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Evaluation of satellite based indices for primary production estimates in a sparse savanna in the Sudan

M. Sjöström¹, J. Ardö¹, L. Eklundh¹, B. A. El-Tahir², H. A. M. El-Khidir²,
P. Pilesjö¹, and J. Seaquist¹

¹Department of Physical Geography and Ecosystem Analysis, Lund, Sweden

²Agricultural Research Corporation, El Obeid, Sudan

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Correspondence to: M. Sjöström (martin.sjostrom@nateko.lu.se)

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Abstract

One of the more frequently applied methods for integrating controls on primary production through satellite data is the Light Use Efficiency (LUE) approach. Satellite indices such as the Enhanced Vegetation Index (EVI) and the Shortwave Infrared Water Stress Index (SIWSI) have previously shown promise as predictors of primary production in several different environments. In this study, we evaluate EVI and SIWSI derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite sensor against in-situ measurements from central Sudan in order to assess their applicability in LUE-based primary production modelling within a water limited environment. Results show a strong correlation between EVI against gross primary production (GPP), demonstrating the significance of EVI for deriving information on primary production with relatively high accuracy at similar areas. Evaluation of SIWSI however, reveal that the fraction of vegetation apparently is too low for the index to provide accurate information on canopy water content, indicating that the use of SIWSI as a predictor of water stress in satellite data-driven primary production modelling in similar semi-arid ecosystems is limited.

1 Introduction

With the emergence of international environmental treaties such as United Nations Framework convention on Climate Change (UNFCCC) and its Kyoto Protocol, there is an urgent request to quantify the global carbon budget and its temporal and spatial variations (IPCC, 2007). One of the least well-covered regions by studies on carbon dynamics and climate change is Africa, a continent with widespread poverty and slow economic development (2007).

Droughts and famines occur frequently for the people living in the African Sahel, a semi-arid grass- and shrubland region located south of the Saharan desert. The region has recently been flagged as a hotspot for climatic change as findings from polar orbiting satellites reveal a widespread increase in vegetation greenness (Eklundh and

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Olsson, 2003; Herrmann et al., 2005; Seaquist et al., 2006). This observed greening has partly been explained by variations in rainfall (Hickler et al., 2005) and could be part of a residual terrestrial sink (Houghton, 2003). Knowledge on primary production in this region is therefore of key importance, both in the light of the climatic fluctuations that have occurred in this region over the last decades (Hulme, 2001) and in the light of the predicted effects of climate change (IPCC, 2007).

Photosynthesis, the process by which plants harness solar energy and carbon needed for ecosystem maintenance, is key for determining ecosystem primary production, the net amount of carbon captured by land living plants (Hanan et al., 1998). Most existing estimates of primary production at continental to global scales have been made with the use of sophisticated process-based ecosystem models driven mainly by climate data (Sitch et al., 2003). However, during the last decade, rapid developments in satellite sensor technology have allowed remote sensing based primary production models to emerge as an attractive approach. Considering the spatial and temporal variations of the processes related to plant growth, repetitive and accurate satellite based measurements may contribute significantly to our knowledge on vegetation dynamics and responses to changing environmental conditions. The improved spatial and spectral resolution of satellite sensors such as the Moderate Resolution Imaging Spectroradiometer (MODIS), in comparison to the extensively used Advanced Very High Resolution Radiometer (AVHRR), has further allowed a reassessment of the potential for modelling primary production solely by the use of satellite data.

One of the more widely applied concepts within the domain of satellite based primary production models is the Light Use Efficiency (LUE) approach, first described by Monteith (1972, 1977). They are generally formulated as:

$$\text{GPP} = \varepsilon \times \text{PAR} \times \text{fPAR}, \quad (1)$$

where GPP is gross primary production, the carbon assimilated by plants, ε is the conversion efficiency, PAR is incoming photosynthetically active radiation between the wavelengths 400–700 nm and fPAR represents the fraction of PAR absorbed by the

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canopy. fPAR is generally estimated through the use of spectral vegetation indices such as the Normalized Difference Vegetation Index (NDVI) (Daughtry et al., 1983; Asrar et al., 1984; Sellers et al., 1994) and the Enhanced Vegetation Index (Xiao et al., 2004) whereas the PAR received at the Earth's surface can be estimated by interpolating point measurements from light sensors or be derived from the use of Earth observation data (Eck and Dye, 1991; Seaquist and Olsson, 1999; Van Laake and Sanchez-Azofeifa, 2005; Liang et al., 2006; Olofsson et al., 2007b). The conversion efficiency factor ε was originally regarded as a fixed empirical constant when first introduced (Monteith, 1972) but during the past decade it has become more common to estimate or scale ε using models or satellite retrievals. Numerous stress factors control ε and estimating this critical parameter can be difficult due to high spatial and temporal variability inherent to site specific and meteorological conditions (Hilker et al., 2007).

In semi-arid environments such as the Sahel, water is generally the most limiting factor for growth and numerous satellite sensor-based primary production studies have focused on the derivation of information related to plant water stress in order to scale ε with the use of modelling (Nemani and Running, 1989; Field et al., 1995; Prince and Goward, 1995; Seaquist et al., 2003). But progress has recently been made using satellite data to detect canopy water stress (Ceccato and Flasse, 2002; Ceccato et al., 2002; Fensholt and Sandholt, 2003; Xiao et al., 2004). However, efforts are still required to strengthen our knowledge regarding indices related to water stress as well as their applicability for estimating primary production using satellite remote sensing.

In this paper, we aim to test satellite-based variables that can be used to upscale estimates of carbon in semi-arid Sahel by comparing these against site-specific measurements of CO₂ fluxes from central Sudan. We further investigate the applicability of these variables by including them in a simple parametric LUE-model, a model that should be regarded merely as a point of progress for future proceedings on satellite data-driven primary production modelling in semi-arid regions.

