

Article

Drought Monitoring over West Africa Based on an Ecohydrological Simulation (2003–2018)

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Abstract: In Africa, droughts are causing significant damage to human health and the economy. In West Africa, a severe decline in food production due to agricultural droughts has been reported in recent years. In this study, we simulated ecohydrological variables using the Coupled Land and Vegetation Data Assimilation System, which can effectively evaluate the hydrological water cycle and provide a dynamic evaluation of terrestrial biomass. Using ecohydrological variables (e.g., soil moisture content, leaf area index and vegetation water content) as a drought indicator, we analyzed agricultural droughts in the Sahel-inland region of West Africa during 2003–2018. Results revealed reasonable agreement between the simulated values and the pearl millet yield, and produced a successful quantification of severe droughts in the Sahel-inland region.

Keywords: drought; West Africa; ecohydrology; data assimilation; microwave remote sensing; vegetation water content; soil moisture; locust plague



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1. Introduction

In Africa, floods and droughts have become a serious issue. The number of flood events is increasing considerably year-to-year, and the occurrence of drought is causing both substantial economic damage and harm to human health (source: Munich Re Nat-CatSERVICE: <https://www.iii.org/graph-archive/96134> accessed on 30 September 2021 and [1]). Furthermore, it is predicted that climate change will cause severe floods and droughts to occur more frequently in the future in land areas within the monsoon domains of North Africa [2]. Additionally, the proportion of the population with access to at least basic drinking water services in 2015 was much lower in sub-Saharan Africa than in the other regions of the world, and 58% of the regional population had no alternative to collecting untreated and often contaminated drinking water directly from surface water sources [3]. Overall, the level of development of basic sanitation infrastructure is <50% in almost all countries within this region [3]. Moreover, this region was the only region during 1990–2013, that registered an increase in the absolute number of people living in extreme poverty [3]. In these circumstances, the occurrence of droughts or floods can be highly detrimental to food security. Africa has an issue with water-related disasters (particularly flood and drought disasters) and their consequences regarding socioeconomic development. Resolving this dire situation will require development of a system for data integration, information fusion, synthesis, information sharing and communication promotion. With such a system, it would be possible to ensure the maximum use of data and information from observation, monitoring, prediction, and socioeconomic surveys and statistics, which can assist African countries in overcoming such problems. In West Africa, the impact of agricultural droughts is becoming increasingly evident because of the Charny effect that links surface albedo and precipitation [4], i.e., an increase in albedo due

to reduced vegetation coverage causes precipitation to decrease, which results in a further increase in albedo because more of the land surface will be exposed owing to diminished growth of vegetation.

In West Africa, many researchers have been studying droughts, and the findings of some have identified the importance of (1) the contrast between the pre-monsoon and peak monsoon seasons, (2) two preferred modes of interannual variability (a latitudinal displacement of the tropical rain belt and changes in its intensity, and (3) the tropical easterly jet [5]. Moreover, other research identified notable trends of decrease in rainfall in the Sahel region (10–20° N, 18°W–20° E) from the late 1950s to the late 1980s. Although, Sahel rainfall recovered somewhat through to 2003, drought conditions within the region did not end [6]. These earlier approaches to drought assessment focused on the investigation of monsoon and rainfall trends using conventional drought indexes. Drought prediction over West Africa using the Standardized Precipitation Evapotranspiration Index (SPEI) and the Standardized Precipitation Index (SPI) has been implemented under the RCP4.5 and RCP8.5 scenarios [7]. In a study of Niger River Basin in West Africa, the performances of three drought indexes, i.e., the Standardized Rainfall Anomaly Index, the Bhalme and Mooley Drought Index, and SPI, were evaluated and compared [8]. Additionally, the question of how rising global temperatures might affect the spatial pattern of rainfall and the resultant droughts in West Africa was also investigated. Furthermore, precipitation and potential evapotranspiration variables have been simulated using the Rossby Centre RCA4 regional atmospheric model driven by 10 global climate levels under the RCP8.5 scenario (CanESM2, CNRM-CM5, CSIRO-Mk3, EC-EARTH-r12, GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-MR, MIROC5, MPI-ESM-LR, and NorESM1-M) [9]. This approach to drought assessment is based on the use of atmospheric and land surface models.

