South-to-South Cooperation in Multi-Source Satellite Data for Improving Food Security

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Abstract

This study aims to highlight the importance of south-to-south cooperation in remote sensing and present preliminary results from our joint project between China and South Africa, focusing on multi-sensor remote sensing data for food security. Scientometric analysis was used to demonstrate growing research output and cooperation among countries in the Global South. Furthermore, the first results of our crop classification methods were presented on a test site in the Sanjiang Plain, China. The preliminary crop classification results from this test site showed promising accuracy. South-to-south cooperation in remote sensing has the potential to address shared challenges and promote sustainable development through exchange of knowledge and resources. The ongoing joint project between China and South Africa demonstrates the benefits of such collaboration in developing robust remote sensing techniques for improved food security monitoring and decision making in the Global South.

1. Introduction

South-to-south cooperation is, as an expression, based on the non-alignment movement during the Cold War period (Weber and Winanti, 2016). Recently, there was an increase in the importance of south-to-south cooperation, which is related to the rise of China (Boer, 2019; Yu, 2020), Asia in broader terms, and other parts of the Global South. In this context, and within this paper, Global South is defined according to (Mahler, 2017) as a term that does not denote a geographic location but is used to describe regions that have been historically dominated and/or negatively affected by capitalist exploitation and/or racial discrimination. Within this definition, China is included in the Global South, as is the case with, e.g., South Korea. This definition is not without criticism, though (Haug and Maihold, 2021).

Within the geopolitical changes that are defined by the following: (i) increased competition between the USA and China (Wyne, 2022), (ii) decoupling between China and the USA and Western Europe, and (iii) fortification of borders and restrictions of open trade between the Global North and the Global South, south-to-south cooperation is becoming increasingly important (Ikenberry, 2024). Furthermore, with the increasing relative economic power of not only China, but also many more Global South countries and the resulting increased trade between the Global South (Diko and Sempijja, 2021), a deepening of relations, including scientific cooperation, is an obvious trend.

Additionally, although countries in the Global South vary significantly in terms of economic development, political systems, traditions, culture, geographies, and so on, they frequently face similar issues. Food security is one of these issues. Being threatened by global change ensuring food security is high on the agenda of many Global South countries, including China and South Africa, which is the focus of our work.

It is well known, at least within the community, that remote sensing plays an important role in improving food security. In this context, there is collaboration in the Sino-South African project on "Earth observation and ground-based monitoring applications for crop food security in China and South Africa."

This paper will introduce the importance and relevance of south-to-south cooperation in remote sensing, introduce the project on "Earth observation and ground-based monitoring applications for crop food security in China and South Africa," and show first results. Scientometric analysis was used to demonstrate the importance of south-to-south cooperation in remote sensing. Then, we cooperation project is introduced, and preliminary results presented. The methods and applications used in this study are introduced and the project in section 2, followed by the results in Section 3. Finally, results were discussed and conclusions drawn in section 4.

2. Methods and applications

2.1 Scientometric analysis of south-to-south research cooperation in remote sensing

Scientometrics was used in the discussion to set the cooperation project in the context of wider south-to-south cooperation. Using scientometric tools, mostly the number of publications, research trends in the field of remote sensing were analysed. The analysis was based on the results from the Web of Science (apps.webofknowledge.com). The Web of Science includes 'Remote Sensing' as a distinguished research field, which allows us to focus our analyses on papers published in the field of Remote Sensing.

By searching for papers based on country (e.g., CU=Italy), all papers with an author from an affiliation of that country will be selected. Therefore, a single paper can have multiple countries. This approach differs from selecting only the first affiliation of the first author as country of origin as, e.g., used in (Balz, 2022).

2.2 Crop classification with multi-sensor remote sensing data to ensure food security.

Food security is a major concern for the Global South countries, especially in the context of global change. In this study e the focus was on using remotely sensed data for crop classification, yield prediction, disease mitigation, and pollution monitoring. First, crop classification was performed within a test site in China.

The study area for this test is the Sanjiang Plain (Figure 1). It is formed by alluvial deposits of the Amur, Songhua, and Ussuri Rivers. This area is affected by a temperate monsoon climate (Liu et al., 2022), with warm summers, cold and long winters, seasonally frozen soil freezing in winter, and melting in summer (Zhang et al., 2017). Crops in the Sanjiang Plain ripe once per year. Sanjiang Plain is the production base of commodity grain with the highest commodity rate in China, where the main crops are rice, maize, and soybean.

