Incorporating Community Science into Arctic Sea Ice Models: Validation of Ice Watch Data

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ABSTRACT

Understanding the wide-reaching impacts of climate change in the Arctic is difficult due to the remoteness of the region. This makes it difficult to create comprehensive, accurate climate models in complex boundary regions. This project investigates the use of community science in the Arctic and its potential use in creating more just models. The central research question for this project is: What is the potential impact of community science on Arctic sea ice models? This study analyzed Arctic sea ice measurements that were collected by Ice Watch, a community science organization. The analysis of accuracy between Ice Watch and National Snow and Ice Data Center (NSIDC) data found that Ice Watch data was not highly accurate in the short term, but demonstrated greater accuracy for seasonal and long-term trends. This makes Ice Watch a valuable dataset. The development of a decision tree model was able to predict the accuracy of individual data points with a high specificity. Ice Watch data, with the incorporation of a validation model, can provide useful information to communities and scientists by filling Arctic data gaps. It could also contribute to the use of community science in models and make the process community oriented. The use of community science can address issues of equity and justice in scientific spaces, engage communities historically excluded from the scientific community, and increase the accuracy of regional climate models in the Arctic.

KEYWORDS

climate modeling, environmental justice, machine learning, Arctic trends, climate change, community engagement

INTRODUCTION

A community scientist is defined as a volunteer who processes or collects data for a scientific purpose (Silvertown 2009). The use of community science allows projects to be done on scales or at resolutions that would be unattainable by a research team or individual. This gives a lot of power to community science efforts, through their ability to involve thousands of individuals across various temporal and spatial planes (Bonney et al. 2014). It also helps to engage communities and reach audiences that have been historically excluded in the scientific community (Conrad and Hilchey 2011). Community science can help to engage marginalized communities most effectively by making community members active participants throughout the creation process. Through the incorporation of communities into the design, collection, analysis, and communication of scientific studies it can empower them to have agency over research conducted in their communities. This will help connect the values of communities and the practice of science (Pandya 2012). The use of community science in climate modeling can help to make the process of model creation more equitable and community driven.

Climate modeling plays an important role in policy making and cultivating a broader understanding of climate change impacts, but has serious ethical issues to consider. The incorporation of communities into the creation of climate models, especially in remote areas of the world, could contribute to the creation of more just models (Schlosberg 2012). The values that are embedded in some models reproduce and create power imbalances that already exist in these scientific spaces and in discourse surrounding climate change and models (McLaren 2018). In addition to the increased equity and justice of climate models that are created through participatory based community research and community science, it could also increase the accuracy of the model. Climate modeling is a rapidly evolving field, with new modeling techniques and ideas being developed to increase the accuracy of earth systems models. Regional climate models (RCM) are a substantial improvement over global climate models (GCM) in modeling spatial weather patterns because of their finer spatial resolution (Semenov 2007). The use of regional climate models will provide better spatial resolution of predicted impacts of climate change at the local level and predicting climate scenarios at this level (Semenov and Stratonovitch 2010). These models need an abundance of data to train on in order to have more accurate predictions, this is where community science could help to overcome those data gaps.

The creation of a regional climate model in the Arctic could be made more accurate and just by utilizing community science efforts.

It is important to more fully understand the impacts of climate change in the Arctic, as it has wide reaching impacts on the globe (Barry et al. 1993). It is hard to obtain comprehensive data for Arctic sea ice models because of the remoteness of the climate. The transport of “experts” to and from the Arctic requires many resources, infringes on communities, and creates many injustices. Community science could be one possibility for filling data gaps, while not contributing to further injustices (Dickinson et al. 2010). Recently, emerging technologies have made the ability to collect scientific data and streamline data collection and communication much easier. Open science networks and the use of online tools have the ability to engage non-traditional communities and create formalized community science networks. This is one possibility in the Arctic through engaging local communities and tourists in the area (Newman et al. 2012). Community partnerships and community decision making could also help to increase the usefulness of climate models after their creation, by directly involving those who are impacted and focusing on local solutions and empowerment (Shaw et al. 2013). The incorporation of communities as the key player in the creation of climate models will facilitate applying the knowledge generated from models and bring more stakeholders together.

