Journal of Engineering Sciences
Vol 11, Issue 4 , April/2020
ISSN NO:0377-9254

CLOUD CLASSIFICATION USING DEEP LEARNING

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***Abstract*— Clouds are beguiled and may influence lives of human beings unknowingly in their day to day life. Clouds are not only the impress of quotidian climate but also valve of weather. Shallow clouds play an important role in the subtropical wind regions by balancing global energy is a big question for science of climate. A common misinterpretation of the shallow clouds is that they can organize themselves into large patterns which are frequently perceived from satellite imagery. Researchers from the Max Planck Institute for Meteorology (MPI-M) and the Laboratoire Météorologie Dynamique (LMD), France, have categorized ten thousand satellite images in four types of classification named as flower, fish, sugar and gravel. The aim of this project is to develop a machine learning algorithm to identify the existence of patterns of cloud by studying the human labels.**

***Keywords*— Deep learning, Remote sensing, Cloud detection, Optical satellite imagery, Open data.**

1. INTRODUCTION

The motive of this project is to develop a model which classifies cloud patterns from satellite imagery data. This will help the researchers to clearly identify and create models that will assist our interpretation for climate change. The existence of this machine learning community and climate science community will support to construct anticipating algorithms that will guide us to discover new information. To enhance the future of our climate, more research on the patterns of clouds to perceive the fundamental physics of the clouds. This interpretation will lead the way to the evolution of next generation climate models and optimistically lower unreliability in climate forecasting. A model is designed to characterize mesoscale of shallow clouds found in the satellite imagery is described. Patterns of mesoscale organization could be identified in four different labels. They are Fish, Sugar, Flower and Gravel. Flowers are formed by circular clumped aspects and are described as their stratiform elements of cloud while fish has fish-bone like or skeletal structure of clouds. Sugar has small, compact clouds with low reflectivity and gravel clouds are formed by flurry fronts. The large areas of clean air are usually surrounded by fish and flower. All the four patterns were identified 40% of a time. The pattern which was found the most was gravel and the least identified pattern included sugar. The above patterns indicate interannual and occasional dissimilarity and also some scale selectivity level. If we compare the cloud patterns with satellite imagery propose that the qualitative and subjective ocular scrutiny of satellite imagery seize some important physical differences between cloud regimes. Satellite images of an individual cloud can demonstrate its impression. It can be seen through the satellite images that cloud forms are not expressed by individual clouds, but through various spatial patterns generated by similar clouds or from sequences of changing forms of clouds. At times, the pattern of clouds can be unequivocal and could be efficacious to the classification techniques and also to realize the parameters that order them by the researchers over decade. But due to some patterns which are ambiguous, where it is onerous to identify the patterns of cloud. To solve the above problem, we tried to build a model where we could identify patterns which are common satellite imagery. The leading concern of mankind to look on to is climate change. Researchers know that shallow clouds play a remarkable character of regulating Earth's climate. Nevertheless, it is laborious to represent climate models.

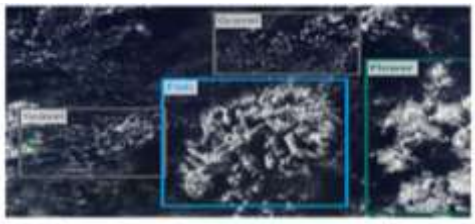
2. OVERVIEW

Clouds periodically abstruse ground information in multipurpose remote sensing images and covered with additional inspection. Nearly, regions filled with shadows of clouds are distinguished by depletion of spectral details and change in spectral shape and should be either abolished or handled using shadow compensation algorithm. The

differentiation among temporal, spatial, spectral and radiometric resolutions of increasing accessible satellite images, such as classification algorithms should have high generation ability. With the increasing accessibility of high-resolution satellite images, it is mandatory to enhance the accuracy and the efficiency of the satellite image indexing, retrieval and classification. Moreover, there is a demand for employ all the available satellite imagery in recognizing types of land cover and keeping track of their modifications time to time disregarding their spatial, spectral, temporal and radiometric resolutions. So, in this paper, we build a deep learning model which can effectively and accurately classify clouds and their shadows in various high-resolution satellite imagery. For many years, climate change has been the most important and leading factor of political decision-making. There are many ways in which clouds can be organized, but the boundaries between different forms of organization are unclear. This makes it provocation to build traditional rule-based algorithms to separate cloud features. It is prerequisite to remove the haze from climate models and bring clarity to cloud identification.