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2 Study area and instrumentation

2.1 Study area

The flux tower is located at the village Demokeya (13.3° N, 30.5° E) in Northern Kordofan state in central Sudan approximately 35 km northeast of the state capital El Obeid (Fig. 1). Soils in the area are mainly sandy and vegetation at the site consists primarily of sparse *Acacia senegal* savanna with a canopy cover of 5–10%, and a ground cover composed mainly of C₄ grasses and herbs, mainly *Aristida pallida*, *Eragrostis tremula* and *Cenchrus biflorus*. Mean annual precipitation is about 320 mm and generally falls from June–October, and mean annual temperature is around 26°C. The deep sandy soil (96.5% sand and 3.5% silt) have estimated minimum (wilting point) and maximum (field capacity) water holding capacities of 5% and 15% respectively, and hence a maximum plant available water content of around 10%. The landscape is gently undulating due to stabilized parallel sand dunes with a N-S orientation.

2.2 Instrumentation

Fluxes of CO₂ (FCO₂), H₂O (FH₂O) and energy were measured with the eddy covariance technique according to the EUROFLUX methodology (Aubinet et al., 2000). Measurements were done at 20 Hz using an open path eddy covariance system (In Situ Flux Systems AB, Ockelbo, Sweden) and stored as 30-min averages. Instruments include a LI7500 (Li-Cor, Lincoln, Nebraska) open path infrared CO₂ and H₂O gas analyzer and a GILL R3 Ultrasonic Anemometer (GILL Instruments, Lymington, UK) mounted at 9 m above the ground, approximately 4 m above the sparse canopy.

Located approximately 400 m from the flux tower is a separate climate station that measures temperature, relative humidity, precipitation, wind and global radiation using standard equipment. Additional measurements at this station include net radiation (NR-Lite, Kipp and Zonen), incoming PAR (JYP1000, SDEC, France), soil moisture (TDR, CS615/CS616, Campbell Scientific) and soil temperature (soil temperature

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probe 107/108, Campbell Scientific).

3 Data and methods

3.1 Eddy covariance data

The carbon budget is described by three components: i) gross primary productivity (GPP), the carbon captured through photosynthesis; ii) net ecosystem exchange (NEE), the net exchange of carbon between the ecosystem and atmosphere and; iii) ecosystem respiration (R_{eco}), which is the sum of plant and heterotrophic respiration. NEE, GPP and R_{eco} were derived from half-hourly values of CO₂ from July to December for the 2007 season (data prior to July were not available).

In order to obtain seasonal estimates of CO₂ exchange eddy covariance data was gap filled according to the method used by Reichstein et al. (2005) (amount of gaps was 39% for the period). This method considers both the covariance between fluxes and meteorological drivers and temporal structure.

Previous studies from the Sahel have shown that soil respiration not only depends on temperature but also on soil moisture content (e.g. Friborg et al., 1997). R_{eco} was thus estimated by using the exponential regression model of Lloyd and Taylor (1994) in combination with a soil water content factor (F_w) derived from volumetric soil moisture (Wang and Leuning, 1998):

$$F_w = \min \left(1, \frac{10(\theta - \theta_{\min})}{3(\theta_{\max} - \theta_{\min})} \right), \quad (2)$$

where θ is the actual soil water content in the upper soil layer (5 cm), θ_{\min} and θ_{\max} is the minimum and maximum soil water content. Using typical values for sandy soils, F_w is thus scaled between wilting point and field capacity (i.e. approximately 5 and 15%) and then integrated with the Lloyd and Taylor (1994) expression:

$$R_{\text{eco}} = F_w R_{10} e^{308.56 \left(\frac{1}{56.02} - \frac{1}{T_{\text{soil}} - 227.15} \right)}. \quad (3)$$

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Daytime GPP was estimated as $GPP=R_e-NEE$ whereas nighttime $GPP=0$ based on a global radiation threshold of 20Wm^{-2} .

3.2 Satellite data

We used satellite data from the MODIS/EOS Terra product MOD09A1, which provides an estimate of surface spectral reflectance in seven bands as it would have been measured at the ground (Vermote et al., 2002). The MOD09A1 surface reflectance product includes correction for the effects of aerosols, thin cirrus clouds and atmospheric gases and serves as an input for several higher order land products such as FPAR/LAI and vegetation indices. The spatial resolution of the MOD09A1 data set is 500 m and data is composed of the best observations during an 8-day period with regards to overall pixel quality and observational coverage (Justice et al., 2002).

The Enhanced Vegetation Index (EVI) was developed to enhance the vegetation signal by reducing influences from the atmosphere and canopy background (Huete et al., 1997; Huete et al., 2002). As with the NDVI, EVI is estimated from surface reflectance in the red (ρ_{red}) and Near Infrared (NIR, ρ_{nir}) bands but it also uses reflectance in the blue band (ρ_{blue}) to correct for effects of aerosols. Using surface reflectance data from MODIS, EVI is calculated as:

$$EVI = 2.5 \times \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + (6 \times \rho_{red} - 7.5 \times \rho_{blue}) + 1} \quad (4)$$

Several studies have previously revealed a good general relationship between EVI and GPP (Xiao et al., 2004; Rahman et al., 2005; Sims et al., 2006b; Olofsson et al., 2007a). Building on this, Sims et al. (2008) developed a temperature and greenness model solely based on the MODIS Land Surface Temperature (LST) and EVI products. Modeled GPP estimates were in good agreement with measured values, highlighting EVI's potential for use as a predictor of GPP, and further demonstrating that GPP can be estimated with relatively high accuracy using only remote sensing data.

