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Cloud-Based Remote Sensing and Analysis of Vegetation Cover Changes in Key Regions of Oceania

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Abstract: The main objective of this research is to use cloud platforms to conduct a shallow survey of vegetation cover variations in Oceania. It is well-known that compared with the northern hemisphere, Oceania has a more unique ecosystem. The geographic position of Oceania is close to the equator. Therefore, the climate of some regions in Oceania is warm and has full precipitation, which is different from that in the Northern Hemisphere. This considerably influences changes in vegetation cover and makes comprehending vegetation cover tendency important for environmental protection measures. The change in vegetation cover from 2015 to 2022 was analyzed using cloud technology and remote sensing data. My findings mainly include the expansion and reduction of vegetation cover in major regions of Oceania. These results provide valuable insight into the dynamic properties of Oceanian ecosystems. This study contributes to a deeper understanding of the ecological environment in Oceania and highlights the potential of cloud platforms in remote sensing and ecological monitoring. These findings have important implications for environmental policies, biodiversity conservation, and sustainable resource management in the region.

Keywords: Cloud platform, Vegetation cover change, Remote sensing data, Ecological environment.

1. Introduction

Since the successful launch of the first US weather satellite in 1960, Remote Sensing(RS) technology has developed rapidly, and the Earth orbit is full of a variety of Earth observation satellites on a global scale. Mankind has accumulated historical remote sensing data for nearly half a century. Meanwhile, with the rapid development of human civilization, the global ecosystem has been greatly damaged due to human activities such as deforestation, industrial emissions, and the overutilization of water resources. These have resulted in various environmental variations including temperature, vegetation, snow cover, and atmosphere. All of them have been recorded as data products by the National Aeronautics and Space Administration (NASA) through RS technology. They are available on some cloud platforms such as Google Earth Engine (GEE). Therefore, the users can use these data products to detect any change related to the ecosystem all around the world. Considering the ever-increasing concern about the variation tendency of vegetation cover all over the world, the objective of this research is to use the RS data product “MOD13A2.061” provided by Moderate Resolution Imaging Spectroradiometer (MODIS) in GEE to investigate the dominating variation inclination of vegetation cover in the primary region in Oceania. I chose the Normalized Difference Vegetation Index (NDVI) in the data product as my research focus. It contains information on vegetation greenness, coverage, and health conditions. I also use some algorithms to generate results such as line charts so it can provide some insight related to the main change of NDVI in the region I chose.

2. Related Work

2.1. Review on RS and cloud computing

In recent years, there has been an ever-increasing concern about how RS datasets can be used easily to detect the situation of natural hazards and ecosystems. In terms of natural hazards, various researchers (Wang et al., 2018) developed a cloud platform called “pipsCloud”. It combined the latest cloud computing and High-Performance Computing techniques to provide a real-time RS data processing system. In this way, they could detect the condition of forest fire and coastline variation more effectively. Particularly, many RS applications require real-time managing ability, such as monitoring large-scale debris flow and ocean oil spills. As it relates to this aspect of the ecosystem, geographists and engineers (Sagan et al., 2020), suggested a more efficient approach to predict water pollution such as algal blooms, and used multi-sensor data fusion in cloud computing to estimate the main indicators of water quality. There is also some research related to the variation of global climate. Considering the impact factor of the global lockdowns that have been adopted to tackle the outbreak of Corona Virus Disease in 2019 (COVID-19), Researchers (Singh et al., 2021) used cloud computing combined with RS supported by Google Earth Engine to create a test platform for climate sensitivity experiments and validation of chemistry-climate models. They found that the coincident variation over most metropolises suggests a strong relationship between declining air pollution and the compulsory lockdowns of COVID-19.

2.2. Review on Whittaker Smoother Method

With the rapid development of science and technology, graphical data analysis methods have gradually become the primary data analysis approach in various fields. However, several problems result from this. Some images such as line charts, have a large fluctuation between extreme values, resulting in poor visualization. Therefore, an advanced method called Whittaker Smoother was introduced to tackle this problem. In the medical domain, a researcher (Cobas, 2018) discovered important applications of Whittaker Smoother in nuclear magnetic resonance (NRM) spectroscopy. It was key in the improvement of graphical representation in NRM. There are also some applications in the biological field, researchers (Chen et al., 2014) aimed at evaluating the quality of corn through infrared (FT-NIR) spectroscopic analysis. Whittaker Smoother is an appealing alternative to traditional data preprocessing methods. It can efficiently help researchers prioritize improvements to modeling results. The Whittaker Smoother Method is also applied to the improvement of Geographical images. Given the fact that the Sentinel–Landsat Normalized difference vegetation index (SL-NDVI) can be easily influenced on rainy, cloudy, and snowy days, the generated optical images have instabilities and inaccuracies. Researchers (Liang et al., 2023) used this algorithm to reduce residual noise in the SL-NDVI time series. That is also the method I use in this research. The data of NDVI in some regions has huge fluctuations so it cannot display the main inclination of local vegetation cover. I employ the Whittaker Smoother Method to narrow down the big gap between extreme points. Therefore, the improved line charts provide better insights into its tendency.

