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Christine Wessollek, Pierre Karrasch, Babatunde Osunmadewa

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Introducing a rain adjusted vegetation index (RAVI) for improvement long term trend analyses in vegetation dynamics

Christine Wessollek^a, Pierre Karrasch^b, Babatunde Osunmadewa^a

^aInstitute of Photogrammetry and Remote Sensing, Technische Universität Dresden,
Helmholtzstraße 10, 01069 Dresden, Germany;

^bProfessorship of Geoinformation Systems, Technische Universität Dresden, Helmholtzstraße
10, 01069 Dresden, Germany

ABSTRACT

It seems to be obvious that precipitation has a major impact on greening during the rainy season in semi-arid regions. First results¹ imply a strong dependence of NDVI on rainfall. Therefore it will be necessary to consider specific rainfall events besides the known ordinary annual cycle. Based on this fundamental idea, the paper will introduce the development of a rain adjusted vegetation index (RAVI). The index is based on the enhancement of the well-known normalized difference vegetation index (NDVI²) by means of TAMSAT rainfall data and includes a 3-step procedure of determining RAVI. Within the first step both time series were analysed over a period of 29 years to find best cross correlation values between TAMSAT rainfall and NDVI signal itself. The results indicate the strongest correlation for a weighted mean rainfall for a period of three months before the corresponding NDVI value. Based on these results different mathematical models (linear, logarithmic, square root, etc.) are tested to find a functional relation between the NDVI value and the 3-months rainfall period before (0.8). Finally, the resulting NDVI-Rain-Model can be used to determine a spatially individual correction factor to transform every NDVI value into an appropriate rain adjusted vegetation index (RAVI).

Keywords: NDVI, Rainfall, GIMMS, TAMSAT, time series, rain-adjusted vegetation index, regression analysis

1. INTRODUCTION

In general it can be said that vegetation is one of the most important resources on Earth. Particularly in regions characterized by severe drought the knowledge of the state of vegetated areas is of paramount importance. For this reason detailed analyses of trends in vegetation dynamics are an obligatory precondition for the general development of the analysed regions and also to decision makers particularly in the chosen study area of Kogi state, a semiarid region of Nigeria. For a first assessment the discrimination between natural vegetation areas or, for example, agricultural land plays a subordinate role. In recent decades, in particular, remote sensing data could be used to perform vegetation analyses with global coverage, geometric high resolution and, dependent on the system used, a high temporal repetition. In this context, a variety of vegetation indices have been established in the same period by using relatively simple mathematical relationships, such as band operations. A comprehensive overview of available vegetation indices offer Jones and Vaughan (2010),³ who classify the indices in the following categories:

1. Simple Indices,
2. Normalized Indices,
3. Multi-channel Indices.³

Further author information: (Send correspondence to Christine Wessollek)
Christine Wessollek: E-mail: christine.wessollek@tu-dresden.de, Telephone: 49 351 463 33830

The most famous vegetation index was established by Rouse et. al. (1974)² and Tucker (1979).⁴ The Normalized Difference Vegetation Index (NDVI) essentially uses the sharp increase in reflection of vegetation from red to the near infrared spectral range and transforms this to a normalized value in the form of an index:

$$NDVI = \frac{NIR - Red}{NIR + Red}. \quad (1)$$

Thus the NDVI represents one of the most important indices for the detection, identification and evaluation of vegetation. In addition, a variety of studies have shown that the use of the NDVI is not the best choice under certain conditions. Among other things, the density of the vegetation has significant impact on the NDVI. The influence of soil reflectance on the spectral signature can be taken into account, for example, by the Soil Adjusted Vegetation Index (SAVI):⁵

$$SAVI = \frac{NIR - Red}{NIR + Red + L} \cdot (1 + L), \quad (2)$$

with correction factor L ranging from 0 to 1 depending on the density of vegetation. Huete (1988) describes the dependence of the reflection curve of partial vegetation coverage on soil reflection. The objective of SAVI is to minimize the influence of soil reflection on the NDVI and to enable the comparability of results despite the high dynamics of soil and vegetation reflection.⁵

Beside the influence of different surface properties on the NDVI other external factors can affect NDVI values. In particular, meteorological influences like rainfall can have impact on the NDVI. Thus, for example, Klein and Roehrig (2006) examined the impact of precipitation on vegetation in different regions (semi-arid / semi-humid) by using a number of different indicators. They showed that in both regions the rainfall variability was higher than that of the vegetation.⁶

