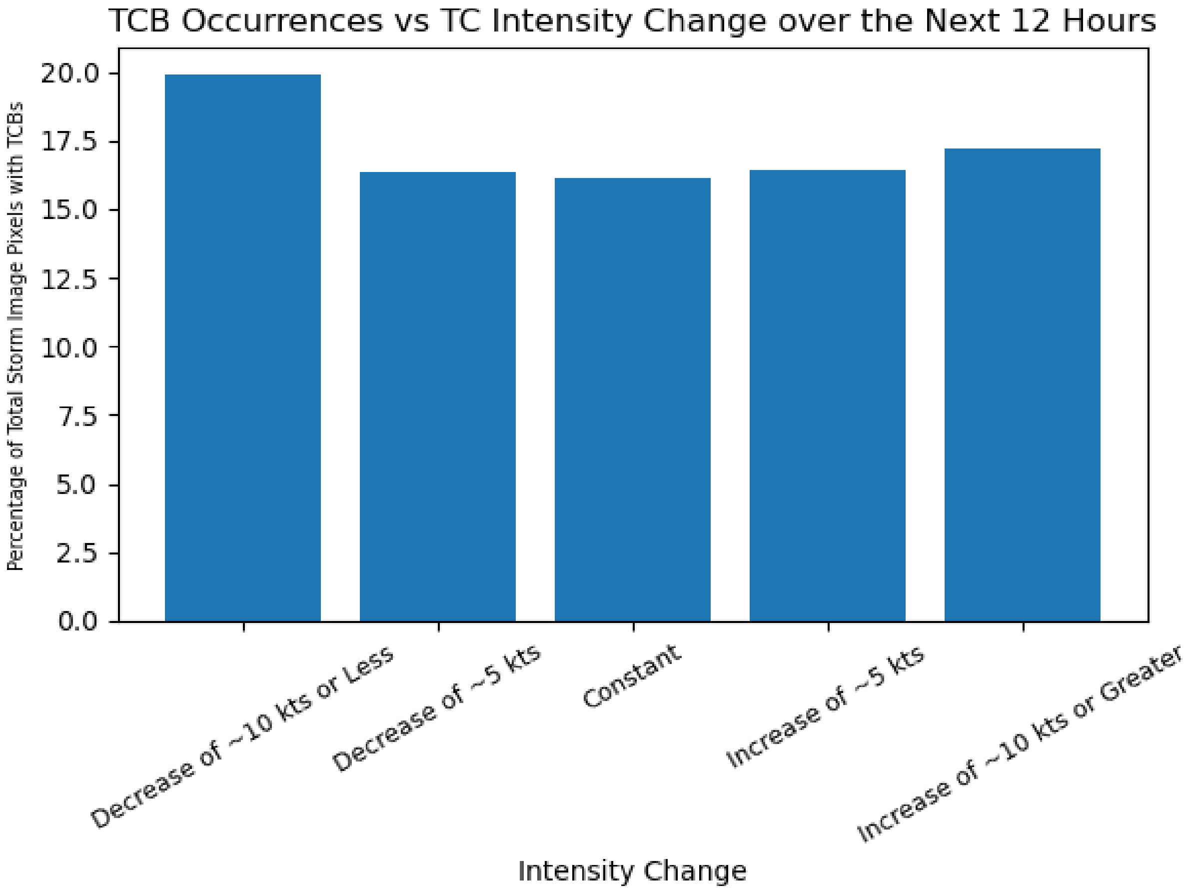

Figure 10.: The percentages of pixels in an image that are TCBs for five different intensity states, which are a decrease of 10kts, a decrease of 5kts, a constant intensity, an increase of 5kts, and an increase of 10kts. The intensity changes are for the next 12 hours.