3. DEEP LEARNING FOR IMPROVING CLIMATE AND EARTH SYSTEM MODELS

Although, machine learning algorithms can be strenuous. The statistical and data driven approaches do not assure physical consistency by itself and are highly dependent on data quality. Apart from this, the requirement for processing of data is very high. The various plan of actions of connecting physical modeling and machine learning is described in this paper. We can combine the results of machine learning and physical modeling in hybrid models. For an instance, we can predict the ocean surface temperature by simulating the movement of sea water. The sea water motion is demonstrated by machine learning algorithm, while the temperature of the ocean water is physically modelled. Markus Reichstein says, “The idea is to combine the best of two worlds –, the consistency of physical models with the versatility of machine learning, – to obtain greatly improved models,” at MPI-M machine learning. Dr Peter Landschützer (Ocean Department): “Machine learning has proven to be a strong tool in rebuild the annual uptake of carbon dioxide by the sea. Undeviating measurements are majority restricted to shipping routes leaving huge parts of the sea - in particular the southern hemisphere – sparsely and heterogeneously sampled or unseen. In combination with environmental proxy data, e.g. ocean surface temperature and sea color measurements from satellites, algorithms of machine learning can create a connection in the available surface ocean carbon dioxide observations and the proxies which further can be used to fill gaps of data.



Cloud pattern classification example in „gravel, fish, and flower“. Imagery from NASA Worldview.

3.1. ENVIRONMENTAL CONSTRAINTS

Clouds can manifest wide ranging miscellany of patterns in the regions of trade wind of the satellite images. Above the tropical Atlantic near to Barbados, the number of low-level clouds can order in a different way and can be classified as that of four clouds patterns labelled as fish, flower, sugar and gravel. This research can show that different cloud patterns which are basically identified subjectively, can be more objectively identified from the space measurements of infrared radiations. It also depicts that the comparative phenomenon of the various cloud patterns related to the power of the trade winds near the sea surface and to the solidity of the lower atmosphere. Ultimately, it depicts that each and every pattern is linked with a different amount of cloud and hence it affects the radiative cooling of the environment differently. These results indicate that under global warming, the change in the conditions of the environment may unsettle the frequency of various patterns, which may vary the Earth’s radiative response to global warming in a negative way which was not contemplated before.

4. A CLOUD DETECTION ALGORITHM FOR SATELLITE IMAGERY BASED ON DEEP LEARNING

Remote Sensing of Environment

Remote sensing is nothing but the science and application of obtaining information regarding an object without actually coming into contact with it. In more suitable terms for our understanding, remote sensing is a mechanism for samplifying reflected and emitted electromagnetic (EM) radiation from the Earth's terrestrial and aquatic ecosystems and atmosphere. In order to do this, images from satellites or airplanes are captured to help identify or better understand the features of Earth's surface area. In this paper, we will learn about wide range of approaches, also known by the alternative name of 'Earth observation' (EO). We will not be covering geomagnetic and acoustic remote sensing techniques (sonar and seismic sounding) as we are only focusing on addressing EM remote sensing. A photographic or digital camera can be considered as an instance of remote sensing instrument. To generate an image, the camera records energy that is reflected from the surface in the form of light. Almost all photographic cameras keep track record of light that is able to be seen so that when we look at the photograph the picture resembles the trait that was photographed. More advanced remote-sensing devices are able to track or record energy outside of the range of the light that is visible. Information from remote-sensing devices can be recorded as pictures or, in the case of lidar, a series of point data.