Prince et. al. (1998)⁷ examined primarily the relationship between the precipitation and NDVI in the Sahel. With the aim to describe desertification processes, they used the accumulated NDVI of the rainy season as well as the precipitation of in situ measuring stations to derive a function between the two variables. They were able to demonstrate the impact of precipitation on long-term trends of vegetation dynamics.⁷

Evans and Geerken (2004) performed various linear regressions between the accumulated precipitation of varying periods of precipitation and the yearly maximum of NDVI with the aim to identify the rainfall period with the maximum influence on the NDVI and finally to describe the relationship between the two variables. The highest correlation was found for the previous four months period of rainfall of maximum NDVI. But they also concluded that the resulting relationship for each region (pixel) must be determined individually to take the different land use into account.⁸ Also Omuto et. al. (2010) conclude that the type of vegetation has to be considered.⁹ Evans et. al. (2004), Omuto et. al. (2010) and Wessels et. al. (2007), who investigated the vegetation in South Africa, conclude that the difference between a modeled NDVI based on rainfall and the associated real NDVI can be interpreted as a human impact.⁸⁻¹⁰

In principle, the sensitivity of the NDVI to rainfall can be rated positive. Nevertheless, it must be noted that depending on the question, to be answered, this influence can also be stated to be negative. That may be the case, amongst others, when the development of vegetation is to be analyzed over a longer period and the influence of short-term meteorological events must be minimized. Hence there is a necessity to analyze the relationship between rainfall and NDVI measurement, to describe this relationship mathematically and to apply a correction to the NDVI. The value of such a method can also be measured by the ability of the correction factor to take into account local differences in the relationship and performing an individual adjustment.

2. USED DATA AND STUDY AREA

To analyse vegetation status, GIMMS AVHRR NDVI3g with a spatial resolution of 8 km is used in this study. These data are available as bi-monthly NDVI measurements derived from the seven NOAA instruments.¹¹ In order to remove artifacts such as solar zenith angle, orbital drifts, and/or volcanic aerosols the NDVI3g has been processed using adaptive empirical mode decomposition.^{12,13} By using the maximum composite technique including radiative-transfer volcanic aerosol correction for the El Chichon and Mt. Pinatubo stratospheric

aerosol periods¹⁴ atmospheric correction was performed to minimize atmospheric and radiative geometry effects.¹³ Information about rainfall distribution are derived from Tropical Applications of Meteorology using Satellite (TAMSAT) rainfall data (1983-2011) with spatial resolution of 0.0375°. The TAMSAT rainfall estimation was locally calibrated by the Reading University using historic rain gauge records which are produced monthly.^{15,16} The bi-monthly NDVI data set (GIMMS NDVI3g) from 1983 through 2011 (28 years) used for this study were re-projected from the global projection to Universal Transverse Mercator (UTM) and subset images of the study area were clipped out of the global data using Kogi state provincial boundary.

As study area in this research Kogi State (Nigeria) is chosen. The climate of Kogi state is mainly tropical and it is characterized by two main seasons (dry and raining/wet season). The raining season starts towards the end of March and ends at the end of October with total annual rainfall ranging from 804.5 mm to 1767.1 mm.¹⁷ However, in some parts of the state the start and end of rainfall varied considerably which may influence vegetation productivity temporal as well as spatially. Kogi state, Nigeria is found in the Guinea Savannah region where gallery forest along water courses is present. The vegetation composition in the southern part is typically that of rain forest while in the Northern part woody derived - Guinea savannah is found.¹⁸ Currently, the analyses of vegetation dynamics using the Normalized Vegetation Index (NDVI) in Kogi state is often performed by time series analyses using constant seasonality. It is obvious and also proven¹ that an annual cycle presents the strongest frequency in vegetation dynamics. Nevertheless, considering this annual seasonality, it is evident from the analyses of the remaining residuals that further research on vegetation modelling is needed. This is also the case if structural break points in the trend component of an original NDVI signal are considered.¹⁹ Detailed analyses of the mean annual seasonality shows their variability over a period of about three decades. Small temporal events of e.g. a dry summer or a comparatively wet dry-season have an impact on the estimated trend component of the original NDVI time series (GIMMS) and also on the linear, segmented-linear or non-linear trend model. This applies particular in regions with strong distinctions in availability of water.