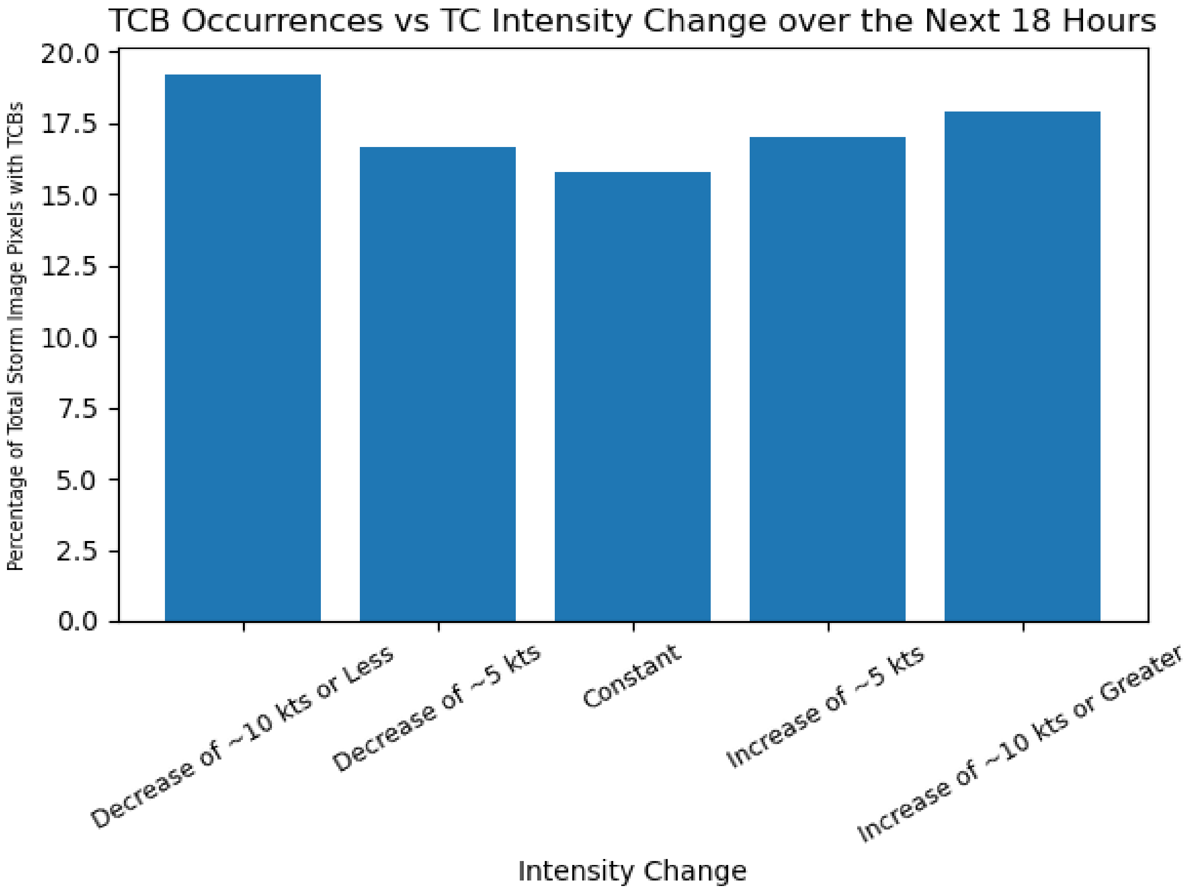

Figure 11.: The percentages of pixels in an image that are TCBs for five different intensity states, which are a decrease of 10kts, a decrease of 5kts, a constant intensity, an increase of 5kts, and an increase of 10kts. The intensity changes are for the next 18 hours.

