Research proposal

Introduction

At the macro level, climate change phenomena such as natural disasters and sea level rise not only affect the ecological environment but also pose physical (the impact of extreme weather on the real economy) and transformational (the impact of changes in policies and technological innovations related to carbon emissions) risks to the global economy. On the other hand, climate change also directly impacts the business activities and investment decisions of financial institutions. On the one hand, with the frequent occurrence of extreme weather, various countries' environmental protection and emission standard requirements gradually increase, limiting the asset flow of enterprises. The solvency of enterprises decreases, thus increasing the credit risk of financial institutions. Also, as the price of carbon emissions rises, falling share prices in high-carbon industries pose liquidity risk. On the other hand, climate change may lead to reduced liquidity of regional assets, and financial institutions may have difficulty obtaining stable funding sources due to changes in market conditions. Financial institutions will also face losses if the frequency and severity of future disasters cannot be predicted more accurately.

S&P Global was founded in New York City from New York in 1917, and it is an organization that utilizes business intelligence technology to make data-driven decisions. S&P Global is operated in the following six markets: S&P Global Rating, S&P Global Market Intelligence, S&P Global Dow Jones Indices, S&P Global Commodity Insights, S&P Global Mobility, and S&P Global Engineering Solutions. And the company currently owns a diversified portfolio of companies by executing acquisitions, which compose a strong brand portfolio for the company. In 2022, they acquired IHS Markit and The Climate Service, both information providers in the industry. Also, the company owns a solid free cash flow, so they are resourceful in executing new acquisitions or mergers. S&P Global's main competitors, fellow credit rating agencies Moody's and Fitch Ratings, have now made the performance of countries and companies in addressing climate change an essential factor in their credit ratings. In 2021, following the first climate vulnerability scores for the utilities, oil and gas, and chemicals sectors, Fitch Ratings extended the system to all corporate sectors globally. In addition, we have conducted an in-depth study of S&P global through SWOT analysis.

S&P global has a diverse range of strengths that contributed to its leadership position in its industry. The first strength is that the company has a diverse product portfolio such as S&P Global Ratings, S&P Global Market Intelligence, S&P Dow Jones Indices and S&P Global Platts etc. Also, S&P Global has a great brand value. It continuously acquires new customers as well as builds profitable relationships with both loyal and new clients.(S&P Global net worth as of October 05, 2022 is $107.27B). The third strength is its successful acquisition. S&P Global has Integrated number of information and technology companies in the past few years to streamline its operations and to build a reliable supply chain. Its most recent completion of their approximately $140 billion merger with IHS Markit signals the suite of offerings will expand to include those of Financial Services.

While the Weakness that S&P Global can improve upon are its relying on several main traditional products to create revenue and lack of investments in R&D. Most profits of S&P Global come from products such as S&P Global Market Intelligence and S&P Dow Jones Indices. It will be helpful if S&P Global invests more in R&D to develop various and more innovative products. Also, Days inventory is high compared to the competitors, which may impact long-term growth

The changing world provides many opportunities for S&P Global. One of the opportunities that related to our project most is investing more in climate-risk consulting. Many companies now realize the transitioning to a low carbon economy is essential for a sustainable future. Climate-risk consulting is still a blue ocean market that can bring S&P Global new opportunities. The second opportunity will be the investment in research and new products development to retain customers. S&P Global can take advantage of new consumer behavior trends to open up new markets, build new revenue streams and diversify into new product categories. The third opportunity will be acquiring and Integrating other business or market expansion. For example, S&P Global could track consumer behavior to help companies improve its loyalty marketing efforts, and develop better pricing strategies through personalization.

While threats S&P Global is now facing are the new products with competitive pricing and instability in the global markets: Trade Relation between US and China, Brexit impacting European Union, overall instability in the middle east can affect S&P Global growth plans.

As the technology developed today, machine learning models which used higher resolution satellite images started to become popular. It gets easy to notice the surface landscape and the atmosphere's changes by reviewing the data sent back from NASA. And the accuracy becomes increased which supports a time-series modeling in the future by focusing on the daily, monthly and yearly trend. The direct visualization of heat maps can also be produced based on different regions to give out a comparison of models. Based on the variety of satellites and models used, it is important to know the optimize model for different surface areas. To specify the detailed methods and data that are introduced in this paper:

In this project, MODIS data and output of GCMs covered by NEX GDDP from 2000 to 2020 are adopted to quantify the differences on observable satellite data (such as, daily mean of the near-surface air temperature, land surface temperature) by plotting RMSE for each GCM, locating the outperforming GCM by comparisons on 4 regions across the world. Furthermore relationships between specific regions' climate and its impact on models RMSE will be illustrated and analyzed, such as the variety results between mediterranean climate or temperate continental climate.