3. Solution

3.1. Solution Design

To investigate the dominating variation inclination of vegetation cover in the primary region in Oceania, I found an excellent reference method on a website called CSDN (http://t.csdn.cn/YD1i7). In step one, I imported the ee module for interacting with Google Earth Engine, gained access to it, and proceeded to its initialization. Next, I imported the Google Drive module of Google Colaboratory (Colab) to connect to the Google Cloud drive so that all my experimental data could be stored in Google Cloud. Colab is a convenient platform that provides a cloud-based Jupyter Notebook environment that enables users to create and run Python code easily. This environment includes commonly used machine learning libraries such as NumPy, Pandas, and Matplotlib which users do not need to install and configure by themselves. It is tightly integrated with Google Cloud services, making it easy for users to import and export data to services such as Google Cloud Storage. Lastly, to gain the data of NDVI in different regions appropriately, I imported the Geemap library for interactive map visualization and geospatial data analysis on Colab, which enables users to get point data by clicking on the map with a mouse.

As for step two, I first created an interactive Map object and imported the data product MOD13A2.061, setting observation time from 2015 to 2022 and selecting the NDVI indices. Next, I added layers to the map to display the MODIS NDVI time series and its visualization results. Lastly, I set plotting options for adding marker clusters and markers to the map so that I could obtain my experimental data easily.

In step three, Because Geemap can record all the points clicked by the user, I set the path to output the CSV files and extract numerical data from maps to CSV files. However, since the visualized NDVI variation line chart shows extensive fluctuations for some time series, the major tendency of NDVI change is less than clear, which can have a negative influence on research results. I found a mathematical method called the Whittaker Smoother Method on a blog (http://t.csdn.cn/ZMCWE). It can smooth the set of time series images and return a new set of time series images. The corresponding function treats the data as constituent data and preprocesses it. Then, it computes the difference matrix of a given order and performs matrix operations, generates a smoothing coefficient image, and solves the linear system between the smoothing coefficient image and the original array image. Finally, the function reassembles the smoothing image set. After using this function, I can easily observe the main change of NDVI in different areas, which is greatly beneficial to my research.

In the last step, to present a better visual effect, I used a method available online (http://t.csdn.cn/YD1i7) to draw line charts that have 2 lines. One line represents the raw NDVI and the other line represents the smoothed NDVI. The original method I found online cannot detect a value that is below zero. When NDVI is less than 0, it usually indicates that the selected point may be non-vegetation areas such as water bodies and urban buildings. This is because of the factors of human activities such as urban development. Areas with NDVI less than 0 are generally not suitable for applications requiring healthy vegetation such as agriculture, forestry, or ecosystem restoration. Therefore, the data points that are less than 0 are not significant as they relate to my research. I improved this method so that it can detect abnormal data. Next, I replaced the smoothed NDVI line with red dots. They indicate the location of the outlier so I know that I cannot use this point data to generate my final result.

3.2. Solution Implementation

I chose the cloud as the main digital solution technology for my research. Google Earth Engine provides many data products that are available to users. These data sources were created by NASA (https://lpdaac.usgs.gov/products/mod13a2v061/), which has reliable technology to obtain related data. The MODIS provides excellent accuracy and reduces the error in vegetation index(VI) to ±0.025. This level of accuracy requires data from high-quality observations, that is, the observation conditions need to have the characteristics of clear, no subpixel cloud occlusion, and low aerosol. To ensure this high-quality accuracy, NASA uses a variety of methods for data validation and correction. First, they contrast the data acquired by the MODIS sensor with data from other spatial and airborne sensors. In addition, a series of biome and seasonal radiation field measurements are performed. These comparisons and measurements ensure the accuracy and reliability of the MOD13A2.06 product. The MODIS vegetation index is derived by retrieving the daily bidirectional surface reflectance after atmospheric correction. The generated vegetation index data has a time interval of 16 days, and low-quality observations can be removed by using a specific MODIS synthesis method. In the following processing, the restricted view Angle method is applied to select a pixel from the high-quality VI values to represent the synthesis period. This selection process is based on the comparison of the two highest NDVI value pixels, and finally, the pixel close to the lowest point is selected.

I undertook this project to inform ordinary people in various countries about the changes in the vegetation cover of the areas where they live. This helps raise awareness of climate change, the state of the environment, and ecosystem health. Besides, I am quite interested in the ecosystem of the Southern Hemisphere which may be much better than that in some developing countries in the Northern Hemisphere, owing to their large population.