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In the Sahel region, water is generally assumed to be the limiting factor for photosynthesis and several attempts have previously been made at developing satellite based stress factors that account for canopy or soil water deficits. The Short wave Infrared Water Stress Index (SIWSI) (Fensholt and Sandholt, 2003) is such an attempt. The Short-wave Infrared (SWIR, ρ_{swir}) and NIR bands available on the MODIS sensor present opportunities to quantify equivalent water thickness (EWT), a term denoting spectral absorption resulting from the leaf water content. SIWSI is based on NIR and SWIR surface reflectance information, and has previously been shown to correlate well with soil moisture (Fensholt and Sandholt, 2003). SIWSI is estimated as:

$$SIWSI = \frac{\rho_{nir} - \rho_{swir}}{\rho_{nir} + \rho_{swir}} \quad (5)$$

SIWSI is thus a normalized index with values theoretically ranging between -1 and 1 . As the water content increases, the reflectance in the SWIR diminishes. Thus, a high SIWSI value, would indicate sufficient amounts of water whereas a low value would indicate water stress (Fensholt and Sandholt, 2003).

We acquired the MOD09A1 8-day product from Earth Observing Systems Data Gateway (EDG, <http://edcimswww.cr.usgs.gov/pub/imswelcome/>) for the year 2007. Data for surface reflectance were extracted from the site pixel, centred on the flux tower and climate station, and its 8 surrounding pixels. The extracted data were then used to calculate EVI and SIWSI according to Eqs. (4) and (5). In order to minimize the effects of sensor disturbances estimated EVI was seasonally adjusted by an adaptive Savitzky-Golay filtering method using the TIMESAT program package (Jönsson and Eklundh, 2002, 2004). TIMESAT fits a function to the upper envelope of the satellite time series data, effectively filtering out negatively biased noise due to, for instance, atmospheric effects (Eklundh and Olsson, 2003; Olofsson et al., 2007a).

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3.3 LUE-model

In order to further assess the applicability of satellite-based measurements we incorporated indices in a simple parametric LUE-model formulated as follows:

$$\text{GPP} = \varepsilon_p \times \varepsilon \times \text{EVI} \times \text{PAR}, \quad (6)$$

- 5 where ε_p represents the maximum biological efficiency of PAR conversion to dry matter ($\text{g C mol}^{-1} \text{ PAR}$).

Most herb layers in the Sahel region consist of a combination of C_3 and C_4 species, where C_3 often dominates in the early part of the growing season (Hanan and Prince, 1997). We therefore prescribed a fixed value of $0.489 \text{ g C mol}^{-1} \text{ PAR}$ for ε_p (Seaquist et al., 2003; Seaquist et al., 2006), which indicates a mixture of C_3 and C_4 plants with the assumption that C_4 grasses dominate for the greater part of the growing season.

10 SIWSI was linearly scaled as ε using maximum and minimum values during the 2007 season to assess its potential as a scalar of maximum light use efficiency. The index has previously been shown to increase predictions of above ground net primary production in the semi-arid Sahel (Fensholt et al., 2006).

15 EVI has been shown to be highly correlated with processes that are dependent on light absorption (Huete et al., 2002; Xiao et al., 2004; Rahman et al., 2005; Olofsson et al., 2007a). It therefore replaces fPAR in Eq. (1) whereas the PAR component, in turn, represents 8-day sums of measurements from the climate station in order to be consistent with the temporal resolution of the MOD09A1 product.

4 Results

4.1 Seasonal variation in carbon exchange, climate and EVI

Figure 2a shows day-to-day variation in GPP, NEE and R_{eco} from July until December 2007, whereas Fig. 2b shows cumulative fluxes together with aboveground net primary

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production (AGNPP) assessments of herbs and grasses (negative values denote net ecosystem CO_2 uptake). It is apparent in these data that net uptake increases as conditions gradually become more favourable for plant growth with the onset of the rain in June (Fig. 2c). Total annual rainfall for the 2007 season was 364 mm, which is slightly higher than the annual average of 320 mm and noticeably higher compared to previous season as Demokeya received a total of 273 mm in 2006. Peak uptake occurs in late August and early September. GPP and R_{eco} decline rapidly as soil water content decreases with the last rains falling on 22 September (Fig. 2c).

5 The seasonal progression of TIMESAT-adjusted EVI is shown in Fig. 2d. Although vegetation index values are relatively low, the site shows a distinct seasonal variation in EVI which corresponds rather well to the seasonal dynamics of 8-day sums of GPP.

4.2 GPP relationships and modelling

Linear regressions between EVI and SIWSI against GPP were computed and results are shown in Fig. 3. A strong linear relationship was observed between EVI and GPP (Fig. 3a) with a coefficient of determination, $R^2=0.89$ and $\text{RMSE}=4.90 \text{ C m}^{-2} \text{ 8d}^{-1}$ (Table 1). We also performed a linear regression analysis between EVI and tower GPP for the central 500 m pixel. Although the analysis did not show a considerable difference with $R^2=0.85$ and $\text{RMSE}=5.73 \text{ g C m}^{-2} \text{ 8d}^{-1}$ we continued to use 3×3 pixel averages throughout our analyses. Nonetheless, the high correlations between tower GPP and EVI suggest that the latter may be usable in estimating seasonal variation of fPAR for semi-arid environments.

20 Furthermore, a strong relationship between SIWSI and GPP was detected (Fig. 3b). This is not surprising as an overall relation between vegetation intensity and water availability as observed by satellite could be expected. However, Fensholt and Sandholt (2003) found SIWSI to be highly correlated with NDVI, indicating a redundancy between SIWSI and EVI. A comparison between EVI and SIWSI was subsequently performed (Fig. 4a). With time series fluctuations occurring at practically the same pace, results showed that there was a significant redundancy between 8-day values of

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EVI and SIWSI for this specific site ($R^2=0.91$).

We further assessed SIWSI's potential as a scalar by testing the index against measurements of soil moisture at a depth of 5 cm (Fig. 4b). Although it can be argued that superficial soil moisture can be regarded as a surrogate measure of EWT, only a weak relationship ($R^2=0.45$) with a RMSE of 1.57% was observed. It is also apparent in Fig. 4b that the correlation is mainly attributed to dry season measurements. Additionally, it was also observed that EVI was stronger correlated to soil moisture with a higher R^2 of 0.57 and a lower RMSE of 1.46%.