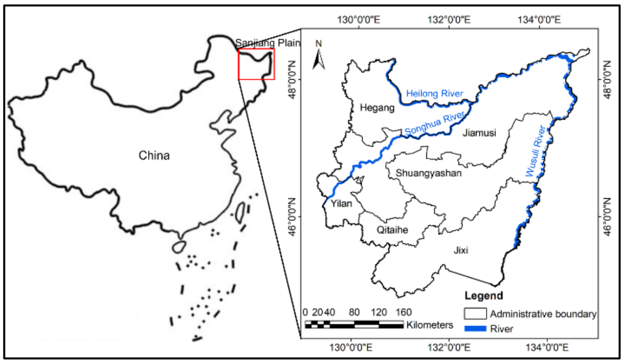

Figure 1. Location of the study area.

The "Sentinel-2 MSI: Multi-Spectral Instrument, Level-2A" dataset on the Google Earth Engine cloud computing platform was used to classify crops. The planting areas of rice, maize, and soybean on the Sanjiang Plain are far larger than those of other crops (You et al., 2021). Therefore, these three crops were classified. The soybean and maize were intercropped and distributed in strips. The maize planting areas were dark green, and the soybean planting areas were relatively brighter.

Crops were classified in the Sanjiang Plain over a period of three years from 2020 to 2022. First, the 5-day NDVI (Normalized Difference Vegetation Index (NDVI) and Normalized Difference Red Edge Index (NDRE) time series for all samples were constructed using the harmonic analysis of time series (HANTS) method. Second, standard time series curves of six land cover types were established. Based on this, and the time-weighted dynamic time warping (TWDTW) method, the types of randomly generated samples were determined. Third, the samples were tested and refined through the iterative process of random forest proximity analysis and bisecting k-means clustering. Finally, random forest classification was carried out with samples whose correctness had been tested.

The following harmonic model (1) was fitted to time series and set ω=1 (one cycle per unit time):

$$\begin{aligned} y_t &= \beta_0 + \beta_1 t + A\cos(2\pi\omega t - \varphi) + e_t \\ &= \beta_0 + \beta_1 t + \beta_2 \cos(2\pi\omega t) + \beta_3 \sin(2\pi\omega t) + e_t \end{aligned} \quad (1)$$

where y_t is the time-series data, e_t is a random error, A is amplitude, ω is frequency, and φ is phase.

NDVI is currently the most widely used vegetation index, which can reflect the growth information of crops; therefore, it is our first choice (Seo et al., 2019). In this study, every 5-day NDVI and NDRE time series of all samples from 2020 to 2022 were obtained using the Google Earth Engine. The growth period of the crops was from May 1st to October 1st, with 31 time series intervals.

Dynamic Time Warping (DTW) is a method used to calculate the similarity between two time series. Compared with Euclidean distance, DTW seeks a path with the minimum cost distance between two time series through the idea of dynamic programming (Moola et al., 2021). This is a non-one-to-one mapping, also known as a warping path (Jeong et al., 2011). However, this algorithm does not account for the phase difference between two time series(Maus et al., 2019). TWDTW adds a time-weight function as a constraint based on DTW, which can be a linear or logistic model (Maus et al., 2019).

Random forest proximity analysis was performed to improve the quality of the remaining samples. The NDRE time series of the remaining samples were taken as explanatory variables and the sample types were taken as dependent variables, which were respectively input into the random forest model. In the output results, proximity is the similarity matrix between samples. MDS (multi-dimensional scaling) is usually used to map the distance matrix of samples to a two-dimensional space.

Bisecting k-means was used to cluster samples mapped to two-dimensional space by MDS. In this method, all sample points are regarded as a cluster at first and divided into two clusters by k-means (Bilge and Polat, 2013). Then, the cluster with the largest error sum of squares (ESS) was divided into two clusters again, and the iterative process was repeated until the specified number of clusters was reached. Compared to k-means, this method was chosen because it can improve the clustering speed and overcome the problem that k-means converging to the local minimum.