Objectives

The central research question for this project is: What is the potential impact of community science on Arctic Sea Ice models? The following three sub questions will be used to evaluate this question. The first sub question is, how accurate is Arctic sea ice data that is collected by Ice Watch in the short term? It is hypothesized that the sea ice data collected will be as accurate as data found in the literature and collected through remote sensing and other instruments. This will be analyzed through the comparison of Ice Watch sea ice index data and National Snow and Ice Data Center (NSIDC) ice index data. The second sub question is, how accurate is Arctic sea ice data that is collected by Ice Watch in the long term? It is hypothesized that the long term trends observed by Ice Watch in Arctic sea ice will reflect the trends that are captured by satellite data and what is happening in the Arctic. This analysis will be accomplished through linear regression trends for both NSIDC and Ice Watch data and comparison of the interaction term for the two categories. The final sub question is, is it possible to remotely validate data from Ice Watch using machine learning models? For this question, it is predicted that the application of non-parametric machine learning methods could be used to remotely validate Ice Watch data as it is received. This will be accomplished using different non-parametric models and comparing their accuracy on a held out test data set. All of these sub-questions will hope to better understand the trends that Ice Watch captures and how this data could be used to make models and their creation more community focused.

METHODS

Study site and data used

In this study, I used community science measurements taken for Arctic sea ice. The data was obtained from Ice Watch, which is an organization that provides training and software to the general public so that they can take measurements of Arctic sea ice from their phones or any other device and upload it to the Ice Watch database. Ice Watch is operated by the Norwegian government and has measurements easily downloaded and visualized on their website. These measurements are separated by ship and date that they were taken on as all measurements are collected on boats. This data also has latitude and longitude as well as other ice characteristics collected for each observation.

Data cleaning and preprocessing

To determine the validity of this dataset, I used data from the National Snow and Ice Data Center (NSIDC) to compare with the community science data from Ice Watch. First, I downloaded the data from Ice Watch and NSIDC. Then I concatenated all of the Ice Watch data so that date and latitude and longitude columns could be filtered for the whole dataset. After initial data exploration, I found that there were data points not located in the Arctic based on a heatmap of coordinates in the dataset, so I removed those measurements and grouped the data by month and year that it was collected. Then I downloaded and processed the data from NSIDC. NSIDC data included Arctic sea ice extent and area but lacked a comparable metric for Ice

Watch data, so I calculated sea ice index for each month. Sea ice index is a measurement from one to ten that represents the percentage of ice cover in that area, and this index was calculated for the NSIDC data by dividing ice area by extent. These metrics were then used for the further comparison of Ice Watch and NSIDC data.

Analysis of short term Ice Watch data validity

After the initial data exploration, I performed a percent difference analysis on monthly average index values to validate the community science data. This was done by comparing the average index value for each month and year from the NSIDC and Ice Watch. Data that had an absolute percent difference of more than 10% was considered invalid, because there is a statistical difference in the sea ice index estimates of the two data sets. I then disaggregated this data to look at how accurate the measurements were in a given month given the number of observations that were collected. This gave a better picture of how many individual data points were collected in valid and invalid months. This metric was used to assess the short term validity of the data.

Analysis of long term Ice Watch data validity

The second objective of this study was to measure how well the Ice Watch data captured long term trends in Arctic Sea Ice. I used an analysis of covariance test on the regression lines for the data from 2006 to 2022 to quantify the difference in the trends of the two data sets. This coefficient was then evaluated at a significance level of $p < 0.05$ to determine if there was a difference in the two trend line coefficients.