As previously stated, EVI and SIWSI performed well when compared against 8-day sums of GPP (Fig. 3). However, results acquired through multiple linear regression, with LUE-model parameters EVI and ε as independent variables, showed that ε did not add further explanation to the observed variance of GPP values (Table 1).

Figure 5 shows 8-day modeled GPP at Demokeya with observed 8-day sums from July to December 2007, where modeled GPP was calculated every 8-day according to Eq. (6). As shown in Fig. 6, seasonal dynamics of modeled GPP agreed well with measured GPP ($R^2=0.83$), with cumulative sums over the period from model start on 12 July to the end on 27 December differing by 3.58% (Fig. 5b). The data points are shown by the equation $GPP_{obs}=0.93 GPP_{mod}+0.68$, which is close to a 1:1 line (Fig. 6). However, the model fails at the beginning of the growing season with the unexplained variance in the measured versus modeled data ($6.15 \text{ g C m}^{-2} \text{ 8d}^{-1}$, Table 1) mainly originating from the effects of ε .

5 Discussion

The aim of this study involved assessing the applicability of two satellite-based indices from MODIS data (EVI and SIWSI) for primary production modelling in a semi-arid environment in the Sahel. Indices were tested through comparison with site-specific measurements of CO_2 fluxes from central Sudan. In order to evaluate the applicability of satellite indices, tower measurements of NEE were used to derive GPP. Soil moisture

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and soil temperature are usually regarded being the primary environmental factors controlling R_{eco} in semi-arid environments and as such R_{eco} was estimated by using a soil water content factor, representing the relative availability of soil water for plants (Wang and Leuning, 1998) together with the exponential regression model of (Lloyd and Taylor, 1994). This step is critical, as accurate estimation of R_{eco} is important with regards to validation of terrestrial carbon models as an erroneous estimate of R_{eco} in turn will result in an error in the estimation of GPP. However, a full evaluation of the environmental factors driving respiration at this site and the applicability of the multiplicative model used to derive R_{eco} is beyond the scope of this study.

A strong relationship between EVI and tower GPP was observed at the Demokeya flux site (Fig. 3a). This clearly indicates the usefulness of EVI in terrestrial carbon modelling. The good correlation was not unexpected, as the utility of this index in satellite-driven primary production modelling has previously been demonstrated for several different biome types (Xiao et al., 2004; Rahman et al., 2005; Sims et al., 2006b; Olofsson et al., 2007a). The highly linear relationship further suggests that GPP can be estimated through a linear regression model for similar environments with relatively high accuracy, using only EVI as independent variable.

We further detected a high correlation between SIWSI and measured tower GPP (Fig. 3b). Although linear regression parameters differed in comparison to the EVI-GPP relationship (Fig. 3a), a similar value range between SIWSI and EVI was apparent. Additionally, the strong relationship between the two MODIS indices (Fig. 4a) indicates that they both may measure the same process at this specific site. Similar results have been reported with NDVI. For instance, Ceccato et al. (2001; 2002) designed a spectral index, the Global Vegetation Moisture Index (GVMI), using NIR, blue and SWIR reflectance data from the VEGETATION sensor onboard the SPOT (Satellite Pour l'Observation de la Terre). The authors demonstrated that GVMI was fully capable of predicting EWT for complete canopy cover, but comparisons between GVMI and NDVI for savanna regions showed a highly linear relationship (Ceccato and Flasse, 2002). Although Ceccato and Flasse (2002) found similar values of NDVI with

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different values of GVMI, the authors mention that NDVI could be used to retrieve vegetation water content for some types of species, mainly for those where the degree of senescence is proportional to moisture content, which seems to be the case at the site used in our study. It is however important to mention that SIWSI does require a certain amount of vegetation to be present in order to be useful (Fensholt and Sandholt, 2003). The rather weak correlation between SIWSI and soil moisture (Fig. 4b) indicates that the sparse vegetation cover at the site causes the index to fail as an indicator of water stress. Furthermore, the stronger, but still rather weak relationship observed between EVI and soil moisture could, to some extent, indicate that the effects of water stress are already manifested through the EVI signal. Cheng et al. (2006) compared several indices, including SIWSI and EVI, to retrievals of EWT from Advanced Visible Infrared Imaging Spectrometer (AVIRIS) imagery. The authors showed that EVI had the highest correlation among indices for an agricultural site and a semi-arid savanna shrub site. However, it would have to be further investigated if EVI can mimic the temporal dynamics of EWT at these specific sites as Cheng et al. (2006) further concluded that errors due to soil background reflectance and canopy architecture were inherent in the retrievals of EWT in both the AVIRIS and MODIS data.

Results derived using a simple parametric LUE-model were shown to agree rather well with measured tower GPP over the 2007 season (Fig. 5). Although correlations showed that the relationship between EVI and GPP was highly linear (Fig. 3a), there are still a number of factors that influence the vegetation signal recorded at the sensor that in turn can greatly influence the 1:1 relationship assumed between fPAR and EVI. Even though TIMESAT minimizes negatively biased noise due to the interference of clouds and atmospheric constituents, effects of varying solar zenith angles on satellite vegetation index data has previously been shown to be considerable at intermediate Leaf Area Index (LAI) values between 0.25 and 2 (Goward and Huemmrich, 1992). A higher solar zenith angle in the beginning and in the end of the season, tends to increase vegetation index values whereas a lower solar zenith angle in the middle of the season results in more soil being directly illuminated, thus reducing values. Al-

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though the site did show a distinct seasonal variation in EVI (Fig. 2d), the applicability of vegetation indices to estimate GPP can still be greatly reduced due to solar angle effects, specifically for sites in semi-arid regions where vegetation is sparse (Sims et al., 2006a). But none of the reflectance values in the 3×3 window during 2007 were acquired at a solar zenith angle of more than 45°, and as vegetation indices estimated by using red and NIR reflectance are relatively unaffected at solar zenith angles less than 50° (Goward and Huemmrich, 1992), the effects of solar angle on derived EVI may be minimal.