Methods

Data Description

There are two data sources used for this project. The first one is NASA's Moderate Resolution Imaging Spectroradiometer, which uses Terra Satellites, which orbit around the Earth, to collect and acquire data through images and output in 36 different spectral bands, reflecting the daytime , nighttime surface temperatures and emissivity. For the purpose of this project, we are using just the daily temperature band to access the temperature data. The second one is NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP), which are the climate simulation datasets generated from the General Circulation Model (GCM) with four greenhouse gas emissions scenarios, and this project focuses on the two of them: SSP 126 and SSP 585. SSP 126 scenario is based on the concept of minimizing material resource and energy usage. SSP 585 scenario is based on the concept that economic development is based on an intensified exploitation of fossil fuel resources with a high percentage of coal and an energy-intensive lifestyle. In terms of overall data quality, there are missing values of over 1000 rows in MODIS data. The Quality flag is embedded in the MODIS data, which can be used to filter the low quality data.

Data Variables

time: 2015/1/1 - 2020/12/31

lat: latitude

lon: longitude

tas: Daily Near-Surface Air Temperature in [K] or [ºC].

tasmax: Daily Maximum Near-Surface Air Temperature in [K] or [ºC].

tasmin: Daily Minimum Near-Surface Air Temperature in [K] or [ºC].

hurs: Near-Surface Relative Humidity in [%].

huss: Near-Surface Relative Humidity in [kg/kg].

CA: California State, USA [300*300 km in -120.146, 36.258 to -117.037, 39.271]

AU: Australia [600*600 km in 141.442, -37.664 to 147.595 to -31.669]

Model Names: NEX_CanESM5, NEX_CMCC-ESM2, NEX_UKESM1-0-LL, NEX_TaiESM1, NEX_INM-CM4-8, NEX_NorESM2-MM

Method Overview and Steps

In this data analysis process, our main research direction is to estimate the performance (accuracy) of the predicted values of the model by calculating the RMSE. For ssp126 and ssp585, we selected two sites and six models for comparative analysis. We very much want to know what their specific performance is. In this case, we will first do data processing to get the date of the change, latitude and longitude, a subset of the surface temperature, but we will only use the geographic location and temperature data.

Data Selection

Let's have a preview of the extracted data, which consists of 26 columns, including date, longitude, latitude, temperature in multiple regions, city location, etc. Of these variables, all are variables except the date which is not a variable. We prioritized the time range, we chose data between 2015 and 2020, to ensure the accuracy of our analysis, we didn't want data that was too long ago, for geographic locations, we chose California and Australia, their dry season and The rainy seasons all have distinct characteristics, which can make our analysis results clearer. Based on these two characteristics, we selected data from California and Australia in the past 6 years. The data we need to prioritize and obtain is: the monthly average temperature of the 25km*25km area. After filtering and processing, for CA's dataset, there are a total of 12 longitudes, 13 latitudes and 2190 days, which means we have 340,000 temperature data. For the AU dataset, there are 24 longitudes and 24 latitudes and 2190 days in total, and there are 1.26 million pieces of temperature data.

Missing Value Imputation

We can observe that there are many missing temperature values. Because this is the daily average temperature, our solution is to fill in the null value of the temperature observed on the previous day, which is equivalent to taking the average value, which will not make the final monthly average temperature vary too much, and will also reduce bias from the subsequent calculation of rmse.

Monthly Aggregation

After filtering and cleaning the data, we need to merge the daily average surface temperature data into monthly average surface temperature data. According to the time series method, we have reordered this and added a new colomn (monthly average temperature), which will help us make subsequent time series charts and make these changes more intuitive and clear.

RMSE Calculation

After we extract the monthly average temperature for both the MODIS data and NEX models over the terms of six years, we will perform the RMSE calculation with the following codes to quantify the differences between NEX models and the MODIS data, which was downloaded from the satellite. As shown below, the 'actual' variable will be the data frame from MODIS, which includes the aggregate monthly average temperature from 2015-2020 and the 'predict' variable will be the data frame from various NEX models, which includes the predicted aggregate monthly average temperature from 2015-2020. Then we will get the result of RMSE of the chosen model after applying the function.

After having the outputs of RMSE from various models, we will use this as one of the criterias to decide which model is the best-performing one since the RMSE measures the magnitude of error between each NEX model and the MODIS data. The lower the RMSE is, the more accurate the corresponding model is. Moving on, we will evaluate the RMSE for each model in each scenario to evaluate the model.

Citation

"S&P Global Completes Merger With IHS Markit, Creating a Global Leader to Power the Markets of the Future." *S&P Global*, investor.spglobal.com/news-releases/news-details/2022/SP-Global-Completes-Merger-with-IHS-Markit-Creating-a-Global-Leader-to-Power-the-Markets-of-the-Future. Accessed 13 Oct. 2022.

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