Building a machine learning validation model

The last objective was to create a machine learning model that could remotely validate the data as it is collected. The input data to the machine learning model was each individual observation from Ice Watch with a valid or invalid label from the previous short term analysis. I coded a datapoint with an invalid label if its latitude was less than 66° N or if it was found to be significantly different from the NSIDC data with a significance value of $p<0.1$. I then partitioned the data into a training and test set, with 30% of the data excluded from the original dataset for the test set. I used 5-fold cross validation to validate different neural network and random forest hyper-parameters and determine which would have the highest accuracy. For the final model, I visualized the feature importance for the random forest model that was chosen. All of this gave a better picture of what the model was using to classify data points and allow us to understand what data points would yield a higher accuracy.

RESULTS

Exploratory data analysis

Of the 9700 data points that were collected by Ice Watch, my initial analysis and cleaning found that 9,685 were in the correct region of the world based on their coordinates. This means 315 observations were located below 66 degrees North of latitude (Figure 1).

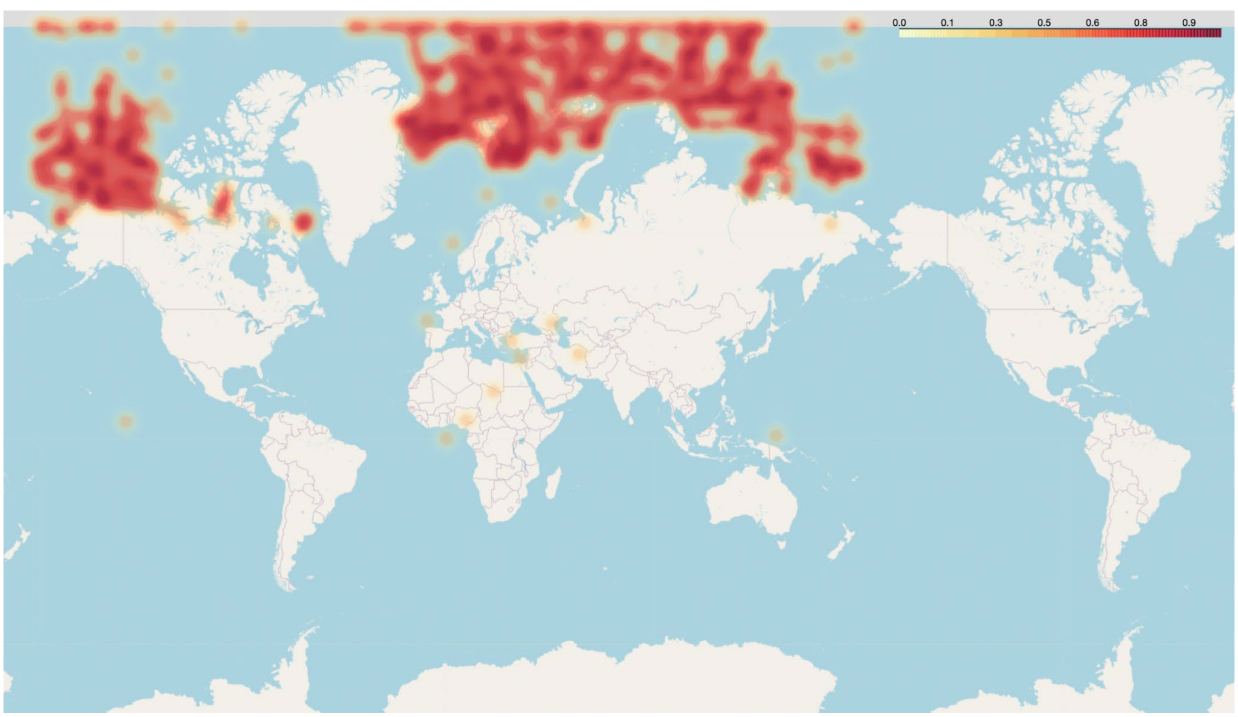

Figure 1. Visualizing Latitudes and Longitudes of Ice Watch Data. Heat map of where data points were collected on a world map. Darker color indicates more data points were collected there.

I also found that the prevalence of summer data points was much higher than winter data points. There were 3,620 values in the summer months and only 1,042 values in the winter months. The rest of the data points were taken in the fall or spring. There were significant data gaps in both the winter and summer months (Figures 2 & 3).