The mainstream approach to the assessment of drought in West Africa has concentrated on monsoons and rainfall trends [5,6] using conventional drought indexes [7,8], e.g., the SPI, SPEI and the self-calibrating Palmer Drought Severity Index. Although drought assessment using conventional drought indexes can be effective, the emphasis of such an approach is placed on precipitation, with limited consideration of land surface hydrology and energy circulation. In studies using satellite remote sensing, the vegetation condition (e.g., the normalized difference vegetation index (NDVI), leaf area index (LAI), and vegetation optical depth (VOD)) is monitored using visible and near-infrared sensors such as the Moderate Resolution Imaging Spectroradiometer. Furthermore, the near-surface soil moisture content can be monitored using passive and active microwave sensors such as the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E), Advanced Microwave Scanning Radiometer 2 (AMSR2), the Soil Moisture Active Passive satellite and the Soil Moisture and Ocean Salinity satellite. Thus, although satellite remote sensing cannot be used to assess the root-zone soil moisture content, which is important for vegetation growth dynamics, it can be used to evaluate the near-surface soil moisture content. Therefore, water absorption from the root-zone layer and vegetation growth dynamics are not considered in the NDVI, LAI and VOD. The Global Land Data Assimilation System (GLDAS) [10] is the land surface data assimilation system integrated between a land surface model and a data assimilation scheme, in which the skin temperature is assimilated. In the GLDAS, not only the near-surface soil moisture content but also the root-zone soil moisture content is calculated by assimilating the skin temperature which is a variable of land surface hydrology and energy circulation used in calculating the flux by the land surface model. For vegetation, NDVI and LAI are used on the basis of visible and near infrared remote sensing. The Coupled Land and Vegetation Data Assimilation System (CLVDAS) [11–13] integrates passive microwave remote sensing techniques, a land surface model, a dynamic vegetation model (DVM) and a data assimilation scheme. CLVDAS assimilates microwave brightness temperatures (6.925 GHz; vertical polarization, 6.925 GHz; horizontal polarization, 10.7 GHz; vertical polarization and 10.7 GHz; horizontal polarization) that represent the product between the skin temperature and microwave emissivity. Thus, CLVDAS can estimate not only the optimized near-surface soil moisture

content but also the optimized root-zone soil moisture content through data assimilation, because the microwave brightness temperature is sensitive to moisture. Additionally, the integrated DVM can be used to estimate the optimized LAI and vegetation water content, which can provide evaluation of vegetation growth dynamics, through data assimilation of microwave brightness temperatures. Thus, the gap between conventional study and CLVDAS-based studies is as follows: (1) evaluation of optimized root-zone soil moisture content through data assimilation, and (2) evaluation of optimized LAI and vegetation water content based on vegetation growth dynamics.

To fill this gap, land surface hydrology and energy circulation were evaluated using CLVDAS [11–13] in this study. Because this approach provides the possibility of drought monitoring and application to agricultural support [14], we evaluated the relationship between the pearl millet yield as a major crop and the simulated vegetation water content as a drought index, and analyzed the applicability of the approach to the assessment of agricultural droughts in the Sahel-inland region of West Africa during 2003–2018.