5. FLOWER, SUGAR, FISH AND GRAVEL

We can interest in the organization of shallow clouds is liquescent by the disparity in the frequency with which we can observe the patterning of satellite images and the degree to which it failed to look after in climate and cloud studies. Now, this puts in the procedure studies to large swirl (e.g., Rieck et al., 2012; Bretherton, 2015) simulations in addition to wide circulation prototype, be it in conventional or astronomical (Arakawa and Schubert, 1974; Parishani et al., 2018). The generality of cloud pattering of cloud satellite imagery guided the ISSI team to recognize four familiar categories of cloud organization: Flower, Fish, Sugar and Gravel. It is not difficult to memorize and keep away from a preconception to the direction of preceding canonical patterns in literature by picking out the reminiscent and new names. As a matter of fact, an implementation of neural network Wood and Hartmann (2006) and Muhlbauer et al. (2014), was instructed to differentiate between "No Mesoscale Cellular Convection (MCC)", "Open MCC", "Closed MCC" and "Cellular, but disorganized" ensued mainly in disordered pattern classification recognized by the ISSI team. Nevertheless, we can identify the link of our patterns with foregoing recognized models of cloud organization and report these at a greater distance in the next subsection. The Sugar pattern indicates extensive region of very thin accreting clouds. Altogether, these fields are not very contemplative and they do not have substantial patches of cloud free areas. They preferably manifest compact corroboration of cloud organization. Frequently, however, they are implanted with extensive flow which helps them in formation. In a powerful glide, the Sugar pattern can manifest thin veins or feathers, which have been already narrated as dendritic clouds. The flower pattern are regions which have circular structure of cloud all varying from 50 -200 kilometer in diameter, having likewise spacious cloud free areas in between. This pattern has a remarkable imbricate to canonical closed cell MCC. Flowers, nonetheless, are frequently slighter dense packed than usually closed cells, which have only tapered cloud free areas at the boundary. They are recognized properly outside of areas where stratocumulus is found. A theory is that they are the inheritor of more firmly packed closed cell MCC which are in the procedure of terminating. The fish pattern is broadened, skeletal like structure that occasionally stretch up to 1000 kilometers, mostly longitudinally. These features seem to be near to close to what Garay et al. (2004) described as actinoform clouds. They showed the specimen of these certain efficiently organized forms of clouds taken from all sea basins, close by but consistently downwind areas where there is maximum stratocumulus. To a degree, the fish patterns are alternatives of actinoform clouds discovered by Garay et al., they might even be more than usual than formerly thought. The usual scare of these arcs is nearly about 20 kilometers. We doubt that these patterns are operated by cold pools created by raining cumulus clouds. So, considering the gravel pattern is structurally non identical from open cell MCC, which got lofty cells that are operated by reversing circulations in the border layer. Although, the line in the middle of these two techniques can obscure at times.

6. REAL TIME APPLICATION

The dataset helps to disparage the varying climatic conditions. This algorithm exhibits high rate of production, even when limited to RGB bands. Less time for processing of the algorithm as is based on GPU calculations. The performance of Cloud identification is remarkably improved as compared to snow/ice. The output of initial cloud detection algorithms can be used to train this algorithm We will mount a model to classify cloud organization patterns from satellite imagery. We can help the researchers to better understand how clouds can shape our future climate. This study will lead to the development of next-generation models which could reduce unpredictability in climate projections. This algorithm will also assist us to abolish the haze from climate models and convey clarity to cloud identification. There are various ways in which clouds can be organized, but the boundaries in the middle of various forms of organization are dull. This makes it challenging to frame traditional rule-based algorithms to separate cloud features Although the human eye is really fine at detecting features—like clouds that resemble flowers.

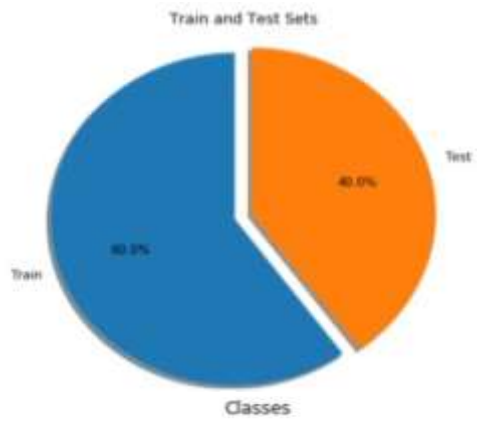
7. DATASET

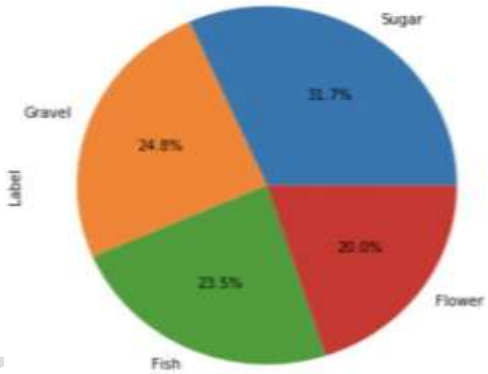
As described in this paper, the data in this dataset was actually a result of collaborative working. The four patterns of cloud were labelled: Sugar, Flower, Fish, and Gravel. Around 67 researchers then deserted 10,000 images to bring up with the final dataset (about 9,000 images). Humans beings are much better than computers at identifying patterns, especially for something so subjective as cloud patterns, which is why this algorithm was used to come up with the training dataset.