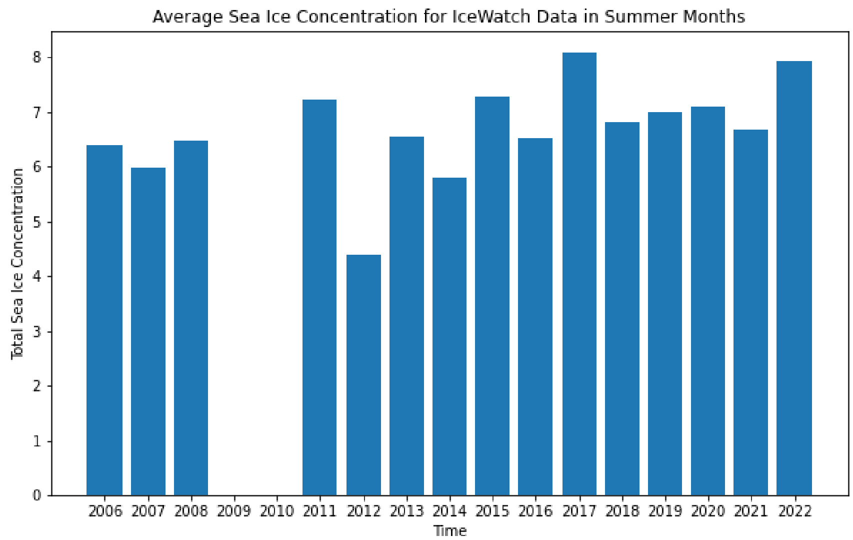

Figure 2. Average Sea Ice Concentration for Ice Watch data from 2006 to 2022 in the Summer. The average sea ice index for all summer months is displayed, and there was no data collected in 2009 or 2010 in the summer.

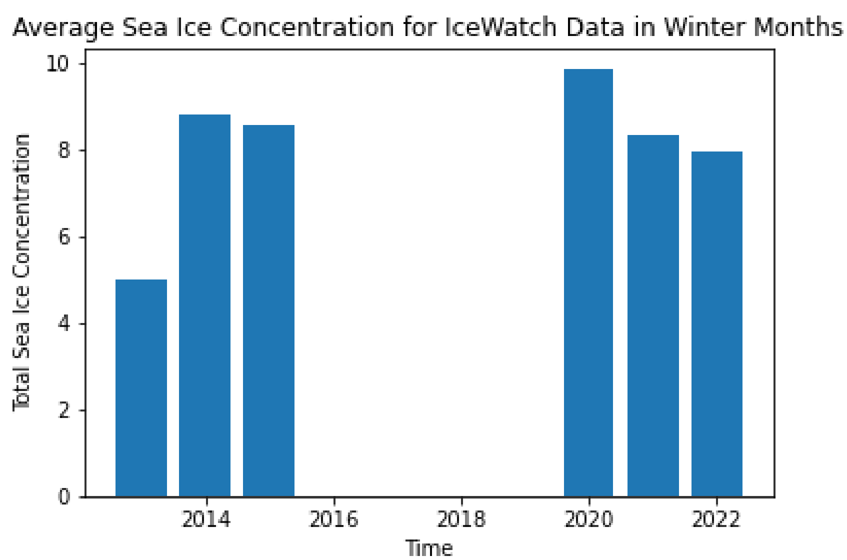

Figure 3. Average Sea Ice Concentration for Ice Watch data from 2006 to 2022 in the Winter. The average sea ice index for all winter months is displayed, and there was no data collected before 2013 and none between 2016 and 2019.

Short term data validation

Analysis of monthly data showed that for the years from 2006 to 2022 for Ice Watch data points that were located in the Arctic, 58% had a percent difference larger than 10% compared to NSIDC satellite data. These months were considered invalid compared to the NSIDC data. After disaggregating this data, this correlated to 95.3% of individual Ice Watch observations being considered valid when compared with NSIDC data.