This project can be used anytime when people want to learn more about the ecosystem they are tightly connected to (see details at https://github.com/123111222/GEE_Cloud-computing.git). It provides further insight into the variation of vegetation cover for local people living in the major regions of Oceania who may lack related data access. Especially in eastern Australia, from late 2019 to early 2020, a large-scale hill fire burnt a huge amount of vegetation, which had a negative influence on local ecosystems. The fire produced a variety of greenhouse gases, which certainly enhanced the surrounding greenhouse effect. The temperature went up as a result and led to burned vegetation that was difficult to recover in a short time. This disaster can raise environmental protection awareness for both citizens and authorities. Local governments must take action and publish related laws to avoid this kind of natural hazard.

Overall, whether people are in Australia, New Zealand, the Pacific Islands, or any other Oceania region, they can use the tools mentioned above to understand the state of local vegetation. This contributes to better participation in environmental protection, sustainable development, and climate action.

4. Research Problems

4.1. The drawbacks of using the Whittaker Smoother Method

Due to large fluctuations in some NDVI line charts, I used the Whittaker Smoother Method to narrow down the gap between extreme points. However, there are some disadvantages to using this approach. Although this algorithm can make the tendencies more obvious in some time series, it is less appropriate in the case of datasets with extreme outliers. These outliers can have an important impact on results smoothing, resulting in inaccuracies in the smoothing curve. Because the Whittaker Smoother Method achieves the smoothing effect by minimizing the second derivative of the smoothing, outliers have a large effect on the second derivative, thereby introducing undesirable oscillations or offsets in the smoothing process.

4.2. The limitation of partial point data

I chose the whole of Oceania as my research object. It is a huge geographical scope that contains multiple countries and various ecosystems. Surveying changes in vegetation cover across this wide range is a very complex task. Hence, I had to make trade-offs and choices as part of my research. I selected partial data points for these cities or regions to represent their vegetation changes. Although these data points are limited in number, they can serve as indicators of changes in vegetation across the region, providing the most fundamental insights.

4.3. Seasonal Factors

NDVI contains information on vegetation greenness, coverage, and health conditions. All of them can be influenced by various factors such as air temperature, solar illuminance, and soil quality. These impact factors have variations with seasons. The rise and fall of temperature can affect the growth rate and seasonal growth cycle of plants. In warmer seasons, plants are generally easier to grow and have higher coverage. Sunshine duration and light intensity also have an important impact on plant photosynthesis and growth. Longer daylight hours and stronger sunlight generally encourage vegetation growth. Lastly, seasonal changes can influence soil quality and nutrient availability, which greatly affects plant growth. However, I did not consider these seasonal factors so my results are inaccurate to that extent.

5. Result and Conclusion

5.1. Eastern Australia

I chose Sydney in New South Wales and Brisbane in Queensland as representative cities of eastern Australia. As shown in the line diagrams below, <Figure1> describes the variation of NDVI between 2015 and 2022 in Sydney. It displayed a decline from 2015 to 2020 and reached its bottom in 2020. That was because the time from late 2019 to early 2020 was considered one of the worst bushfire seasons in Australia's history. Many areas have suffered widespread fires, destroying millions of hectares of forest and grassland, especially in New South Wales. After that, the vegetation cover in this area has gradually recovered. Besides, <Figure2> shows the change in vegetation cover in Brisbane. It is obvious that the value of NDVI is much higher than that in Sydney, both its minimum and maximum. This phenomenon can be explained by the difference in their population and climate type. Brisbane had 2.28 million residents by 2019 but Sydney had 5.312 million citizens which was almost twice as many as Brisbane. This means that more human activities may harm the environment in Sydney, leading to its lower NDVI. Additionally, the climate type in Brisbane is a Subtropical humid climate, which cannot be influenced by monsoons as compared with Sydney's. This means its precipitation was more stable.