7.1. Process

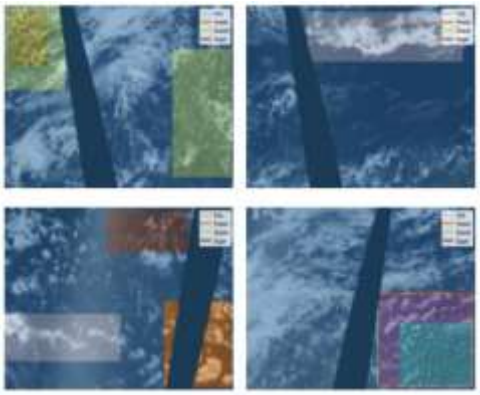
- Data cleaning
- Image Segmentation
- Modeling
- Pre-Processing/Image Segmentation

Initially, we need to take a look at the dataset:

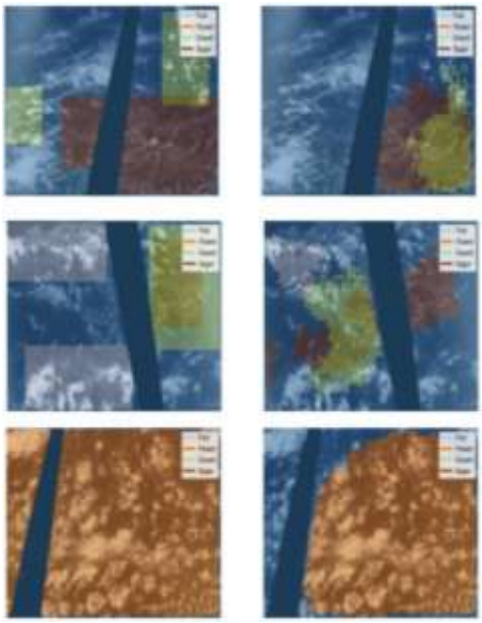




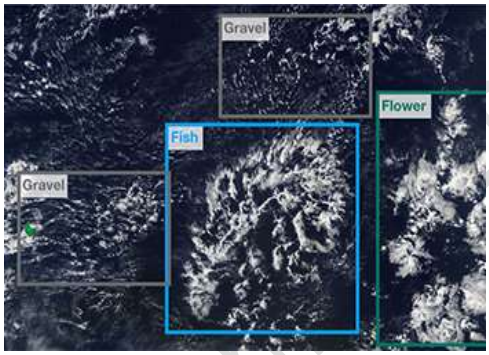
We can observe that the classes are pretty much balanced, which is a good thing if we want accuracy in the results. We can also notice that most images have at least 2 classes. We tried using a number of various libraries for image segmentation and was able to apply a segmentation function to the training data:



While creating the model, we used a technique called transfer learning, where a model that has been previously trained is applied to your dataset. In this case, we used ResNet-18, which was trained on more than a million images. The resultant images after we done training the model are:

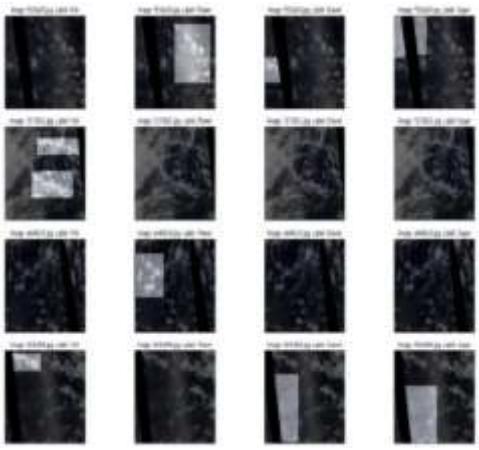


Again, our model did it correctly, but we get to see that it is not as accurate as our images in training dataset. To calculate the total amount of our prediction, we use the Dice coefficient, which measures the likeness between images. In this case, for an instance, it compares the test images classes with that of the training images classes.