Analysis of long term Ice Watch data validity

After analysis of the interaction coefficient for the NSIDC and Ice Watch sea ice index data a p-value of 0.370 was found for the interaction term indicating that there is no significant difference between the two model slopes with a significance level of $p<0.05$. Both linear regression lines capture the same trends (Figures 4 and 5).

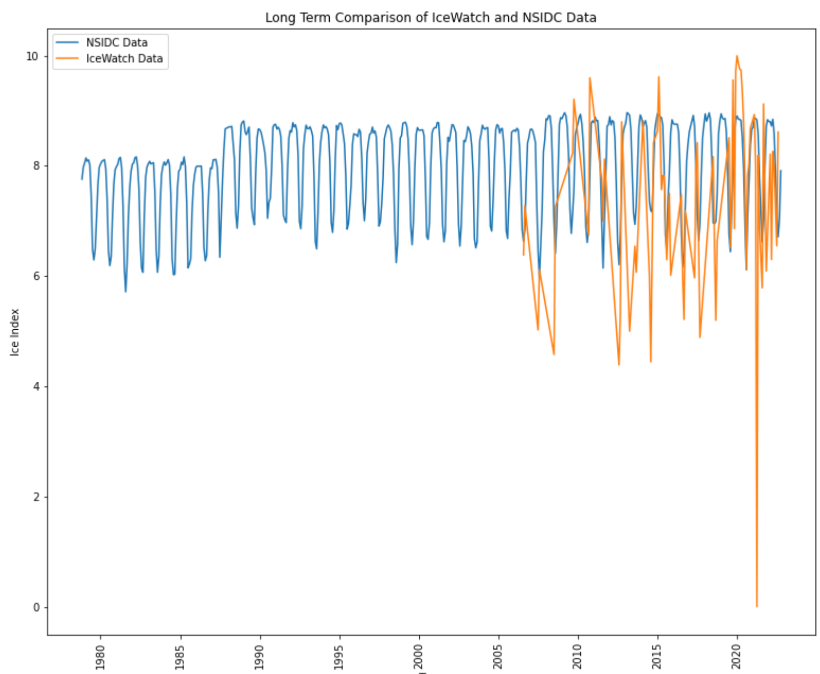

Figure 4. Visualizing Ice Watch and NSIDC ice index data from 1977 to 2022. The orange line is Ice Watch data and the blue line is NSIDC data.