After bisecting k-means clustering, the same type of samples may be clustered into different clusters, and different types of samples may be clustered into the same cluster. For example, among 100 rice samples, 3 may be clustered into cluster 1, 13 into cluster 3, and the remaining 84 into cluster 8. Only cluster 8, to which most rice samples were assigned, was retained. Cluster 8 contains other types of samples besides rice samples, so random forest proximity analysis and bisecting k-means clustering are then iterated until most of the samples of each type are clustered into different clusters. Through this iteration process, some samples with unclear types were abandoned; therefore, the refined samples were used for subsequent crop classification.

Random forest classification combines multiple decision tree classifiers and assigns each pixel to the class that receives the most votes from all the decision trees. Given the excellent performance of the random forest classification algorithm for crop classification (T.Li et al., 2022; Maponya et al., 2020; Pringle et al., 2012), this method is adopted in this paper.

In this study, the Fisher function (2) is used to determine the optimal classification period. The Fisher function is:

$$f = \frac{(m_1 - m_2)^2}{v_1 + v_2} \quad (2)$$

where m and v are respectively input as the mean and variance of NDVI, and subscripts 1 and 2 represent different categories of visually interpreted samples (Ashourloo et al., 2019). The larger the Fisher value, the higher is the divisibility between classes; thus, the best classification period can be determined (H.Li et al., 2022).

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3. Results

Figure 2 depicts the Fisher values of NDVI and NDRE during the growth periods of rice, maize, and soybean. The figure illustrates that the Fisher values of rice and maize, rice and soybean, and soybean and maize in the NDVI layer reached their peaks around May 1, June 25, and September 1 in 2020, respectively, indicating that choosing images from these periods is optimal for crop classification. However, on May 1, August 25, and September 20, the Fisher values of rice and maize, rice and soybean, and soybean and maize in the NDVI layer were all near zero in 2020, making it relatively difficult to distinguish between the three crop types during these periods. Furthermore, distinguishing between rice and maize is relatively straightforward; however, this is only possible when using images from the later stages of crop growth. This is because, except for the Fisher value of NDVI between the two crops in 2020, the Fisher values of rice and maize have only one peak, and this peak value is distributed in early September.

Because of the expansive size of the Sanjiang Plain, obtaining images on the same day is often unfeasible, and at times, images can be obscured by extensive cloud cover. During classification, it is important to consider the optimal time period when there is a clear differentiation between crops, and to select images from dates with a peak Fisher value whenever possible.

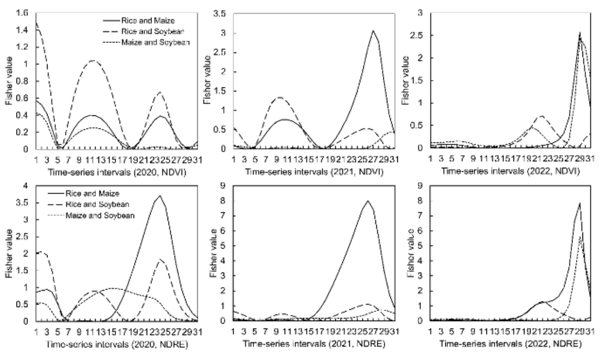

Figure 2. Fisher values of rice and maize, rice and soybean, maize, and soybean in NDVI and NDRE standard time series curve from May 1 to September 30.

Figure 3 illustrates the screening process used to identify the best classification for crops in the Sanjiang Plain in 2020. After B8, B8A, and B6 bands were successively removed, the overall accuracy reached a maximum value of 0.8916. Consequently, the bands and remote sensing indices involved in crop classification in the Sanjiang Plain included NDRE, EVI, NDVI, IBI, B12, MCARI, DEM, B1, B3, B11, B5, NDWI, B9, BSI, B7, B2, and B4. When the IBI, NDVI, EVI, and NDRE bands were removed, classification accuracy decreased rapidly. Furthermore, it is apparent from the figure that NDRE, EVI, and NDVI, which were the last bands to be removed, played the most important role in distinguishing between different crop types.

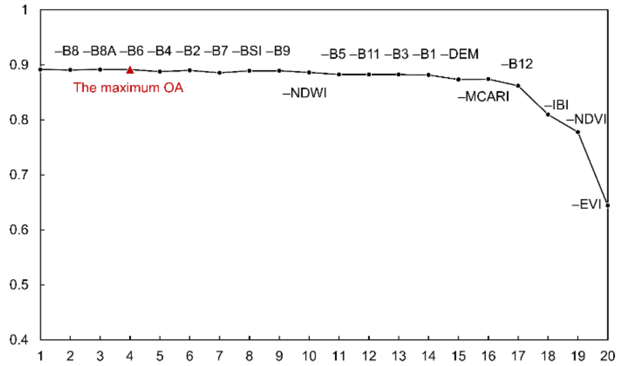

Figure 3. Relationship between the classification features and overall classification accuracy.