The large differences between modeled GPP and observed GPP, specifically for a few 8-day periods early in the model run (Fig. 4a), can be attributed to ε (i.e. scaled SIWSI) which primarily fails due to the low vegetation cover at the beginning of the growing season. As the water content of the soil gradually increases over time with the first rainfall, the overall albedo of the soil decreases. The reflectance in the SWIR, in turn, rapidly diminishes, causing a peak in the modeled GPP during the middle of the growing season. This rather deceptive temporal pattern of ε in the early vegetative stage is further enhanced due to scaling. Finally, multiple linear regression analysis confirmed that no significant improvement was obtained by adding ε to the model, suggesting that, in this case, the parameter is of limited predictive use.

6 Conclusions

In order to test the applicability of MODIS EVI and SIWSI in primary production modelling for semi-arid areas in the Sahel, tower measurements of CO₂ fluxes from central Sudan were partitioned into R_{eco} and GPP using a model that incorporates the Lloyd and Taylor (1994) equation together with a soil water factor (Wang and Leuning, 1998). Both indices showed consistent agreement with GPP with EVI having the highest correlation. The strong GPP-EVI relationship observed demonstrates that EVI show significant promise for efficient determination of primary production at similar ecosystems.

SIWSI was compared against data on soil moisture to assess its applicability as a

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measure of water stress. A rather weak correlation was observed and comparison between SIWSI and EVI illustrated that there is a considerable redundancy between the two indices. Results obtained through multiple linear regression as well as through implementing a simple parametric LUE-model demonstrated that SIWSI did not add further explanatory power to measured GPP values. The index broke down early in the season due most likely to low vegetation cover, indicating that its use as a predictor of water stress in similar ecosystems, where vegetation fraction is low, is restricted. Research using multi-year and site-wide flux tower and climate data sets is however required to further test the use of EVI and SIWSI in satellite data-driven primary production modelling over semi-arid areas in the Sahel.

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References

- Climate change, here and now, *Nature*, 446, 701–701, 2007.
- Asrar, G., Fuchs, M., Kanemasu, E. T., and Hatfield, J. L.: Estimating Absorbed Photosynthetic Radiation and Leaf Area Index from Spectral Reflectance in Wheat, *Agronomy Journal*, 76, 300–306, 1984.
- Aubinet, M., Grelle, G., Ibrom, A., Rannik, U., Moncrie, J., Foken, T., Kowalski, A. S., Martin, P. H., Berbigier, P., Bernhofer, C., Clement, R., Elbers, J., Granier, A., Grunwald, T., Morgenstern, K., Pilegaard, K., Rebmann, C., Snijders, W., and Valentini, T. R. V.: Estimates of the annual net carbon and water exchange of European forests: the EUROFLUX methodology, *Advances in Ecological Research*, 30, 113–175, 2000.
- Ceccato, P., Flasse, S., Tarantola, S., Jacquemoud, S., and Gregoire, J. M.: Detecting vegetation leaf water content using reflectance in the optical domain, *Remote Sens. Environ.*, 77, 22–33, 2001.

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- Ceccato, P. and Flasse, S.: Designing a spectral index to estimate vegetation water content from remote sensing data - Part 2. Validation and applications, *Remote Sens. Environ.*, 82, 198–207, 2002.
- Ceccato, P., Gobron, N., Flasse, S., Pinty, B., and Tarantola, S.: Designing a spectral index to estimate vegetation water content from remote sensing data: Part 1 - Theoretical approach, *Remote Sens. Environ.*, 82, 188–197, 2002.
- Cheng, Y. B., Zarco-Tejada, P. J., Riano, D., Rueda, C. A., and Ustin, S. L.: Estimating vegetation water content with hyperspectral data for different canopy scenarios: Relationships between AVIRIS and MODIS indexes, *Remote Sens. Environ.*, 105, 354–366, 2006.
- Daughtry, C. S. T., Gallo, K. P., and Bauer, M. E.: Spectral Estimates of Solar Radiation Intercepted by Corn Canopies, *Agronomy Journal*, 75, 527–531, 1983.
- Eck, T. F. and Dye, D. G.: Satellite estimation of incident photosynthetically active radiation using ultraviolet reflectance, *Remote Sens. Environ.*, 38, 135–146, 1991.
- Eklundh, L. and Olsson, L.: Vegetation index trends for the African Sahel 1982-1999, *Geophys. Res. Lett.*, 30, p. 1430, 2003.
- Fensholt, R. and Sandholt, I.: Derivation of a shortwave infrared water stress index from MODIS near- and shortwave infrared data in a semiarid environment, *Remote Sens. Environ.*, 87, 111–121, 2003.
- Fensholt, R., Sandholt, I., Rasmussen, M. S., Stisen, S., and Diouf, A.: Evaluation of satellite based primary production modelling in the semi-arid Sahel, *Remote Sens. Environ.*, 105, 173–188, 2006.
- Field, C. B., Randerson, J. T., and Malmstrom, C. M.: Global Net Primary Production: Combining Ecology and Remote Sensing, *Remote Sens. Environ.*, 51, 74–88, 1995.
- Friborg, T., Boegh, E., and Soegaard, H.: Carbon dioxide flux, transpiration and light response of millet in the Sahel, *Journal of Hydrology*, 189, 633–650, 1997.
- Goward, S. N. and Huemmrich, K. F.: Vegetation canopy PAR absorptance and the normalized difference vegetation index: An assessment using the SAIL model, *Remote Sens. Environ.*, 39, 119–140, 1992.
- Hanan, N. P. and Prince, S. D.: Stomatal conductance of West-Central Supersite vegetation in HAPEX-Sahel: measurements and empirical models, *Journal of Hydrology*, 189, 536–562, 1997.
- Hanan, N. P., Kabat, P., Dolman, J. A., and Elbers, J. A.: Photosynthesis and carbon balance of a Sahelian fallow savanna, *Glob. Change Biol.*, 4, 523–538, 1998.