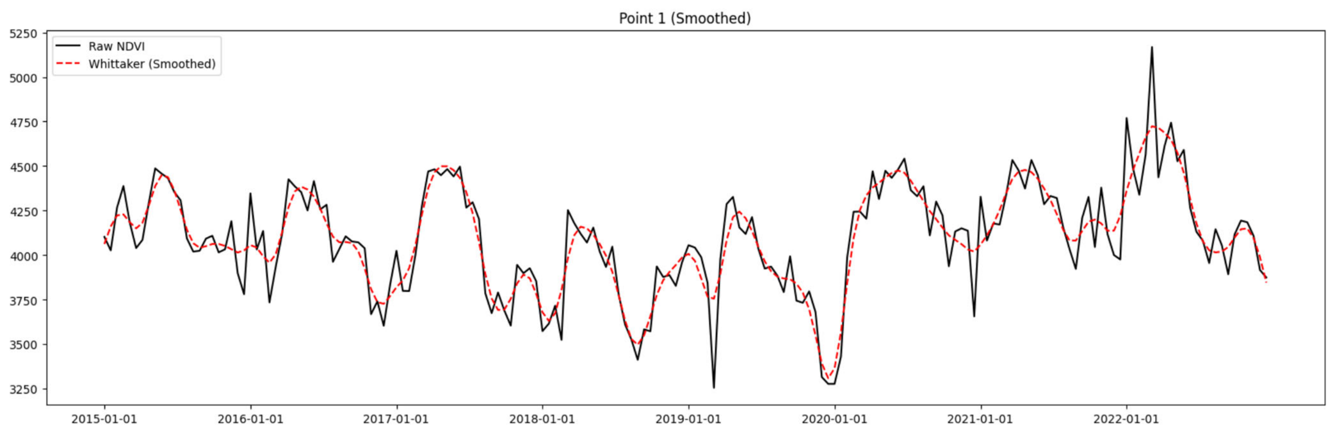

Figure 1. Variation of NDVI IN Sydney

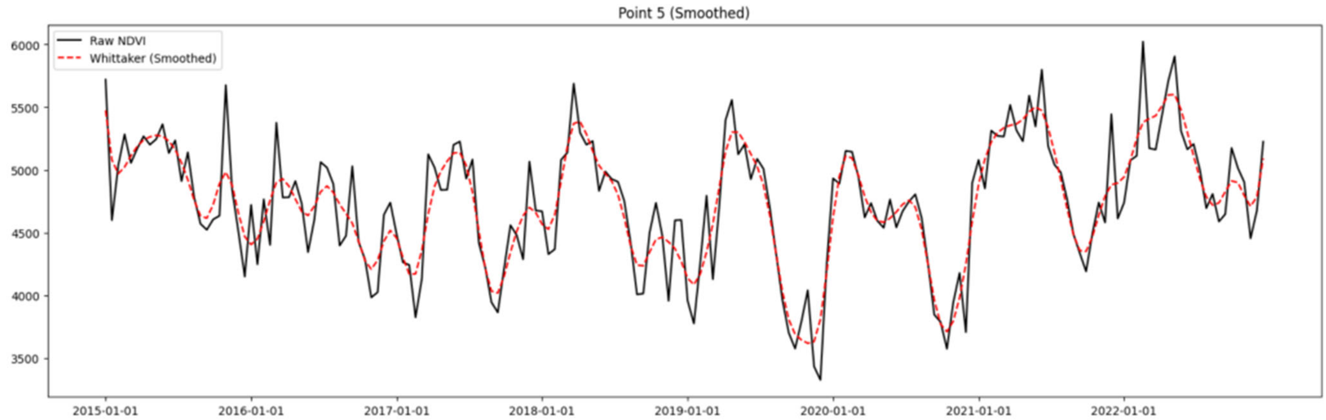

Figure 2. Variation of NDVI IN Brisbane

5.2. Western Australia

The western region of Australia is mostly covered by deserts and the key influence factor is rainfall. Therefore, the Great Sandy Desert and Victoria Desert were selected, as well as their rainfall distribution. <Figure3> illustrates the variation of NDVI in the Great Victoria Desert and <Figure4> represents the same in the Great Sandy Desert. It is evident that both of these regions had a dramatic drop from 2019 but their vegetation cover gradually recovered in 2020 and 2021 respectively. I visited the Australian National Bureau of Meteorology website (http://www.bom.gov.au/) to search for the rainfall since 2019. As shown in the <Figure5>, <Figure6>, and <Figure7> diagrams and compared to 2018, the rainfall in 2019 had a considerable decline which almost approached to “lowest on record”. After 2019, the rainfall in these two regions gradually increased, leading to a rise in NDVI.