Figure 4 displays high-precision maps of crop distribution in the Sanjiang Plain from 2020 to 2022. The top row of the image showcases crop classification results obtained using the $V_{600} + R$ method proposed in this paper, which relies on the time series similarity tests of samples. The second and third rows illustrate crop spatial distribution maps generated using the $(V_{600} + R)_{600}$ and R methods, respectively. Columns 1, 2, and 3 correspond to crop distributions in 2020, 2021, and 2022.

By comparing the first and second images in the first row, it can be observed that between 2020 and 2021, there was an increase in the planting scale of maize, a decrease in the planting scale of soybean, and little change in the planting scale of rice. It is worth noting that the Heilongjiang Statistical Yearbook only collects data at the municipal level; therefore, Yilan County was excluded from the analysis. The sown areas of rice, maize, and soybean in the Sanjiang Plain region in 2021 were 2239981.6 hectares, 1492446.4 hectares, and 811694.2 hectares, respectively, while in 2020, the sown areas of rice, maize, and soybean were 2264295.1, 1129503.6, and 1054088.5 hectares, respectively. Hence, the classification result of the method proposed in this study depicted in the figure is consistent with the statistical yearbook data.

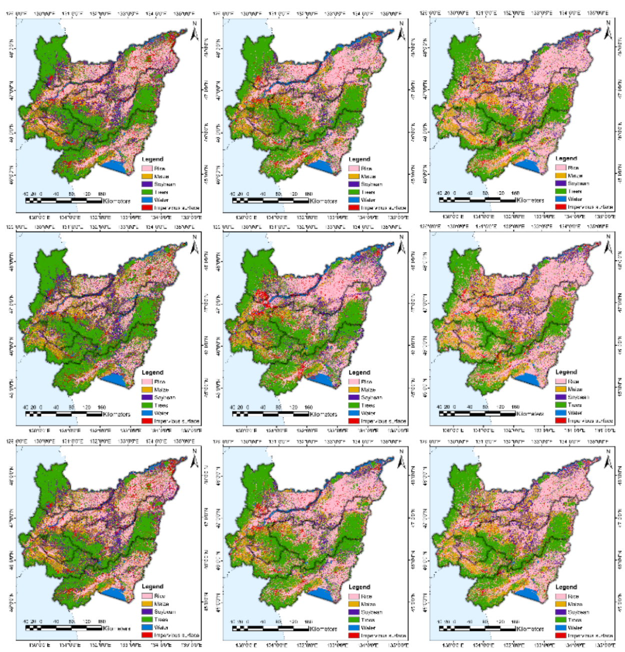

Figure 4. Crop distribution map of Sanjiang Plain in 2020-2022
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4. Discussion

Food security is an important aspect of remote sensing. The results above shows some preliminary results from the classification that must be replicated in different test sites in China and South Africa. These initial results from the classification methods are promising.

In this project, the focus is on south-to-south cooperation as a concept of scientific cooperation that is expected to become more important in the future. However, research is expensive. There is a strong correlation between the overall research expenses of a country and the research results. Similarly, there is a strong relationship between the gross domestic product (GDP) and the research output as shown in Figure 5.

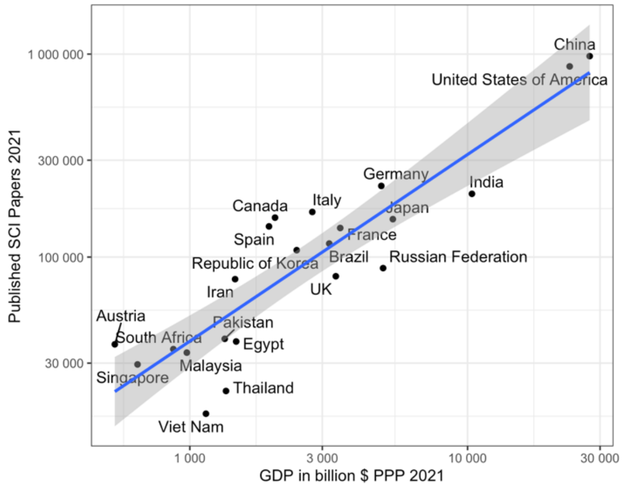

Figure 5. Published SCI papers in 2021 according to the Web of Science in relation to the GDP in billions of $ (PPP) on a logarithmic scale.