3. CONCEPT OF A RAIN ADJUSTED VEGETATION INDEX (RAVI)

The concept of a rain adjusted vegetation index is based on the assumption that the relationship between NDVI and rainfall can be described mathematically. This relationship can be used to normalize the NDVI value regarding a reference rainfall (e.g. 100 mm). The concept consist of three modules which are run for every NDVI value individually (see Figure 1).

Figure 1: Concept of a rain adjusted vegetation index (RAVI)

In the analysis module the regression analysis between NDVI and rainfall is performed. In a first step the cross correlation between NDVI and rainfall time series is calculated. Therefore two different approaches are tested, to determine the rainfall period with the maximum influence on vegetation growth. The first one is performed like a standard cross correlation by shifting the input time series. In this case only the original monthly values are compared. The second approach is based on the assumption that the NDVI value is influenced by periods of more than one month. For this reason moving windows of different size are used to calculate the mean rainfall of the period covered by the one-sided window expressed by

$$mRain = \frac{Rain_t + Rain_{t-1} + .. + Rain_{t-i}}{i + 1}, \quad (3)$$

where t is the actual month and i is the number of past months used to calculate the mean rainfall. This newly generated rainfall time series are then compared with the original NDVI time series to find the maximum correlation.

In the second step of the analysis module regression modelling is performed based on the findings of the correlation analysis. In accordance with the *ladder of re-expression* of Mosteller and Tukey (1993)²⁰ the following regression functions are tested for modelling:

$$Y = a + b \cdot X \quad (4)$$

$$Y = a + b \cdot \sqrt{X} \quad (5)$$

$$Y = a + b \cdot \sqrt[4]{X} \quad (6)$$

$$Y = a + b \cdot \log(X) \quad (7)$$

In the second module all used regression models are evaluated in a two-stage process combining inferential statistics as well as methods of descriptive statistic. In the inferential statistic part different stationary tests are used to assess the quality of the regression analyses and to assure that the relationship between rainfall and NDVI is modelled entirely. Therefore the residuals of the tested regression functions should fulfill two main conditions, which can be tested by means of stationary tests:

- the mean value of residuals should be constant over the range of x values and the expectation value is 0;
- the variance should be constant over the whole range of the regression function.

In this study, two tests for stationarity were applied. The augmented Dickey–Fuller test (ADF) is used for testing unit root. If there is a unit root, the regression function is not stationary. Hence, the ADF is a test on non-stationarity and the null hypothesis need to be rejected in order to confirm the stationarity of the residuals.²¹ In contrast, test of Kwiatkowski–Phillips–Schmidt–Shin (KPSS) changed the null hypothesis and alternative hypothesis.^{21,22} The KPSS test is performed in two different modes. The first option allows a remaining trend in the residuals (trend stationarity). The second mode of KPSS test assumes that the residuals contain no further trend and is used for the level stationarity test.²²

Whereas the standard deviation of the residuals represents the essential indicator in the descriptive statistics stage. The outcomes of both statistical stages lead to the decision for the best suitable regression function for each pixel. The last module uses the determined regression function to adjust the NDVI value of each pixel in relation to a reference rainfall. This is done by

$$k = \frac{NDVI(100\text{ mm})}{NDVI(Rain)}, \quad (8)$$

where k is the ratio between the modelled NDVI value of a specific rainfall and the modelled NDVI value of the reference rainfall of 100 mm. This rain-depended factor is than used to adjusted the measured NDVI value based on the specific rainfall. This NDVI normalized to 100 mm rainfall can be termed as rain adjusted vegetation index (RAVI):

$$RAVI = k \cdot NDVI. \quad (9)$$

Thus the individual character of NDVI is retained but only adjusted for different rainfall conditions. This way other impacts on NDVI values are still present in the RAVI values. This presented approach is based on the availability of long time series which are needed to derive rainfall-NDVI-regression models. However updated or additional information can be used to adapt the model parameters or model structure and thus the introduced concept has a self-learning character.

4. RESULTS

The following results show the procedure of the RAVI concept based on four selected example locations in Kogi State, Nigeria. These locations are characterized by the dependency of vegetation on water availability. The implementation of the RAVI for the selected location follows the introduced concept in chapter 3 and the results of the method used in each stage are presented step-wise.