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- Herrmann, S. M., Anyamba, A., and Tucker, C. J.: Recent trends in vegetation dynamics in the African Sahel and their relationship to climate, *Global Environmental Change*, 15, 394–404, 2005.
- Hickler, T., Eklundh, L., Seaquist, J. W., Smith, B., Ardö, J., Olsson, L., Sykes, M. T., and Sjöström, M.: Precipitation controls Sahel greening trend, *Geophys. Res. Lett.*, 32, L21415, doi:10.1029/2005GL024370, 2005.
- Hilker, T., Coops, N. C., Wulder, M. A., Black, T. A., and Guy, R. D.: The use of remote sensing in light use efficiency based models of gross primary production: A review of current status and future requirements, *Science of the Total Environment*, doi:10.1016/j.scitotenv.2007.11.007, in press, 2007.
- Houghton, R. A.: Why are estimates of the terrestrial carbon balance so different?, *Glob. Change Biol.*, 9, 500–509, 2003.
- Huete, A., HuiQing, L., and van Leeuwen, W. J. D.: The use of vegetation indices in forested regions: issues of linearity and saturation, *Geoscience and Remote Sensing*, 1997. IGARSS '97. "Remote Sensing – A Scientific Vision for Sustainable Development", 1997 IEEE International, 4, 1966–1968, 1997.
- Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., and Ferreira, L. G.: Overview of the radiometric and biophysical performance of the MODIS vegetation indices, *Remote Sens. Environ.*, 83, 195–213, 2002.
- Hulme, M.: Climatic perspectives on Sahelian desiccation: 1973–1998, *Global Environmental Change*, 11, 19–29, 2001.
- IPCC: Summary for policymakers, In: *Climate Change 2007: The Physical Science Basis*, in: Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, edited by: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M., and Miller, H. L., Cambridge, United Kingdom and New York, NY, USA, 2007.
- Jönsson, P. and Eklundh, L.: Seasonality Extraction by Function Fitting to Time-Series of Satellite Sensor Data, *IEEE Transactions on Geoscience and Remote Sensing*, 40, 1824–1832, 2002.
- Jönsson, P. and Eklundh, L.: TIMESAT – a program for analyzing time-series of satellite sensor data, *Computers & Geosciences*, 30, 833–845, 2004.
- Justice, C. O., Townshend, J. R. G., Vermote, E. F., Masuoka, E., Wolfe, R. E., Saleous, N.,

3001

- Roy, D. P., and Morisette, J. T.: An overview of MODIS Land data processing and product status, *Remote Sens. Environ.*, 83, 3–15, 2002.
- Liang, S., Zheng, T., Liu, R., Fang, H., Tsay, S.-C., and Running, S.: Estimation of incident photosynthetically active radiation from Moderate Resolution Imaging Spectrometer data, *J. Geophys. Res.*, 111, D15208, doi:10.1029/2005JD006730, 2006.
- Lloyd, J. and Taylor, J. A.: On the temperature dependence of soil respiration., *Functional Ecology*, 8, 315–323, 1994.
- Monteith, J. L.: Solar Radiation and Productivity in Tropical Ecosystems, *Journal of Applied Ecology*, 9, 747–766, 1972.
- Monteith, J. L.: Climate and the Efficiency of Crop Production in Britain, *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, 281, 277–294, 1977.
- Nemani, R. R. and Running, S. W.: Estimation of regional surface resistance to evapotranspiration from NDVI and thermal-IR AVHRR data, *Journal of Applied Meteorology*, 28, 276–284, 1989.
- Olofsson, P., Lagergren, F., Lindroth, A., Lindström, J., Klemedtsson, L., and Eklundh, L.: Towards operational remote sensing of forest carbon balance across Northern Europe, *Biogeosciences*, 4, 3143–3193, 2007a, <http://www.biogeosciences.net/4/3143/2007/>.
- Olofsson, P., Van Laake, P. E., and Eklundh, L.: Estimation of absorbed PAR across Scandinavia from satellite measurements, *Remote Sens. Environ.*, 110, 252–261, 2007b.
- Prince, S. D. and Goward, S. N.: Global Primary Production: A Remote Sensing Approach, *Journal of Biogeography*, 22, 815–835, 1995.
- Rahman, A. F., Sims, D. A., Cordova, V. D., and El-Masri, B. Z.: Potential of MODIS EVI and surface temperature for directly estimating per-pixel ecosystem C fluxes, *Geophys. Res. Lett.*, 32, doi:10.1029/2005GL024127, 2005.
- Reichstein, M., Falge, E., Baldocchi, D., Papale, D., Aubinet, M., Berbigier, P., Bernhofer, C., Buchmann, N., Gilmanov, T., Granier, A., Grunwald, T., Havrankova, K., Ilvesniemi, H., Janous, D., Knohl, A., Laurila, T., Lohila, A., Loustau, D., Matteucci, G., Meyers, T., Miglietta, F., Ourcival, J.-M., Pumpanen, J., Rambal, S., Rotenberg, E., Sanz, M., Tenhunen, J., Seufert, G., Vaccari, F., Vesala, T., Yakir, D., and Valentini, R.: On the separation of net ecosystem exchange into assimilation and ecosystem respiration: review and improved algorithm, *Glob. Change Biol.*, 11, 1424–1439, 2005.
- Seaquist, J. W. and Olsson, L.: Rapid estimation of photosynthetically active radiation over