As indicated on Figure 5, the relationship between GDP and research output is typically linear. There are exemptions of countries that show good research output, as measured by the number of publications with respect to their GDP, such as Canada or Italy. Similarly, countries such as Vietnam, Thailand, and Russia show much lower research output than their GDP.

As spending on research is not static, the number of publications is quite dynamic. Taking the number of publications as a measure of research output, which is certainly a simplified measurement and definition of what research is or should be, we can see changes in the development of research capacities over time. Figure 6 shows the overall number of publications in the Web of Science databases for China and the USA.

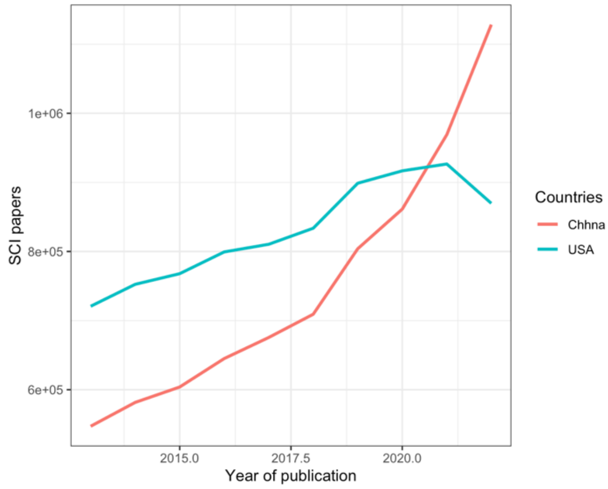

Figure 6. SCI papers published over time with at least one author from China or the USA

As show on Figure 6, China overtook the USA in the number of publications in 2021. Remarkably, is not only this event but also the much stronger growth of publications in China. In remote sensing, China overtook the USA States in 2015 (Balz, 2022).

Although this strong increase in publications is unique to China, an increase in publication output can be observed in several countries. In Figure 7, this output is compared for the field of remote sensing between the G7 and BRICS+ countries. BRICS+ is defined here as BRICS members (Brazil, Russia, India, China, and South Africa) and new member countries (Egypt, Ethiopia, Iran, Saudi Arabia, and the United Arab Emirates).

If the situation in the field of remote sensing is analysed, which is a key interest in this study, it can be revealed that that BRICS+ countries are publishing far more papers in the field than countries from the Global North among the G7 countries, (Figure 7). This strong publication record in remote sensing is mostly because of publications from China.

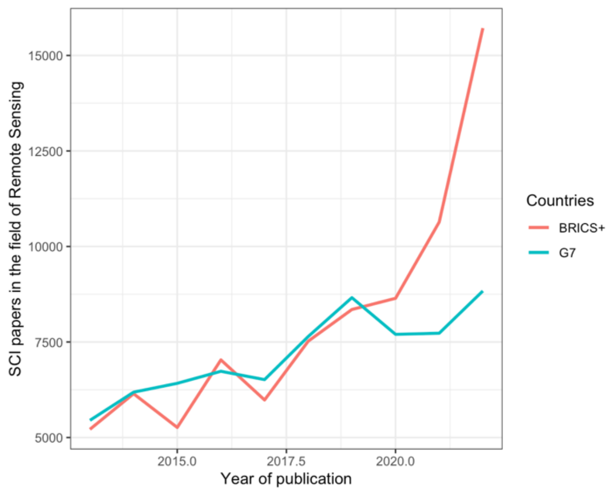

Figure 7. SCI papers published in the field of remote sensing over time, with at least one author from the BRICS+ countries among the G7 countries.

A tendency of scientific decoupling in remote sensing between the USA and China has been shown before in (Balz, 2022). In the context of this current analysis, the interest is in the development of co-authorship as a form of scientific cooperation. Therefore, in Figure 8, papers with co-authors from China and the USA, and papers with co-authors from China and G7 countries without the USA, were analysed.