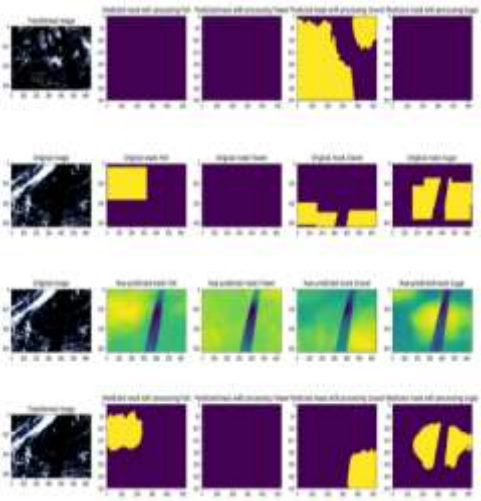


8. RESULT & DISCUSSION

The result includes identifying the regions in the satellite images that contain certain cloud formations, with label names: Fish, Flower, Gravel, Sugar. For each image in the test set, it performs the segmentation of the regions of each cloud formation label. Each and every image has at the minimum one formation of cloud and can perhaps accommodate up to all four. The images were downloaded from NASA Worldview. Three regions were chosen spanning 21 degrees longitude and 14 degrees latitude. We took the true-color images from the two satellites, TERRA and AQUA which are polar-orbiting and once a day, each of them passes a specific region. Even though the different patterns have common properties, these patterns have a degree of randomness that they showcase which therefore encourages various classification techniques. Instead a subjective procedure was developed whereby the patterns were described, and other scientists (labelers) were trained to identify and label these patterns. This procedure involved determining whether a particular pattern dominated a $10° \times 10°$ area upwind of the Barbados Cloud Observatory (48°W to 58°W, 10°N to 20°N) in the season where the trade winds predominate (1 December–28 February). We found that four recognizably different cloud patterns appear after the research, which are Fish, Sugar, Flower or Gravel, and are characterize as follows: Sugar: Dusting of very thin scale clouds with small upright extension and small proof of self-organization. Gravel: Cloud fields patterned along meso-β i.e. 20 to 100 km lines or arcs defining cells with intermediate granularity, and brighter cloud elements (as compared to Sugar), but with little proof of occurring with stratiform cloud veils. Fish: Meso-α scale (200 to 2,000 km) are often fishbone-like skeletal networks of clouds unrelated from each other, or from additional cloud forms, by explicit cloud-free areas and occasionally follow with a stratiform cloud shield. Flowers: Irregularly shaped meso-β scale i.e. 20 km to 200 km stratiform features of cloud, with frequent higher reflectivity cores, and is visible in quasi-regular spaced bunches with every single feature well separated from one another by areas that do not have clouds. From the study we have found out that while a majority of labelers had agreed one of the four labels with a probability of 0.4.in almost all satellite images its features were present in such a way that at least one pattern was dominant in the image. Surprisingly sugar dominated the least in the study that was conducted. Also, the most dominant pattern was that of gravel. In the study, flowers were evinced the most seasonality which appeared mostly in February which often persisted for days. The differences in patterns of the clouds are related to the differences in the structure of the cloud field as also visualized by its radar presentation, with Fish pattern being most associated with deeper clouds and precipitation.



Cloud pattern classification example in gravel, fish, and flower. Imagery from NASA Worldview.



The above diagram showcases the different classified patterns of clouds based on the satellite images among them are Sugar, Flower, Fish and Gravel.

9. CONCLUSION

As we know that shallow clouds play an important role in regulating the Earth's climate. Clouds need much effort to understand and to represent in climate models. By classifying different types of cloud organization, scientists at Max Planck hope to improve our physical understanding of these clouds, which in turn will help us build better climate models. This research has encouraged different types of follow-up activities. One of them has been designed to see if the different patterns can be measured by essential methods and if the patterns distinguish themselves in terms of their radiative effects, or the environment in which they form. While another aims to form more labels, and allow the labelling of smaller subdomains, which would then provide the basis for asking to what extent machines could learn the labels assigned by humans. Based on this we can understand the emergence of different patterns. It might also help us understand weather changes resulting.

10. FUTURE WORK

In the future after classifying different clouds using the abovementioned method, we can predict the weather. We can also improve the classifier.

We can enhance the current model.

We can test other different deep learning libraries.

We can predict the weather more accurately.

There is still a room for improvement in this project.

We can see that it is certainly possible for a machine to learn how to perform subjective tasks like classifying images of clouds, but there is a lot of work to be done.

ACKNOWLEDGMENTS

First and foremost, we would like to express our sincere and heartfelt gratitude to our teacher Prof. Teena Varma who gave us the golden opportunity to do this wonderful project on the topic Cloud Classification using Deep Learning, which also helped us in doing a lot of Research and we learned about so many new things. Special thanks to her for sharing her knowledge with us and guiding us throughout this project.

We acknowledge the use of imagery from NASA Worldview, part of the NASA Earth Observing System Data and Information System (EOSDIS).