2. Data

CLVDAS needs global meteorological forcing data, such as precipitation (mm/s), air temperature (K), air pressure (mbar), shortwave radiation (W/m^2), longwave radiation (W/m^2), wind speed (m/s) and specific humidity (kg/kg), for EcoHydro-SiB and the assimilation of global satellite-observed microwave brightness temperature data for data. The suitability for CLVDAS of GLDAS ver. 2.1 global meteorological forcing data has been recognized [11–14] and therefore the GLDAS global meteorological forcing data, which can be downloaded from <https://urs.earthdata.nasa.gov> accessed on 30 September 2021, were used in this study. The GLDAS meteorological data have 3-h temporal resolution and $0.25^\circ \times 0.25^\circ$ gridded spatial resolution, i.e., the same as the output of CLVDAS. Satellite-observed microwave brightness temperatures (vertical and horizontal polarizations at 6.925, 10.65, and 18.7 GHz) from the AMSR-E and AMSR2, which can be downloaded from <https://gportal.jaxa.jp/gpr/?lang=en> accessed on 30 September 2021, were also used. These data have daily temporal resolution (descending orbit only), but $0.25^\circ \times 0.25^\circ$ gridded spatial resolution, i.e., the same as the output of CLVDAS. The period from October 2011 to December 2012 represents the period of transition from AMSR-E to AMSR2, and data assimilation was not conducted because microwave brightness temperatures were not observed by the satellites. Therefore, the ecohydrological variable was not provided by CLVDAS during this period (Table 1). Crop yield data, obtained from the Food and Agriculture Organization of the United Nations, were downloaded from <http://faostat3.fao.org/download/Q/QC/E> accessed on 30 September 2021.

Table 1. List of input and output datasets.

	Items	Unit	Source	Spatial Resolution	Temporal Resolution	Regions	Periods in This Study
Input dataset	Precipitation	mm/s	GLDAS 2.1	0.25°	3 h	Global	2003.1–2018.12
	Air temperature	K	GLDAS 2.1	0.25°	3 h	Global	2003.1–2018.12
	Air pressure	mbar	GLDAS 2.1	0.25°	3 h	Global	2003.1–2018.12
	Shortwave radiation	W/m^2	GLDAS 2.1	0.25°	3 h	Global	2003.1–2018.12
	Longwave radiation	W/m^2	GLDAS 2.1	0.25°	3 h	Global	2003.1–2018.12
	Wind speed	m/s	GLDAS 2.1	0.25°	3 h	Global	2003.1–2018.12
	Specific humidity	kg/kg	GLDAS 2.1	0.25°	3 h	Global	2003.1–2018.12
	6.925 GHz microwave brightness temperature (V polarization)	K	AMSR-E, AMSR2	0.25°	1 day	Global	2003.1–2011.9 2013.1–2018.12
	6.925 GHz microwave brightness temperature (H polarization)	K	AMSR-E, AMSR2	0.25°	1 day	Global	2003.1–2011.9 2013.1–2018.12
	10.7 GHz microwave brightness temperature (V polarization)	K	AMSR-E, AMSR2	0.25°	1 day	Global	2003.1–2011.9 2013.1–2018.12
	10.7 GHz microwave brightness temperature (H polarization)	K	AMSR-E, AMSR2	0.25°	1 day	Global	2003.1–2011.9 2013.1–2018.12

Table 1. Cont.

	Items	Unit	Source	Spatial Resolution	Temporal Resolution	Regions	Periods in This Study
Output dataset	Near-surface soil moisture content	m^3/m^3	CLVDAS	0.25°	1 day	West Africa	2003.1–2018.12
	Root-zone soil moisture content	m^3/m^3	CLVDAS	0.25°	1 day	West Africa	2003.1–2018.12
	Vegetation water content	m^3/m^3	CLVDAS	0.25°	1 day	West Africa	2003.1–2018.12

3. Methods

To assess agricultural droughts in West Africa, a methodology for estimating ecohydrological variables such as soil moisture content and vegetation water content is described.

3.1. Study Area and Period

The selected simulation domain of West Africa comprised the region $0^\circ 30' - 25^\circ 7' \text{ N}$, $18^\circ 7' \text{ W} - 16^\circ 7' \text{ E}$. The Sahel-inland region ($10^\circ \text{ N} - 16^\circ \text{ N}$, $12^\circ \text{ W} - 16^\circ \text{ E}$), which is an active agricultural area, was selected as the specific study area for the assessment of agricultural droughts during 2003–2018 (Figure 1).