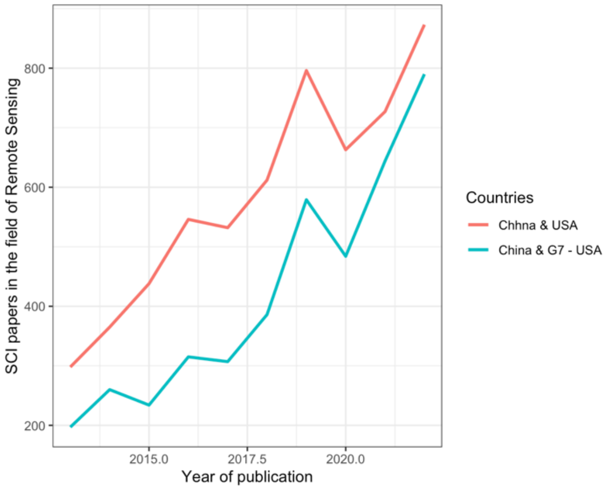

Figure 8. SCI papers published in the field of remote sensing over time with co-authorship from authors from China, the USA, China, and G7 countries without the USA.

Similar to the effect reported in Balz (2022), a reduction in cooperation can be seen with its low point in about 2020. However, it seems that co-authorship between China and the USA continued to grow. A similar dip can be seen for co-authorship between China and the G7 without the USA; however, after 2020, the growth of co-authored papers between these countries seems stronger than the growth of cooperation between the USA and China, hinting at some ongoing pressure on the scientific cooperation between the USA and China.

International scientific cooperation is not limited to the USA, China, or the G7 countries. Therefore, this study assessed the joint publications of BRIS countries (i.e., BRICS without China) and the USA and China in Figure 9.

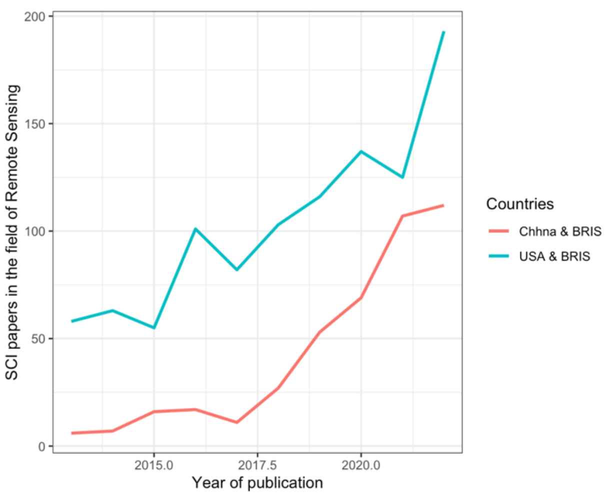

Figure 9. SCI papers published in the field of remote sensing over time with co-authorship from authors from China and the BRIS (BRICS without China) or the USA and BRIS

As illustrated in Figure 9, overall, the co-authorship between China and the BRIS countries accelerated after 2017 but recently seemed to slow down, while the USA and BRIS cooperation recently accelerated strongly in the field of remote sensing. Currently, the slowdown of China and BRIS cooperation is only visible for one year and might not be an ongoing trend. Nevertheless, this shows that, overall, there is a strengthening of research output from the Global South, not only from China. Cooperation between Global South countries is increasing, as is cooperation between the Global North and the Global South. However, cooperation between China and the Global North countries suffers from geopolitical tensions.

Therefore, the analysis shows that south-to-south cooperation does not replace cooperation with G7. Instead, there is a general increase in cooperation and restoration of the number of cooperative papers after the pandemic. South-to-south cooperation in remote sensing is, therefore, not replacing other forms of cooperation, but offering an additional path to scientific cooperation.

5. Conclusions

In this paper, the importance of south-to-south cooperation in remote sensing and introduce a joint project between China and South Africa was discussed. Scientometric analysis demonstrated growing research output and cooperation among countries in the Global South, especially within the BRICS+ group. These results highlight the potential for increased collaboration and knowledge exchange between these nations in the field of remote sensing. Furthermore, preliminary results from our project was presentedfocusing on crop classification using multi-sensor remote sensing data to ensure food security. The initial findings from the Sanjiang Plain test site in China showed promising accuracy in identifying rice, maize, and soybean crops, which is consistent with the statistical data from the region.

As this research continues, the aim is to refine the classification methods and expand their application to test sites to South Africa. Using the expertise and resources of both countries, robust remote sensing techniques will be developed and these can contribute to improved food security monitoring and decision-making.

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