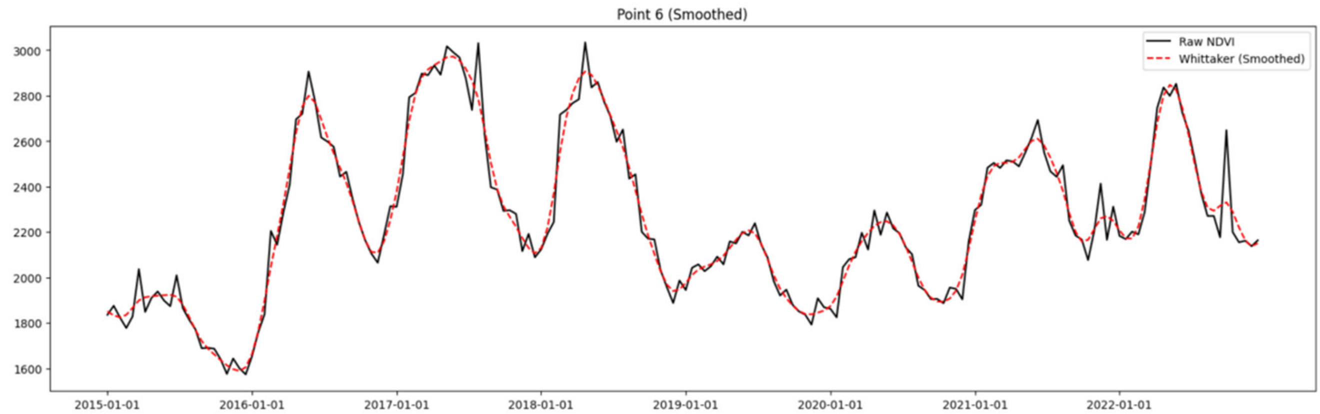

Figure 3. Variation of NDVI IN The Great Victoria Desert

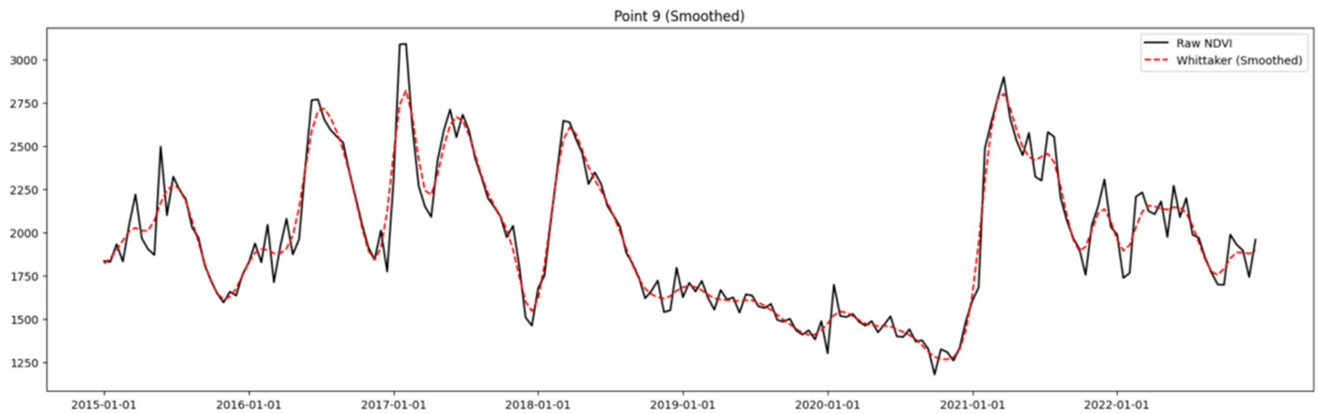

Figure 4. Variation of NDVI IN The Great Sandy Desert

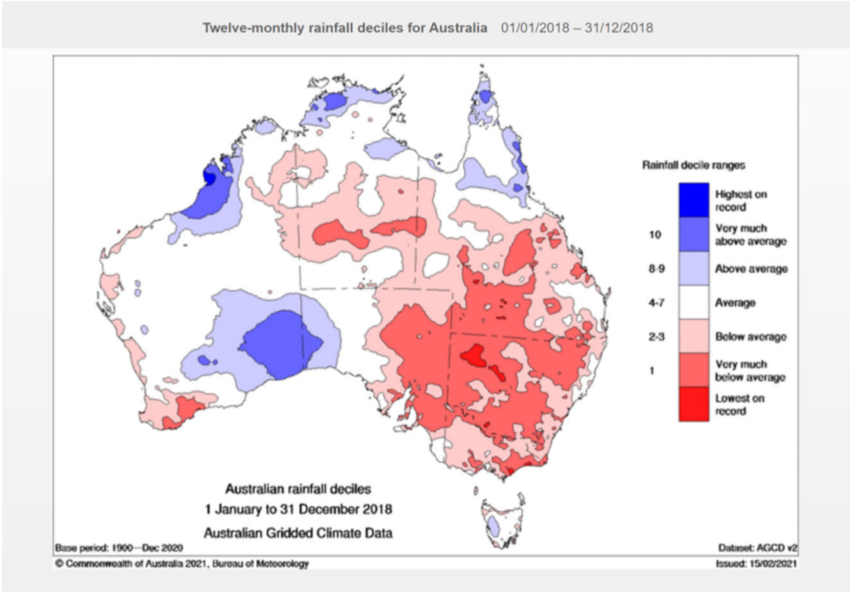

Figure 5. Twelve-monthly rainfall deciles for Australia in 2018

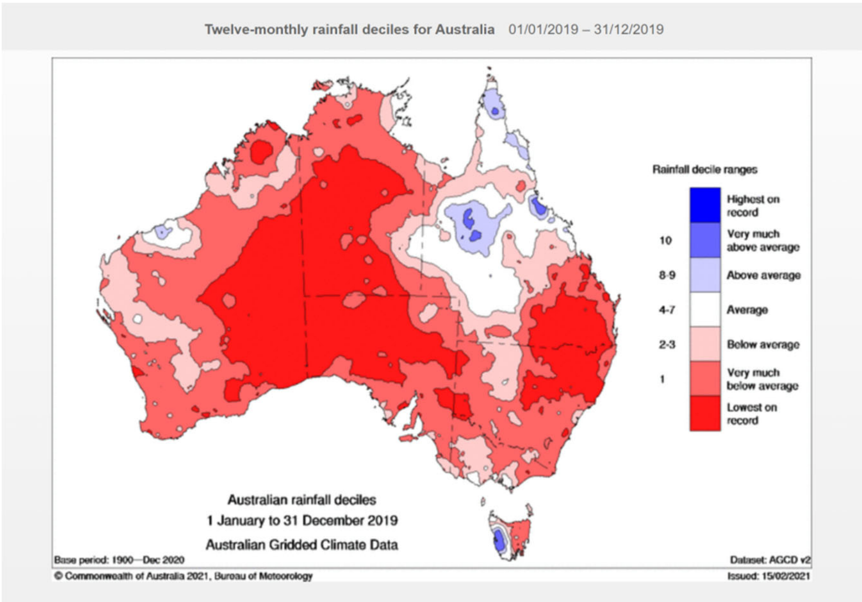

Figure 6. Twelve-monthly rainfall deciles for Australia in 2019

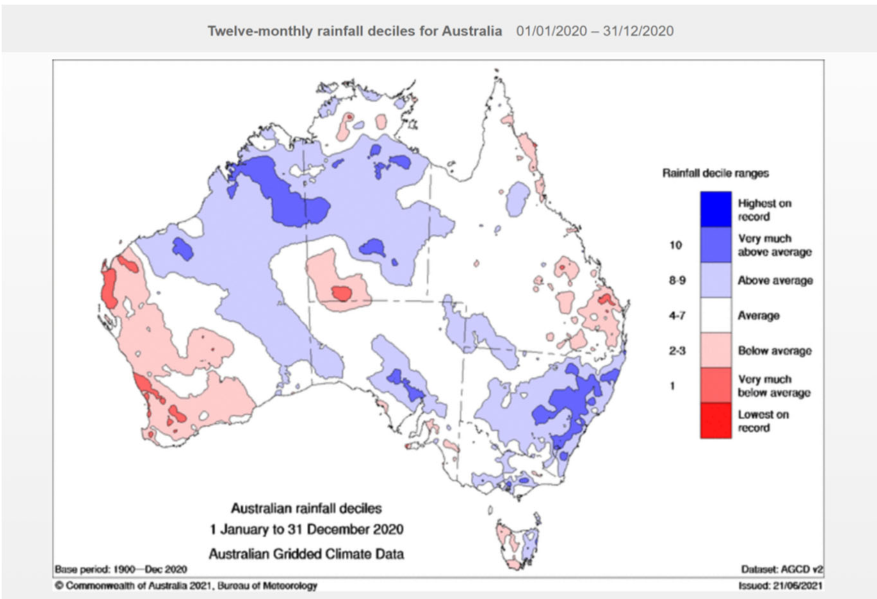

Figure 7. Twelve-monthly rainfall deciles for Australia in 2020

5.3. Major cities in New Zealand

Wellington and Christchurch were selected as representatives of the north and south islands in New Zealand respectively. <Figure8> illustrates the variation of NDVI in Wellington and <Figure9> represents the same for Christchurch. The maximum of their NDVI is the highest one among the other regions in Oceania. It means that the ecosystem of New Zealand is much better than that of Australia and so on, mainly owing to their special climate type "temperate marine", which has full precipitation and moderate temperature all year round. As is shown in the first diagram, the change in vegetation cover is more stable and it has a much higher NDVI value compared to the second chart. This is because Wellington had 212,700 residents but Christchurch had 381,500 citizens by 2017, leading to a more abundant vegetation cover.