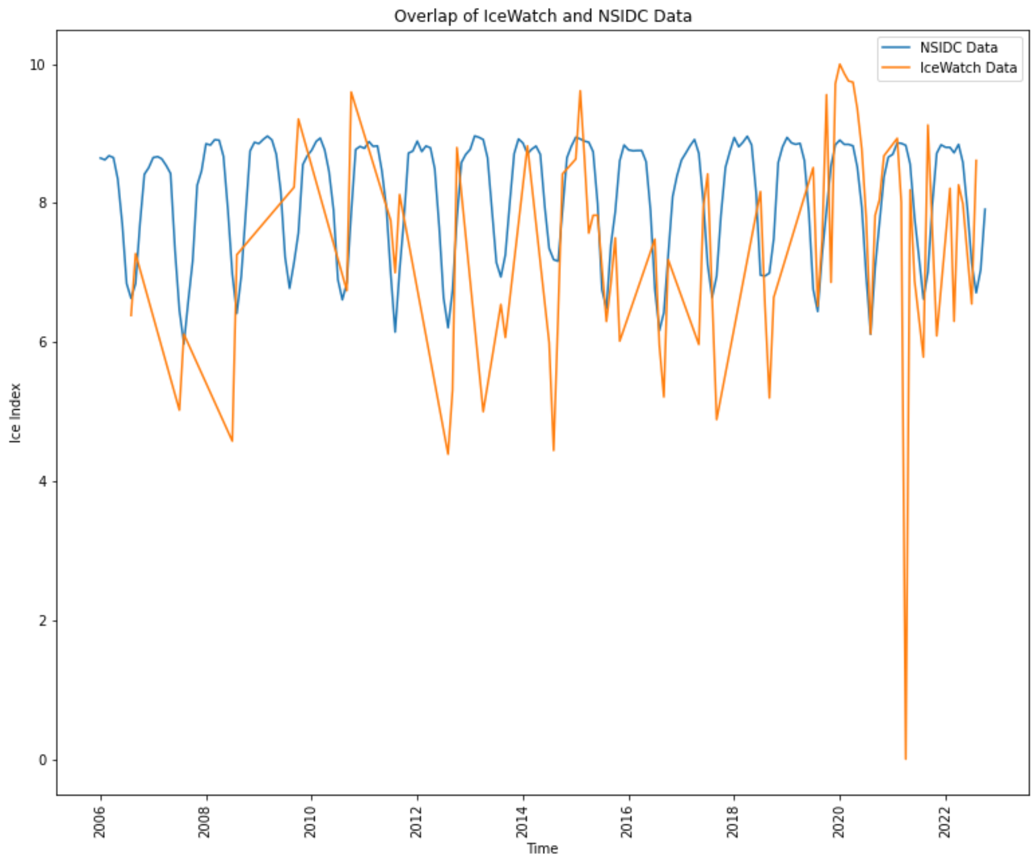

Figure 5. Visualizing Ice Watch and NSIDC ice index data from 2006 to 2022. The orange line is Ice Watch data and the blue line is NSIDC data. This figure is a shorter timeline of figure 5, showing only the years where Ice Watch and NSIDC data overlap. Shows the monthly averages for each of the two data sets over the same time period.

Building a Machine Learning Validation Model

The neural network model that I created was able to classify the test set with a 94.5% accuracy and created a strong foundation for a remote validation model. The optimal hyperparameters were one hidden layer of size 10, a logistic activation function, and the lbfgs solver. Building off of that, the random forest model that I created was found to have a maxdepth of 5 as the optimal parameter and a specificity of 97.9% on the training set. The baseline accuracy that the models needed to outperform was 95.2% and I found that the random forest model I created had a higher accuracy (Figure 6). I then visualized which features had the greatest importance for the optimal model. The features that reduced the GINI index the most were year, month, latitude, and longitude (Figure 7).

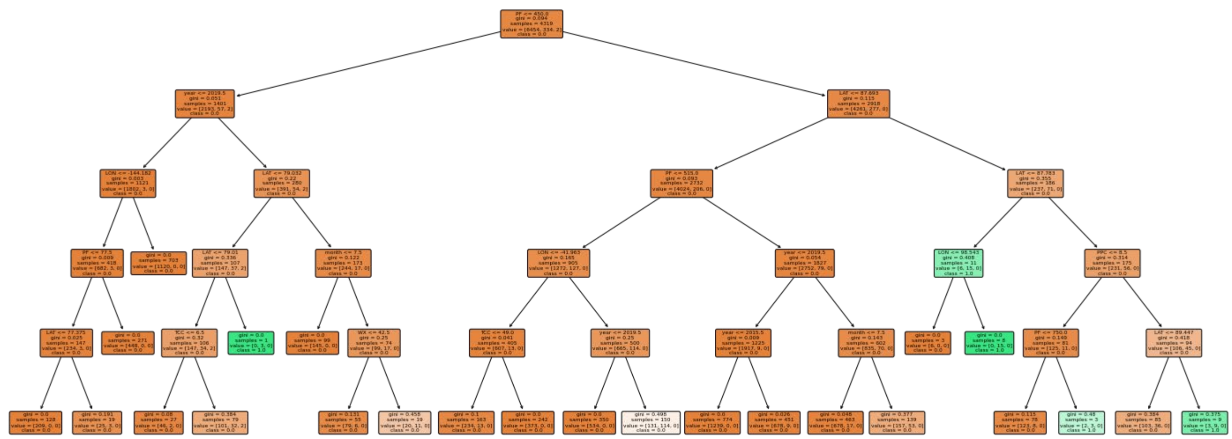

Figure 6. Visualization of the optimal decision tree model. The gradient and color indicates how homogenous the branch is. If the branch is a darker orange it means that the node is not very homogenous for valid data points. If the color of the node is a darker green it means that it is not a very homogenous node of invalid data points.