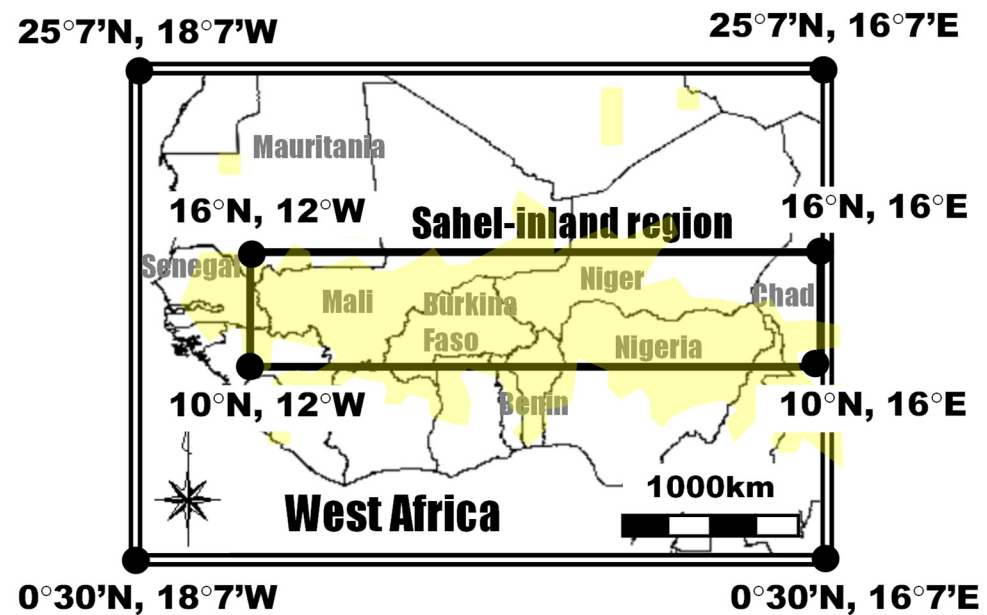


Figure 1. Simulation domain ($0^\circ 30' - 25^\circ 7' \text{ N}$, $18^\circ 7' \text{ W} - 16^\circ 7' \text{ E}$) and study area ($10^\circ - 16^\circ \text{ N}$, $12^\circ \text{ W} - 16^\circ \text{ E}$) in West Africa. Agricultural drought assessment was conducted for the Sahel-inland region; yellow shading indicates the general area of pearl millet cropland [15].

3.2. System Overview

As listed in Table 1 and illustrated in Figure 2, this research used CLVDAS [11,12] to calculate the ecohydrological variables. Meteorological forcing data (Figure 2a) are input to EcoHydro-SiB (Figure 2b), which is a land surface model that can calculate various ecohydrological variables (Figure 2c). EcoHydro-SiB (Figure 2b) is coupled with Hydro-SiB and the dynamic vegetation model (DVM). The Simple Biosphere Model 2 (SiB2) [16] was improved, Hydro-SiB was developed based on a one-dimensional Richards's equation, and the vertical interlayer flows within the unsaturated zone [17]. Soil water dynamics are described by van Genuchten's water retention curve [18], and the LAI and vegetation are calculated on the basis of carbon-pool dynamics. For a detailed explanation and the formulations, the reader is referred to Section 2.1 [11]. The calculated ecohydrological variables (Figure 2c) are used to drive a microwave radiative transfer model (RTM; Figure 2d) to calculate microwave brightness temperatures (Figure 2e). The RTM (Figure 2d) combines

the advanced integral equation model (AIEM) with a shadowing effect [19] to evaluate land surface scattering and the omega-tau model [20], which evaluates the microwave radiative transfer process in the ground surface. The cost is calculated on the basis of the difference between the calculated microwave brightness temperature (Figure 2e) and the satellite observed microwave brightness temperature (Figure 2f) of the land surface (Equation (1)). The calculated cost (Figure 2g) is minimized through data assimilation.

$$Cost = \sum_{F=6,10GHz} \sum_{P=H,V} (TBe_F^P - TBo_F^P)^2, \quad (1)$$

where TBe_F^P is the calculated microwave brightness temperature, TBo_F^P is the satellite observed microwave brightness temperature, and F and P are frequency (GHz) and polarization (H-horizontal, V-vertical) respectively.