4.1 Correlation Analysis

As described in Chapter 3 the analysis starts with a comparison of the both time series in order to find the best (NDVI/Rainfall) data pair to be used in the regression modelling. For this reason different kinds of cross correlation analyses are done. At first the classic cross correlation coefficients between both time series are calculated. The results of this correlation analysis are shown in Figure 2.

Figure 2: Cross correlation between the original time series of NDVI and rainfall for selected locations [from left: location 1 - location 4]

It is obvious that the highest correlation is obtained between the NDVI value and the rainfall value of the previous month ($lag = 1$). These correlation value, ranging from 0.70 to 0.84 for the four selected locations (cf. Figure 2 [location 1-4]), are quite high and indicate a strong relationship between both measurements. But this approach is based on the assumption that only one month (the previous one) has influence on the NDVI. To resolve this limitation further correlation analysis, as explained in Chapter 3, was performed. Therefore temporal windows of different size were used as a moving window to calculate the mean rainfall inside the window (cf. Equation (3)). This new generated rainfall time series were then used for correlation analysis together with the original NDVI time series.

The results, presented in Figure 3, show, that the highest correlation is reached for NDVI of the actual month and the mean rainfall of the actual and the two previous month ($i = 2$ in Equation (3)) (cf. Figure 3 [location 1-4]). The correlation calculated with this second approach ranging from 0.71 to 0.88 and are therefore a little higher than in the first analysis. Hence considering a rainfall period of three month is preferable in regression modelling between NDVI and rainfall. This findings are in line with results of other studies like that of Herrmann et. al. (2005).²³

Figure 3: Cross correlation between the original NDVI and mRain for selected locations (window size in months) [from left: location 1 - location 4]

4.2 Regression Analysis

The results of the correlation analysis indicate how to combine NDVI and rainfall in the regression analysis in order to describe the relationship of both measurements with a mathematical function $NDVI = f(Rain)$. With regard to the introduced functions (Eq. (4) - (7)) in Chapter 3 the regression models used in this analysis can be specified to:

$$NDVI = a + b \cdot Rain \quad (10)$$

$$NDVI = a + b \cdot \sqrt{Rain} \quad (11)$$

$$NDVI = a + b \cdot \sqrt[4]{Rain} \quad (12)$$

$$NDVI = a + b \cdot \log(Rain), \quad (13)$$

where $NDVI$ is the original $NDVI$ value and $Rain$ is either the rainfall of the previous month (first approach of correlation analysis) or the $mRain$ with $i = 2$ based on Eq. 3 (second approach of correlation analysis). Although the results of Chapter 4.1 indicate higher correlation for the second approach regression analysis was performed for both methods. Additionally a second question, how to handle rainless periods in the time series, was taken into account. Based on this consideration the regression analyses were performed including dry months and second by excluding the dry months from the regression modelling, which follows the idea that a nonexistent rainfall can have no influence on the $NDVI$. As a consequence of both decisions the regression analyses were performed for four different data sets:

Case 1: $lag = 1$ & dry month included ($Rain = 0 \rightarrow 0$)

Case 2: $lag = 1$ & dry month excluded ($Rain = 0 \rightarrow NA$)

Case 3: $mRain, i = 2$ & dry month included ($Rain = 0 \rightarrow 0$)

Case 4: $mRain, i = 2$ & dry month excluded ($Rain = 0 \rightarrow NA$)

For *Case 1* and *Case 3* only the first three regression models can be performed because the logarithmic function is not defined for $Rain = 0$. In total 14 regression analyses were performed per location. Since it is not possible to present all results. The procedure for stage one presented in Chapter 3 is demonstrated by the outcomes of location 1 in Figure 4.

Figure 4: Results of the regression modelling for location 1; upper left = Case 1, upper right = Case 2, lower left = Case 3, lower right = Case 4; green = Equation (10), red = Equation (11), blue = Equation (12), yellow = Equation (13).

As can be seen from the graphs in Figure 4 there are significant differences between the different approaches. This applies for the several regression models as well as for the handling of dry months. The comparison with the results for another location (cf. Figure 5) confirms the demand for an individual regression modelling and therefore individual rain-adjustment for different locations.