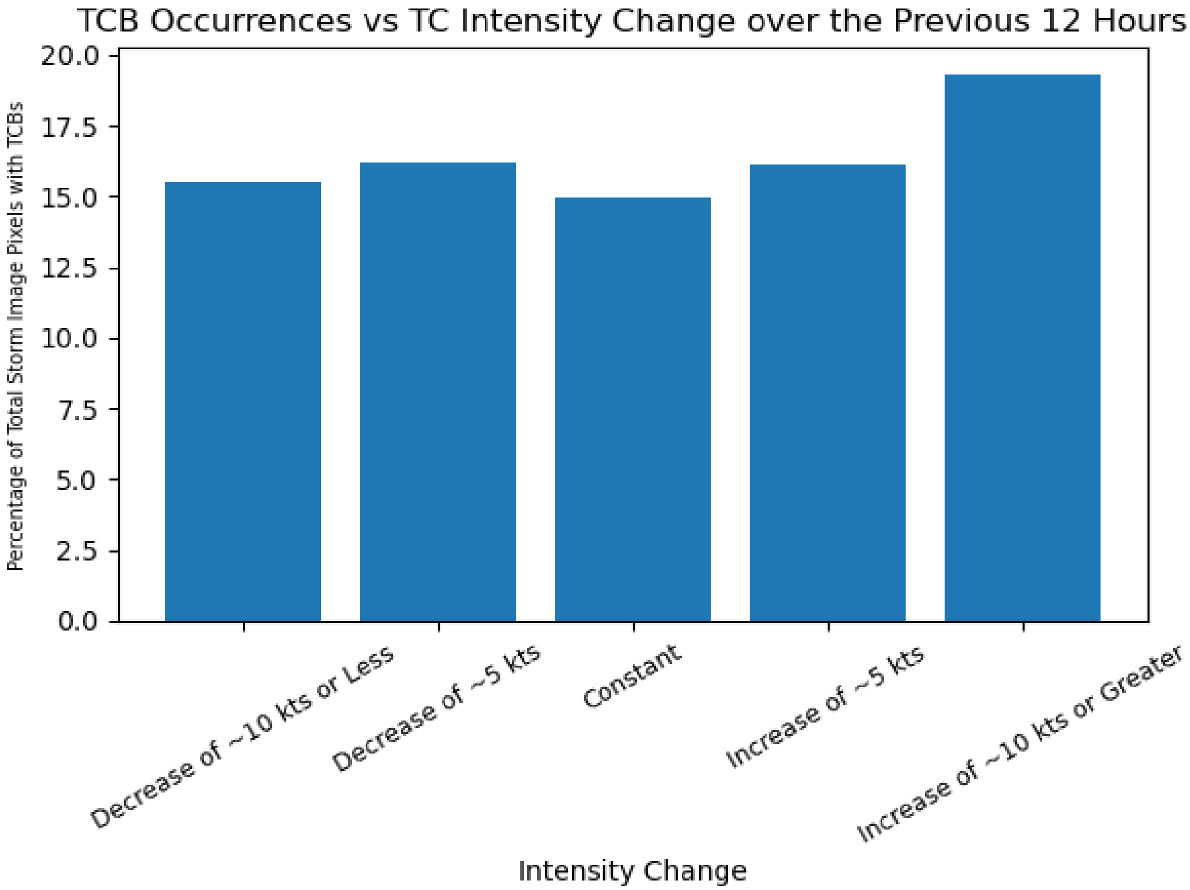

Figure 12.: The percentages of pixels in an image that are TCBs for five different intensity states, which are a decrease of 10kts, a decrease of 5kts, a constant intensity, an increase of 5kts, and an increase of 10kts. The intensity changes are for the previous 12 hours.

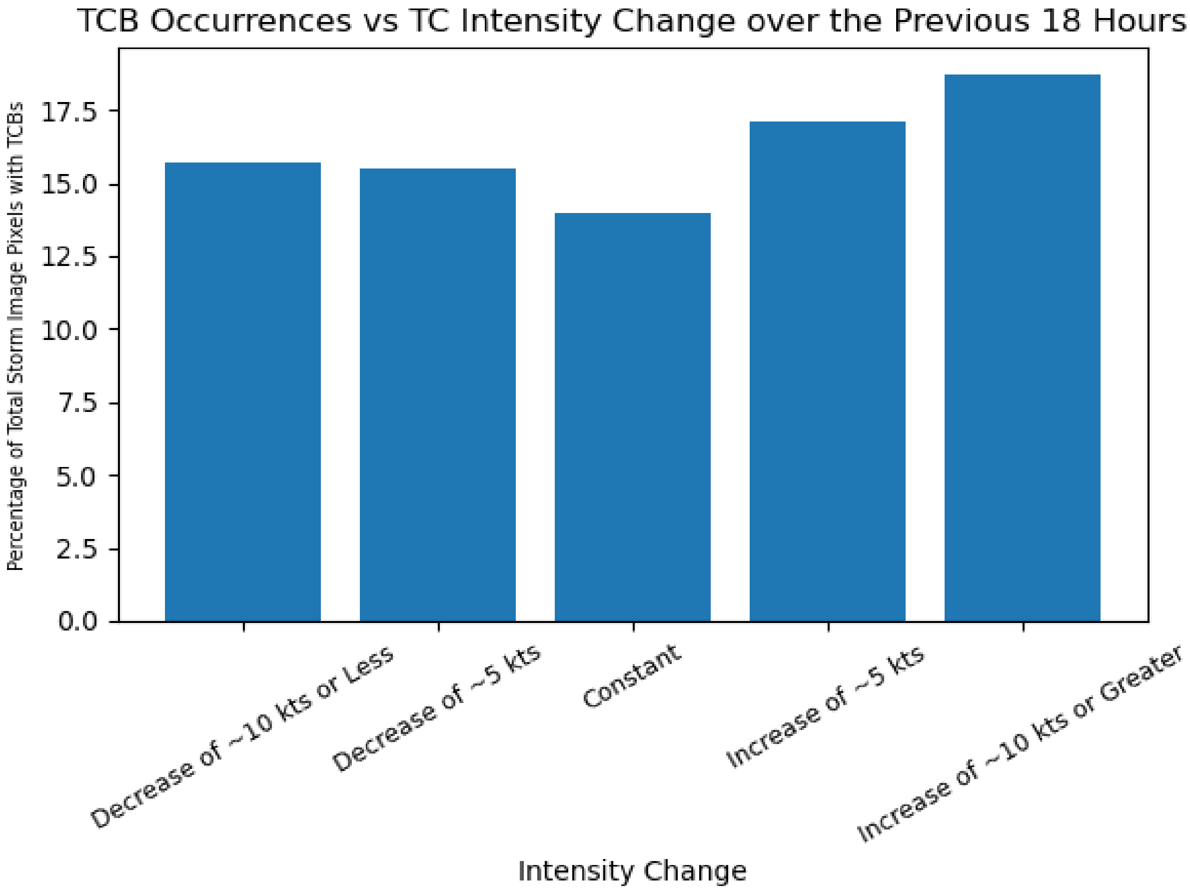

Figure 13.: The percentages of pixels in an image that are TCBs for five different intensity states, which are a decrease of 10kts, a decrease of 5kts, a constant intensity, an increase of 5kts, and an increase of 10kts. The intensity changes are for the previous 18 hours.

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