Using the above methodology, the optimized ecohydrological variables (Figure 2j), e.g., near-surface soil moisture content, root-zone soil moisture content, evapotranspiration, LAI, and vegetation water content, can be estimated. By assimilating the satellite microwave brightness temperatures of the land surface, it is possible to estimate all ecohydrological variables spatiotemporally on the global scale. This system has two different modules: parameter optimization and data assimilation. In the parameter optimization module (Figure 2h), the shuffled complex evolution (SCE as a data assimilation scheme) [21] (Figure 2i), determines the most important optimized parameter. In the data assimilation module, the genetic particle filter (GPF as a data assimilation scheme) [22], estimates optimized ecohydrological variables (Figure 2i) sequentially.

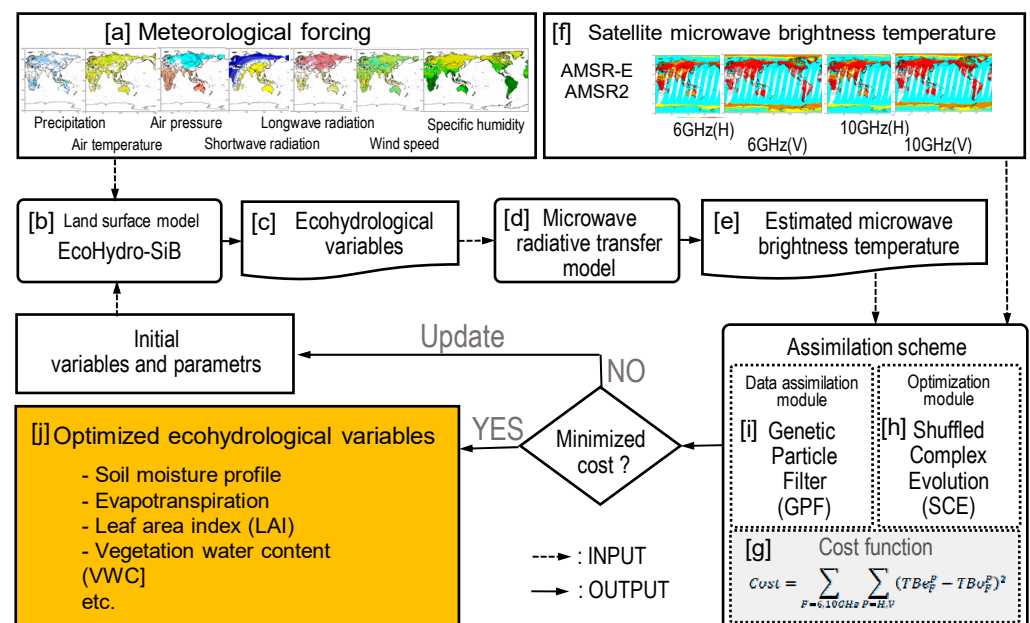


Figure 2. CLVDAS framework used in this study. Optimized ecohydrological variables are outputted from this system, and the near-surface soil moisture content, root-zone soil moisture content, and the vegetation water content, as optimized ecohydrological variables, are analyzed. The meteorological forcing dataset comprises precipitation (mm/s), air temperature (K), air pressure (mbar), shortwave radiation (W/m^2), longwave radiation (W/m^2), wind speed (m/s), and specific humidity (kg/kg). Satellite-observed brightness temperature dataset comprises brightness temperatures for 6.925 GHz horizontal polarization (6 GHz(H)), 6.925 GHz vertical polarization (6 GHz(V)), 10.7 GHz horizontal polarization (10 GHz(H)), and 10.7 GHz vertical polarization (10 GHz(V)). Meteorological forcing data (a) are input to EcoHydro-SiB (b). EcoHydro-SiB is a land surface model that calculates various ecohydrological variables (c). The calculated ecohydrological variables (c) are used to drive a microwave