Figure 5: Results of the regression modelling for location 2; upper left = Case 1, upper right = Case 2, lower left = Case 3, lower right = Case 4; green = Equation (10), red = Equation (11), blue = Equation (12), yellow = Equation (13).

4.3 Evaluation of Regression Modelling

The evaluation of the different regression modelling approaches starts with a comprehensive analysis of the residuals. It is based on the requirement that the residuals are stationary related to the independent variable (rainfall), because only if this demand is fulfilled, it can be assumed that all systematic impacts are considered in the regression model. As an example of the inferential statistics an overview of the results of the stationary tests (cf. Chapter 3) on residuals for location 1 is given in Table 1. Obviously the results of the stationary tests vary considerably depending on the chosen regression function (cf. Equation (10) - (13)) as well as depending on the input data sets (*Case 1 - Case 4*). Examining the results of the KPSS test on trend stationary (KPSS.T) leads to the conclusion that none of the regression models fits independent from the chosen Case. Only the logarithmic model (Eq. (13)) approaches the critical value for *Case 2*. As the interpretation based on the critical value has to be handled carefully, further stationary tests were performed. The KPSS test on level stationary (KPSS.L) already shows that stationary can be verified for the fourth root function for *Case 1, 2* and *4* as well as for the logarithmic model for *Case 4*. Another option which can be used for evaluating the regression models is provided by the augmented Dickey-Fuller test. The results show an increasing number of combination of *Case* and location were stationary is indicated. Especially the data sets where the dry month were excluded from the regression model (*Case 2, 4*) indicate stationary for all regression models.

In summary it can be said, that tests on stationary are appropriate to evaluate the quality of regression modelling. However it must be pointed out that the irregular distribution of the residuals across the range of rainfall values can have impact on the test results. Nevertheless it can be concluded that Equation (12) and Equation (13) combined with *Case 2* and *Case 4* provide the best results.

The ambivalence of these findings shows, that the best fitting regression model can not only be chosen based on the results of the stationary tests. Therefore the standard deviation of the residuals can be used as a indicator

Table 1: Stationary tests for residuals of regression modelling approaches for location 1. KPSS: Kwiatkowski–Phillips–Schmidt–Shin test on trend (T) and level (L) stationarity; ADF: augmented Dickey–Fuller test (5 % significance level); N = Number of Observations.

Case 1 ($N = 347$)	KPSS.T	KPSS.p	KPSS.L	KPSS.p	ADF.DF	ADF.p
Eq. (10)	1.04	0.01	1.06	0.01	-3.09	0.12
Eq. (11)	0.44	0.01	0.48	0.05	-4.88	0.01
Eq. (12)	0.31	0.01	0.36	0.09	-4.34	0.01
Case 2 ($N = 289$)	KPSS.T	KPSS.p	KPSS.L	KPSS.p	ADF.DF	ADF.p
Eq. (10)	0.94	0.01	0.96	0.01	-3.57	0.04
Eq. (11)	0.54	0.01	0.70	0.01	-4.64	0.01
Eq. (12)	0.29	0.01	0.43	0.07	-5.07	0.01
Eq. (13)	0.17	0.03	0.17	0.10	-5.01	0.01
Case 3 ($N = 346$)	KPSS.T	KPSS.p	KPSS.L	KPSS.p	ADF.DF	ADF.p
Eq. (10)	1.14	0.01	1.14	0.01	-2.46	0.38
Eq. (11)	0.54	0.01	0.54	0.03	-3.74	0.02
Eq. (12)	0.36	0.01	0.55	0.03	-4.63	0.01
Case 4 ($N = 336$)	KPSS.T	KPSS.p	KPSS.L	KPSS.p	ADF.DF	ADF.p
Eq. (10)	1.10	0.01	1.10	0.01	-3.17	0.09
Eq. (11)	0.58	0.01	0.59	0.02	-4.43	0.01
Eq. (12)	0.35	0.01	0.34	0.10	-4.65	0.01
Eq. (13)	0.37	0.01	0.63	0.02	-4.41	0.01
Critical value [5%]	0.146		0.463		-3.42	

Table 2: Standard deviation of residuals for each location and all combination of regression model and *Case*.