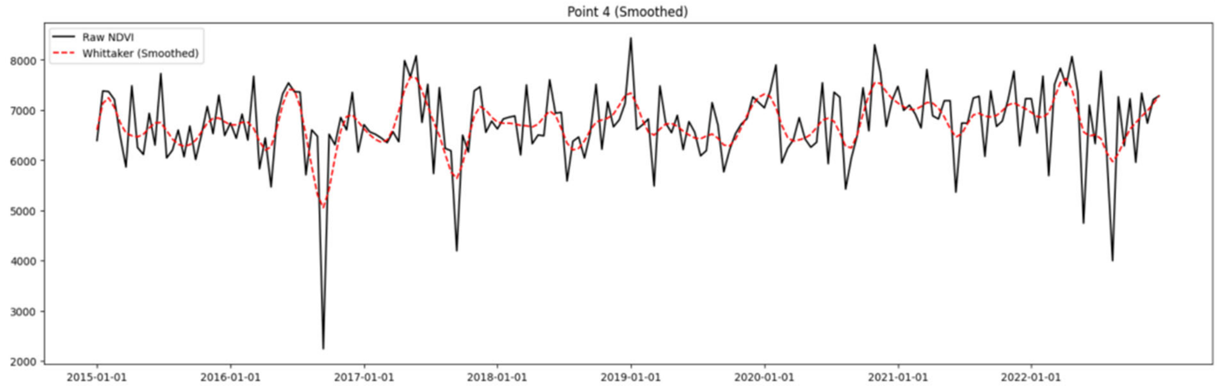

Figure 8. Variation of NDVI IN Wellington

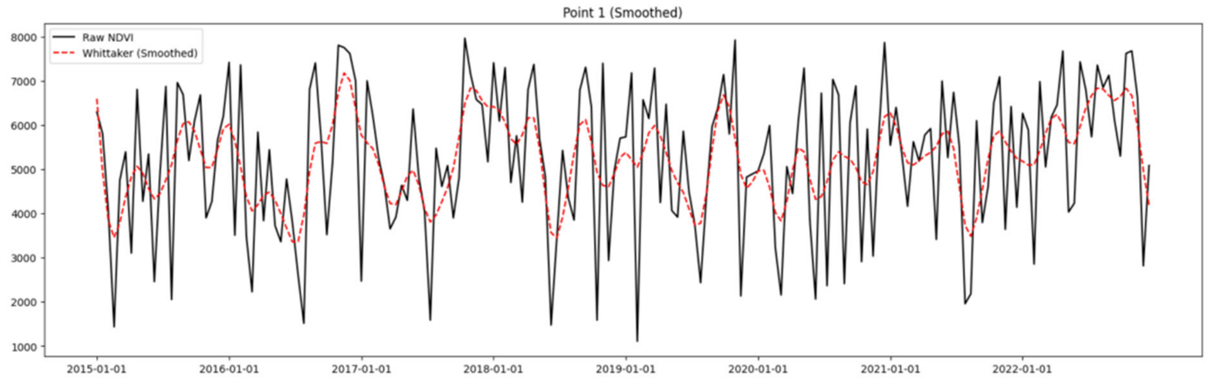

Figure 9. Variation of NDVI IN Christchurch

5.4. Some regions have small acreage

Since there are various small islands in Oceania, I selected the two most famous cities namely Jayapura in New Guinea and Suva in Fiji. <Figure10> illustrates the variation of NDVI in Jayapura and <Figure11> represents the same in Suva. Both of them had a very stable vegetation cover from 2015 to 2021, benefiting from their special climate type which is Tropical Rainforest Climate and Tropical Marine Climate. Both of them have full rainfall all year round. However, Suva has a much higher NDVI than Jayapura, because Suva has 93970 citizens but Jayapura has 315872 residents which leads to more human activities and lower vegetation cover.