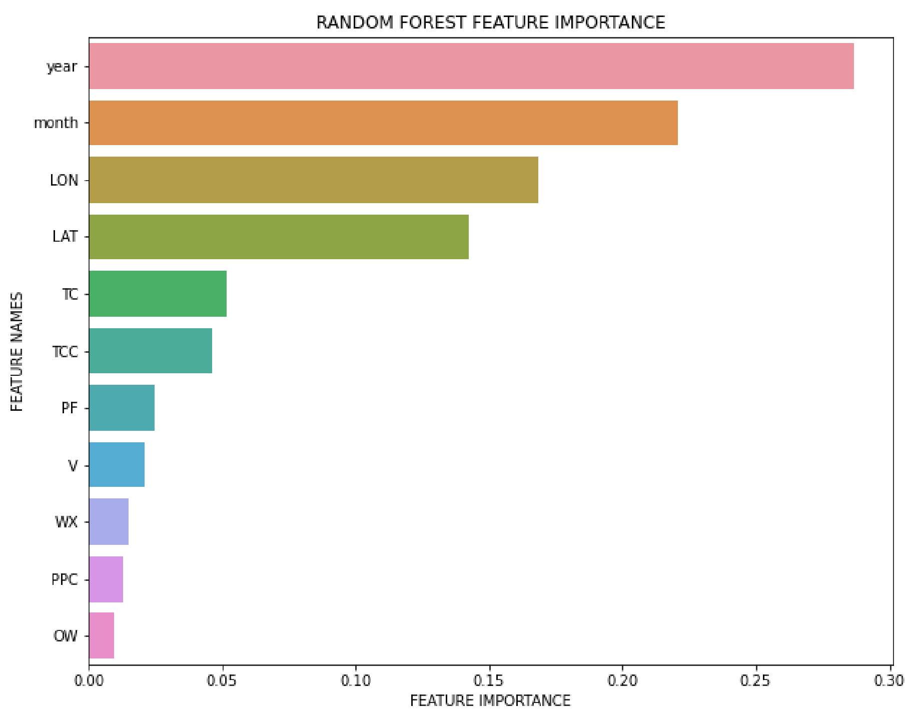

Figure 7. Visualization of the decision tree models feature importance. In the case of the random forest model used this is based on its contribution to lowering the GINI index which is a measure of impurity in each node.

DISCUSSION

This study analyzes the potential impacts of community science data on climate models. While Ice Watch community science data did not have a very robust accuracy in the short term, it had higher applicability when disaggregated. This then extended into a high accuracy for long term trends, which makes the data highly usable and important. After the evaluation of various models, it was possible to create a decision tree model that could predict individual data point validity with a high accuracy. This is promising for applying the Ice Watch data to climate models and increasing the use of community science.

Interpretation of validity of short term Ice Watch data

Analysis of short term sea ice index data from Ice Watch shows that there are significant discrepancies between Ice Watch data and NSIDC data. About 40% of the Ice Watch data points are not within 10% of the NSIDC sea ice index, and so are considered invalid. Seasonally summer numbers tend to be less accurate because of the Ice Watch rating system and the subjectivity of it. The winter numbers tend to be more accurate but there are less measurements. This is not what I initially hypothesized but in the context of how Ice Watch data is collected and the metrics for collection this makes sense. In the Ice Watch data collection process, it only allows integers to be taken as measurements for the total concentration of sea ice. This is also because the concentration is based on observations which will be subject to some bias and inaccuracies.

The high number of invalid data points based on monthly data is concerning for the applicability of data to climate models. While this is not ideal, this does not really affect climate modeling of Arctic sea ice because of the unpredictability of monthly sea ice data (Guemas et al. 2014). The trends in disaggregated and seasonal validity are promising, because there is a much greater accuracy for individual data points. Seasonal data is also more important for the creation of models (Tietsche et al. 2014). So despite monthly errors compared with NSIDC data, there is still applicability because of the accuracy of individual data points (Guemas et al. 2016). Despite having inaccurate data points Ice Watch still provides useful data in a field with many data gaps.