Case 1	location 1	location 2	location 3	location 4
Eq. (10)	797.9	762.5	697.0	742.7
Eq. (11)	711.3	669.3	633.8	656.8
Eq. (12)	742.3	729.5	642.5	660.9
Case 2				
Eq. (10)	804.7	754.2	675.9	732.5
Eq. (11)	739.2	684.2	625.9	677.5
Eq. (12)	719.0	678.2	605.9	659.2
Eq. (13)	721.0	709.9	600.0	658.9
Case 3				
Eq. (10)	740.3	685.9	689.7	720.1
Eq. (11)	668.2	607.8	627.6	645.6
Eq. (12)	708.8	728.3	637.9	654.2
Case 4				
Eq. (10)	745.1	701.4	689.7	719.7
Eq. (11)	674.6	623.6	628.1	653.2
Eq. (12)	670.6	645.0	612.5	641.3
Eq. (13)	705.5	738.2	626.6	669.0

of the descriptive statistic to estimate the uncertainties of each NDVI-Rain-model (cf. Table 2). In detail, the decision process for each location starts with evaluation of the stationary tests. Normally there is more than one combination of *Case* and regression model which passes the first stage. But after the first step only a few

combination remain. For these remaining combination the standard deviation of the residuals are used to choose the best fitting model for each location. For the four selected location these evaluation steps lead to the following results:

location 1: $mRain, i = 2$ & dry month excluded, $NDVI = a + b \cdot \sqrt[4]{Rain}$;

location 2: $mRain, i = 2$ & dry month included, $NDVI = a + b \cdot \sqrt{Rain}$;

location 3: $lag = 1$ & dry month excluded, $NDVI = a + b \cdot \log(Rain)$;

location 4: $mRain, i = 2$ & dry month excluded, $NDVI = a + b \cdot \sqrt[4]{Rain}$.

Based on these findings the adjustment factor k is calculated (cf. Figure 6). This factor k can than be used to correct all NDVI values of a specific location if information on rainfall is available as explained in Chapter 3.

Figure 6: Adjustment factor k for the four selected locations; black = location 1, red = location 2, green = location 3, blue = location 4

5. DISCUSSION

The presented results show the influence of rainfall on vegetation growth in arid and semi-arid regions, based on NDVI data, the most common and widely used vegetation index. First analyses have proven the assumption of a strong relationship between rainfall and NDVI. It could also be shown, that the highest correlation between both values exist, if beside the rainfall of the actual month the rainfall of the two previous month is taken into account. The aim of this study was to find a mathematically describable relationship between the NDVI value and the actual and previous rainfall. Therefore several linear and non-linear regression approaches with increasing complexity (ladder of re-expression)²⁰ were investigated. From the functions obtained a correction factor could be derived, which enables the transformation of a NDVI time series to a freely selectable (in this case 100 mm) standard rainfall (RAVI).

It has to be noted that this type of rain adjustment is only possible with the availability of very long time series of precipitation and the NDVI, covering a large range of values. Additionally the available data pairs should be evenly distributed within the value range. In particular for the last requirement it has to be mentioned that by the character of rainfall events in the semi-arid regions, mainly in the mid-range of precipitation intensity

significantly fewer measurement pairs are available (see Figure 4). Nevertheless, descriptive and inferential statistical methods could show that the resulting models describe the relationship between rainfall and NDVI with sufficient precision.

The main advantage of transforming a NDVI times series in a RAVI time series is that this allows to investigate trends of vegetation while minimizing the impact of short-term rainfall events on an existing long-term vegetation trend without eliminating natural cycles of vegetation development by the transformation. The results showed that the generation of individual correction functions is required and the existence of long-term precipitation series in a comparable spatial resolution is essential. The used models are also based on the assumption that temperature plays a subdominant role for the development of vegetation and consequently rainfall has to be considered as the most important driving factor.²⁴ For Kogi State (Nigeria) this precondition is fulfilled. From these limitations a need for further analysis can be derived. In particular the spatial variability of the adjustment function and their relationship to land use and land cover should be investigated. In addition, the question, how far the presented methodology is transferable to regions in which other natural factors (e.g. temperature) can have a significant influence on the NDVI, arises.

In summary it can be stated the here presented rain adjusted vegetation index (RAVI) provides a tool, which considers the spatial distribution of rainfall individually and thus represents an advanced method of trend assessment based on long-term NDVI time series.

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