3002

- the West African Sahel using the Pathfinder Land Data Set, *International Journal of Applied Earth Observation and Geoinformation*, 1, 205–213, 1999.
- Seaquist, J. W., Olsson, L., and Ardö, J.: A remote sensing-based primary production model for grassland biomes, *Ecological Modelling*, 169, 131–155, 2003.
- 5 Seaquist, J. W., Olsson, L., and Eklundh, L.: Broad-scale increase in NPP quantified for the African Sahel, 1982–1999, *International Journal of Remote Sensing*, 27, 5115–5122, 2006.
- Sellers, S. J., Tucker, C. J., Collatz, G. J., Los, S. O., Justice, C. O., Dazlich, D. A., and Randall, D. A.: A global 1-degree by 1-degree NDVI data set for climate studies, Part 2: The generation of global fields of terrestrial biophysical parameters from the NDVI, *International Journal of Remote Sensing*, 15, 3519–3545, 1994.
- 10 Sims, D. A., Luo, H., Hastings, S., Oechel, W. C., Rahman, A. F., and Gamon, J. A.: Parallel adjustments in vegetation greenness and ecosystem CO₂ exchange in response to drought in a Southern California chaparral ecosystem, *Remote Sens. Environ.*, 103, 289–303, 2006a.
- Sims, D. A., Rahman, A. F., Cordova, V. D., El-Masri, B. Z., Baldocchi, D. D., Flanagan, L. B., Goldstein, A. H., Hollinger, D. Y., Misson, L., Monson, R. K., Oechel, W. C., Schmid, H. P., Wofsy, S. C., and Xu, L. K.: On the use of MODIS EVI to assess gross primary productivity of North American ecosystems, *J. Geophys. Res.*, 111, G04015, doi:10.1029/2006JG000162as, 2006b.
- 15 Sims, D. A., Rahman, A. F., Cordova, V. D., El-Masri, B. Z., Baldocchi, D. D., Bolstad, P. V., Flanagan, L. B., Goldstein, A. H., Hollinger, D. Y., Misson, L., Monson, R. K., Oechel, W. C., Schmid, H. P., Wofsy, S. C., and Xu, L.: A new model of gross primary productivity for North American ecosystems based solely on the enhanced vegetation index and land surface temperature from MODIS, *Remote Sens. Environ.*, 112, 1633–1646, 2008.
- Sitch, S., Smith, B., Prentice, I. C., Arneth, A., Bondeau, A., Cramer, W., Kaplan, J. O., Levis, S., Lucht, W., Sykes, M. T., Thonicke, K., and Venevsky, S.: Evaluation of ecosystem dynamics, plant geography and terrestrial carbon cycling in the LPJ dynamic global vegetation model, *Glob. Change Biol.*, 9, 161–185, 2003.
- 20 Van Laake, P. E., and Sanchez-Azofeifa, G. A.: Mapping PAR using MODIS atmosphere products, *Remote Sens. Environ.*, 94, 554–563, 2005.
- 30 Vermote, E. F., El Saleous, N. Z., and Justice, C. O.: Atmospheric correction of MODIS data in the visible to middle infrared: first results, *Remote Sens. Environ.*, 83, 97–111, 2002.
- Wang, Y.-P. and Leuning, R.: A two-leaf model for canopy conductance, photosynthesis and partitioning of available energy I: Model description and comparison with a multi-layered

3003

- model, *Agricultural and Forest Meteorology*, 91, 89–111, 1998.
- Xiao, X., Hollinger, D., Aber, J., Goltz, M., Davidson, E. A., Zhang, Q., and Moore, B.: Satellite-based modeling of gross primary production in an evergreen needleleaf forest, *Remote Sens. Environ.*, 89, 519–534, 2004.

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3004

Table 1. Linear regression and multiple linear regression statistics with observed GPP as dependant variable (number of observations=22).

Independent variable(s)	B0	B1	B2	R2	RMSE ($\text{g C m}^{-2} \text{ 8d}^{-1}$)
EVI	-39.73	265.38	-	0.89	4.90
SIWSI	-6.26	55.44	-	0.81	6.46
EVI, ε	-35.06	224.73	9.56	0.89	4.96
Modeled GPP	0.68	0.94	-	0.83	6.15
-	-	-	-	-	-

3005

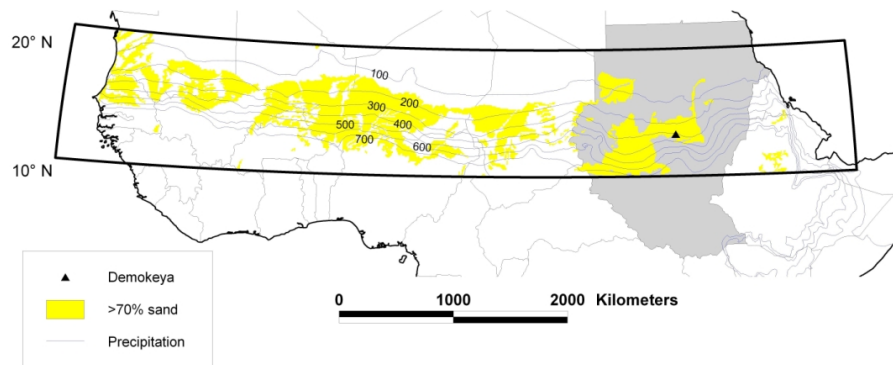


Fig. 1. Map showing the location of the study area in central Sudan. Yellow denotes areas of >70% sand whereas isohyets show mean annual rainfall in mm.

3006

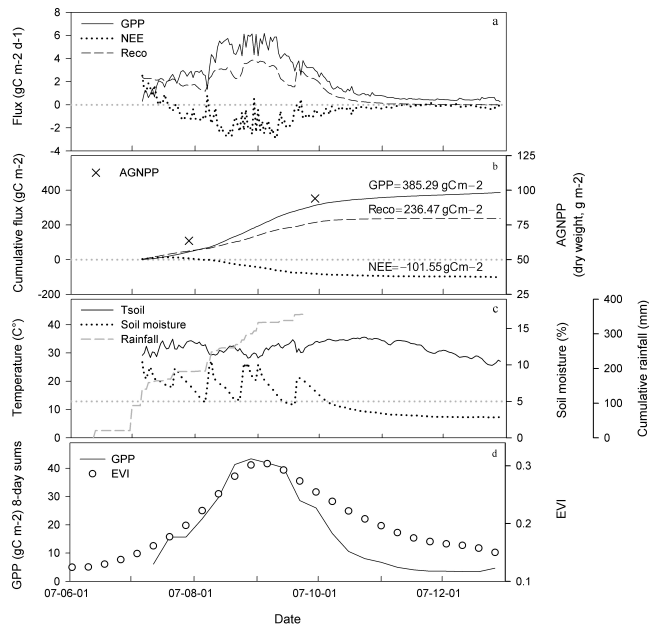


Fig. 2. Seasonal patterns of (a) daily GPP, NEE and R_{eco} , (b) cumulative GPP, NEE, R_{eco} and assessments of above ground biomass, (c) daily average soil temperature (5 cm), soil moisture (5 cm) and cumulative rainfall (dotted gray line denotes maximum plant-available water content) and (d) 8-day sums of GPP plotted against 8-day values of EVI for the Demokeya site from June to 31 December 2007.