REFERENCES

[1] Bony, S., H. Schulz, J. Vial, and B. Stevens, 2019: Sugar, Gravel, Fish and Flowers: Dependence of Mesoscale Patterns of Tradewind Clouds on Environmental Conditions. Geophys. Res. Lett., 1–20– submitted.

[2] Bony, S., and Coauthors, 2017: EUREC4A: A Field Campaign to Elucidate the Couplings Between Clouds, Convection and Circulation. Surveys in Geophysics, 38 (6), 1529–1568, doi: 10.1007/s10712-017-9428-0.

[3] Liu, Y., E. Racah, J. Correa, A. Khosrowshahi, D. Lavers, K. Kunkel, M. Wehner, and W. Collins, 2016: Application of Deep Convolutional Neural Networks for Detecting Extreme Weather in Climate Datasets. https://arxiv.org/abs/ 1605.01156.

[4] Medeiros, B., and L. Nuijens, 2016: Clouds at Barbados are representative of clouds across the trade wind regions in observations and climate models. Proc Natl Acad Sci USA, 113 (22), E3062–E3070.

[5] Mudigonda, M., and Coauthors, 2017: Segmenting and Tracking Extreme Climate Events using Neural Networks. Deep Learning for Physical Sciences, NIPS workshop.

[6] Muhlbauer, A., I. L. McCoy, and R. Wood, 2014: Climatology of stratocumulus cloud morphologies: microphysical properties and radiative effects. Atmospheric Chemistry and Physics, 14 (13), 6695–6716, doi:10.5194/ acp-14-6695-2014.

[7] Nicholls, S. D., and G. S. Young, 2007: Dendritic patterns in tropical cumulus: An observational analysis. Monthly weather review, 135 (5), 1994–2005.

[8] Nielsen, M. A., 2015: Neural Networks and Deep Learning. Determination Press, http://neuralnetworksanddeeplearning.com.

[9] Norris, J. R., 1998: Low cloud type over the ocean from surface observations. Part II: Geographical and seasonal variations. Journal of Climate, 11 (3), 383–403.

[10] Parishani, H., M. S. Pritchard, C. S. Bretherton, C. R. Terai, M. C. Wyant, M. Khairoutdinov, and B. Singh, 2018: Insensitivity of the Cloud Response to Surface Warming Under Radical Changes to Boundary Layer Turbulence and Cloud Microphysics: Results From the Ultraparameterized CAM. Journal of Advances in Modeling Earth Systems, 10 (12), 3139–3158.

[11] Racah, E., C. Beckham, T. Maharaj, S. E. Kahou, Prabhat, and C. Pal, 2016: ExtremeWeather: A large-scale climate dataset for semi-supervised detection, localization, and understanding of extreme weather events. http://arxiv.org/ abs/1612.02095.

[12] Rasp, S., M. S. Pritchard, and P. Gentine, 2018: Deep learning to represent subgrid processes in climate models. Proceedings of the National Academy of Sciences of the United States of America, 115 (39), 9684–9689, doi:10.1073/pnas. 1810286115.

[13] Stevens, B., and Coauthors, 2019a: A high-altitude long-range aircraft configured as a cloud observatory–the NARVAL expeditions. Bulletin of the American Meteorological Society, BAMS–D–18–0198.1, doi:10.1175/BAMS-D-18-0198.1.

[14] Stevens, B., and Coauthors, 2019b: Sugar, gravel, fish, and flowers: Mesoscale cloud patterns in the tradewinds. Quarterly Journal of the Royal Meteorological Society, doi:10. 1002/qj.3662.

[15] Caron, M., P. Bojanowski, A. Joulin, and M. Douze, 2018: Deep Clustering for Unsupervised Learning of Visual Features. https://arxiv.org/abs/1807.05520.

[16] Garay, M. J., R. Davies, C. Averill, and J. A. Westphal, 2004: ACTINOFORM CLOUDS: Overlooked Examples of Cloud Self-Organization at the Mesoscale. Bull. Amer. Meteor. Soc., 85 (10), 1585–1594.

[17] Gneiting, T., and A. E. Raftery, 2007: Strictly Proper Scoring Rules, Prediction, and Estimation. Journal of the American Statistical Association, 102 (477), 359–378, doi:10.1198/ 016214506000001437.

[18] He, K., X. Zhang, S. Ren, and J. Sun, 2015: Deep Residual Learning for Image Recognition. http://arxiv.org/abs/1512. 03385.