Ice Watch data and long term trends in Arctic sea ice

Ice Watch data accurately reflects long term Arctic sea ice trends. The 16 years of Ice Watch data accurately capture trends in Arctic sea ice when compared with NSIDC data. This is important because long term trends are important in the model building and predictions in Arctic sea ice (Laniak et al. 2013). This data is especially useful since coastal regions have their own complex sea ice dynamics (Overland and Pease 1988). This data can help to bridge gaps in coastal sea ice data and better characterize and utilize these trends in models (Girard et al. 2009). Accurate trends in long term sea ice concentrations near coastal areas is promising, and will help bridge gaps in Arctic sea ice data (Loew et al. 2017). This is promising not only for climate models, but also for better transparency and equity in model creation (Dickinson et al. 2010). Ice Watch can not only engage diverse communities but can help to incorporate and empower communities to have agency over the scientific efforts conducted in their spaces.

Machine learning validation model of Ice Watch data

It is possible to create an accurate machine learning model that can remotely validate Ice Watch data. A high accuracy for validation models greatly increases the usability of data for analysis and trend extraction. One of the best validation metrics that reviewers have found to ensure quality in community science are data mining and other analytical approaches (Wiggins et al. 2011). This model has a high accuracy and employs data mining techniques to extract patterns to determine the validity of data points. In this study, it was found that, year, month, latitude, and longitude are strong correlators for data points that are considered valid. This is helpful because it can be used to give feedback to participants when their data correlates with a high number of invalid data points in any of these categories. It also gives us insights on where and when data collection needs to be more robust to ensure a higher accuracy of Ice Watch data. Since data quality is one of the primary concerns when people discuss the use of community science, validation is an important step in the process (Riesch and Potter 2014). By making these validation metrics specific, it greatly reduces doubts about the data to participants, scientists, funders, and third parties. (Stevenson et al. 2021) It is clear from this that volunteers and community participants can produce high quality data (Kosmala et al. 2016). Data collection devices will only become more accessible as technology advances and this will further augment the data collection process used for Ice Watch data.

Limitations and Future Directions

Some of the limitations of this study include the data from years with covid-19 interferences and the limited amount of data to train the machine learning model on. Because the NSIDC data had a different granularity than the Ice Watch Data there were less data points to train the machine learning validation model on and this impacts the applicability of the algorithm. Another limitation were the metrics used by satellites and the Ice Watch data. Because of the inherent differences in these collection methods, it is possible that some measurements were deemed invalid by the NSIDC data when they reflected ground truth measurements at the time.

There is room to apply this study to other data that is already being collected by Ice Watch. One possibility is using the photos that are taken for each data entry and extracting information from these photos that could be used to bridge data gaps. Additionally, there are other community science efforts in the Arctic that include cloud, marine mammal, and phytoplankton data in the Arctic. This study could also be improved upon by combining metrics to create modified features that might better reflect sea ice measurements. One gap in this research was not examining ice age data, as this is extremely important and this data from Ice Watch should be looked into to determine if it could be used in climate models and trend predictions. All of this data and analysis could be used to further contribute to the use of community science in climate model creation and making the process more just.

Implications and conclusions

Data collection in the Arctic is especially difficult because of the remoteness of the landscape. Community science is one promising possibility for bridging that gap and increasing community participation and narratives. Data collected by boats and individuals who live in the Arctic area can help us to better understand climate change impacts there and the complex dynamics in Arctic sea ice and boundary locations. The most important steps moving forward are not just stimulating the creation of data from communities in an extractive way, but to take Ice Watch to a place where it is actually empowering communities (Stevens et al. 2014). The implications of this project are that community science can generate data for Arctic sea ice that is usable, and now this must be taken down the road of co-creation with communities and broader inclusion and empowerment.

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