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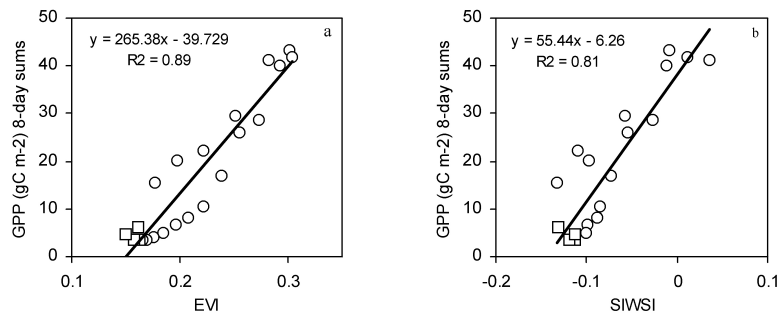


Fig. 3. Linear regression analysis between 8-day sums of GPP and (a) EVI and (b) SIWSI for the Demokeya site 2007, July–December (squares denote points not within the growing season).

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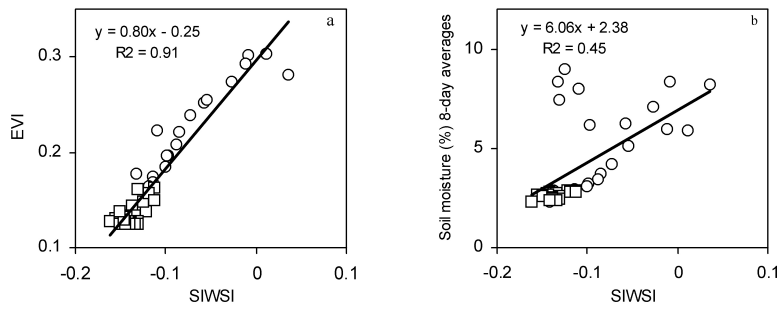


Fig. 4. Linear regression analysis between 8-day values of SIWSI and **(a)** EVI and **(b)** 8-day average soil moisture measured at a depth of 5 cm (soil moisture measurements failed during May and June) for the Demokeya site 2007, January–December (squares denote points not within the growing season).

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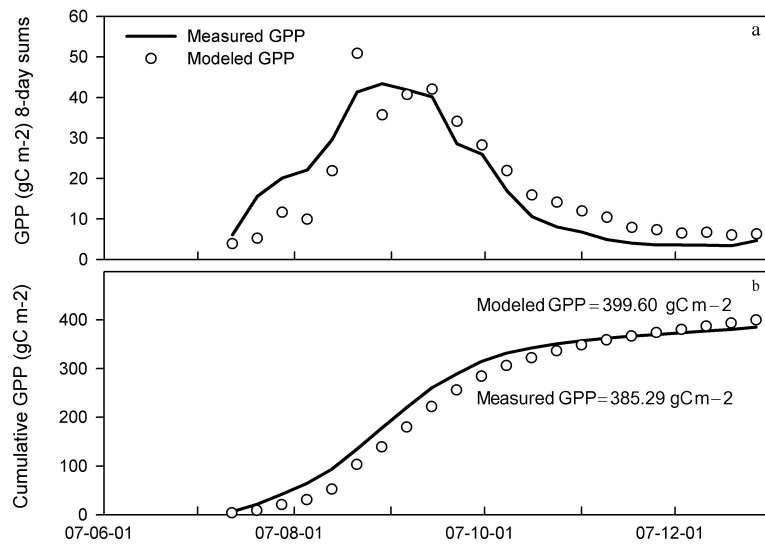


Fig. 5. Seasonal dynamics of **(a)** 8-day sums of measured GPP and modeled GPP and **(b)** measured and modeled cumulative GPP for the Demokeya site 2007, July–December.

3010

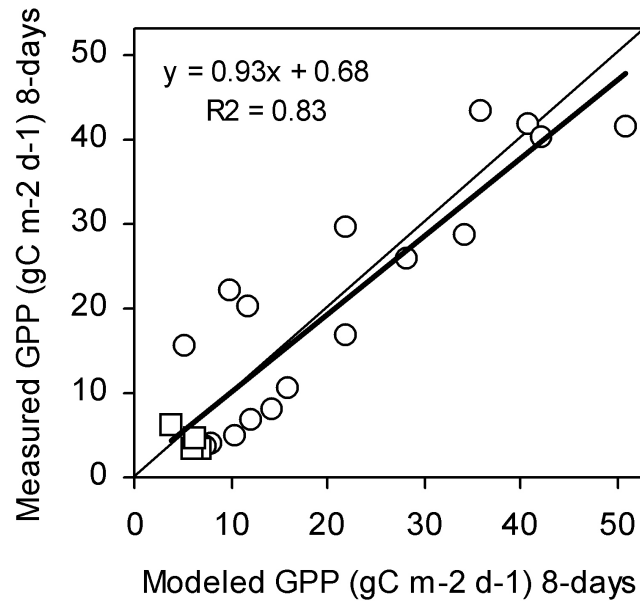


Fig. 6. Linear regression analysis between 8-day sums of measured GPP and modeled GPP for the Demokeya site 2007, July–December (squares denote points not within the growing season).