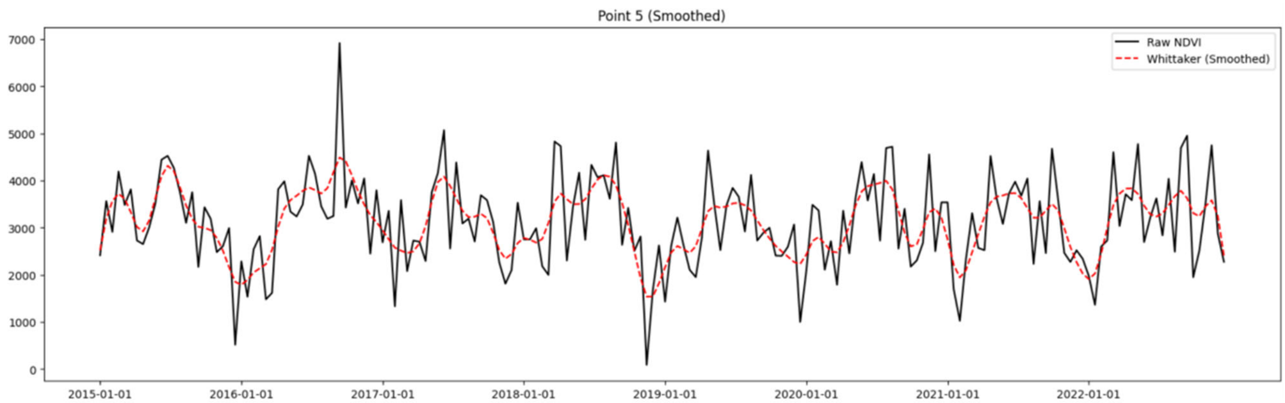

Figure 10. Variation of NDVI IN Jayapura

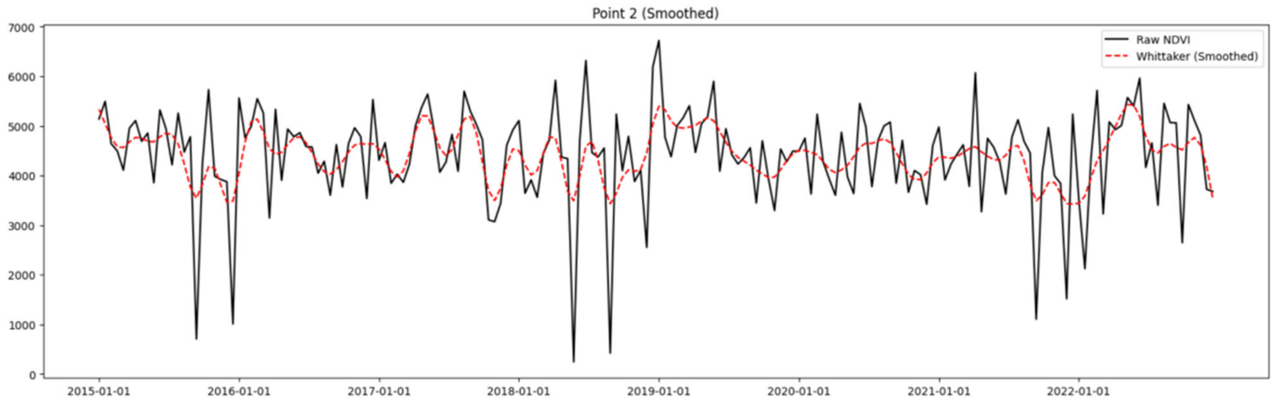

Figure 11. Variation Of NDVI IN Suva

6. Conclusion

In conclusion, this research utilized cloud platforms to conduct a shallow survey of vegetation cover variations in partial regions of Oceania, focusing on the dominant changes observed from 2015 to 2022. The study employed the RS data product "MOD13A2.061" provided by MODIS through Google Earth Engine, focusing on NDVI as a key indicator, and used the Whittaker Smoother Method to enhance the visualization of vegetation trends.

The study's contribution lies in providing valuable insights into the dynamic properties of Oceanian ecosystems, enhancing our understanding of the ecological environment in the region. It highlights the potential of cloud platforms in remote sensing and ecological monitoring, emphasizing their significance in environmental policies, biodiversity conservation, and sustainable resource management.

In general, this project is a valuable and essential tool for residents in Oceania to comprehend environmental protection, sustainable development, and climate variation. It also increases awareness of natural hazards' impact on the local ecosystem. The presented results contribute to the global effort to monitor and protect our environment for a sustainable future.

References

[1] Wang, L., Ma, Y., Yan, J., Chang, V., & Zomaya, A. Y. (2018). pipsCloud: High-performance cloud computing for remote sensing big data management and processing. Future Generation Computer Systems, 78, 353-368.

[2] Sagan, V., Peterson, K. T., Maimaitijiang, M., Sidike, P., Sloan, J., Greeling, B. A., ... & Adams, C. (2020). Monitoring inland water quality using remote sensing: Potential and limitations of spectral indices, bio-optical simulations, machine learning, and cloud computing. Earth-Science Reviews, 205, 103187.

[3] Singh, M., Singh, B. B., Singh, R., Upendra, B., Kaur, R., Gill, S. S., & Biswas, M. S. (2021). Quantifying COVID-19-enforced global changes in atmospheric pollutants using cloud computing-based remote sensing. Remote Sensing Applications: Society and Environment, 22, 100489.

[4] Cobas, C. (2018). Applications of the Whittaker smoother in NMR spectroscopy. Magnetic Resonance in Chemistry, 56(12), 1140-1148.

[5] Chen, H., Ai, W., Feng, Q., Jia, Z., & Song, Q. (2014). FT-NIR spectroscopy and Whittaker smoother applied to joint analysis of duel components for corn. Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy, 118, 752-759.

[6] Liang, J., Ren, C., Li, Y., Yue, W., Wei, Z., Song, X., ... & Lin, X. (2023). Using Enhanced Gap-Filling and Whittaker Smoothing to Reconstruct High Spatiotemporal Resolution NDVI Time Series Based on Landsat 8, Sentinel-2, and MODIS Imagery. ISPRS International Journal of Geo-Information, 12(6), 214.