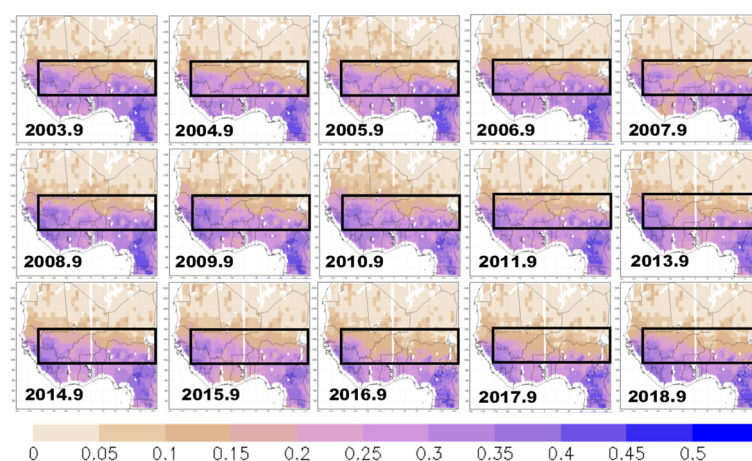
radiative transfer model (d) to calculate microwave brightness temperatures (e). The cost is calculated on the basis of the difference between the calculated microwave brightness temperatures (e) and the satellite-observed microwave brightness temperatures (f) of the land surface. The calculated cost (g) is minimized through data assimilation scheme of the Shuffled Complex Evolution (SCE) (h) and the Genetic Particle Filter (GPF) (i). Ultimately, the optimized eco-hydrological variables (j) are estimated.

3.3. Drought Index

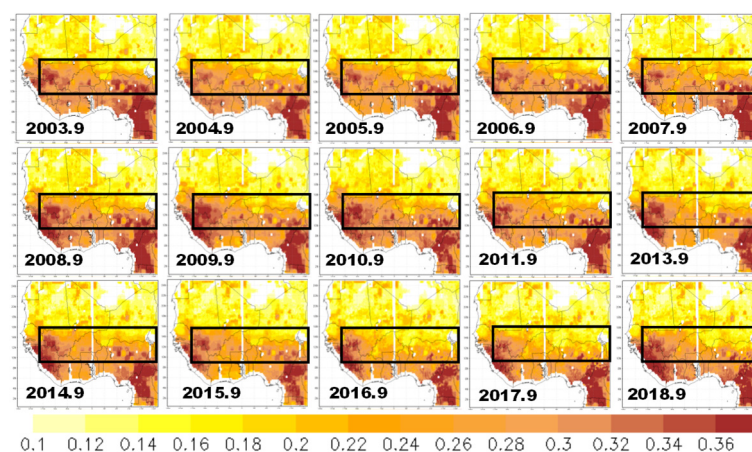
In this study, the near-surface soil moisture content (0–3 cm depth, m^3/m^3) [11,12], root-zone soil moisture content (3–20 cm depth, m^3/m^3), and vegetation water content (m^3/m^3) were estimated using CLVDAS to investigate the ecohydrological water cycle and agricultural drought. This study considered that by absorbing sufficient water from the roots, crops can store ample water in the plant body, grow well, and bear much fruit. Therefore, this study focused on vegetation water content (m^3/m^3) as an indicator of agricultural droughts. In West Africa, the cultivation of rain-fed crops for domestic consumption is widespread and pearl millet represents the principal staple crop. Therefore, pearl millet was selected as another indicator of agricultural drought in this study. In West Africa, pearl millet is sown during June–July, grows during August–September, and is harvested after October. Therefore, September, representing the period of maximum growth to the fruiting period, is an important time in which to assess agricultural drought. Thus, the vegetation water content in September (temporal average) and the pearl millet crop yield were also selected as drought indicators in this study. Because it is not possible to compare various ecohydrological variables, such as soil moisture content, vegetation water content, and crop yield quantitatively, the normalized index (NI_i) based on the z-score theory was calculated for each day from 2003 to 2018 using Equation (2):

$$NI_i = \frac{x_i - \mu}{\sigma}, \quad (2)$$

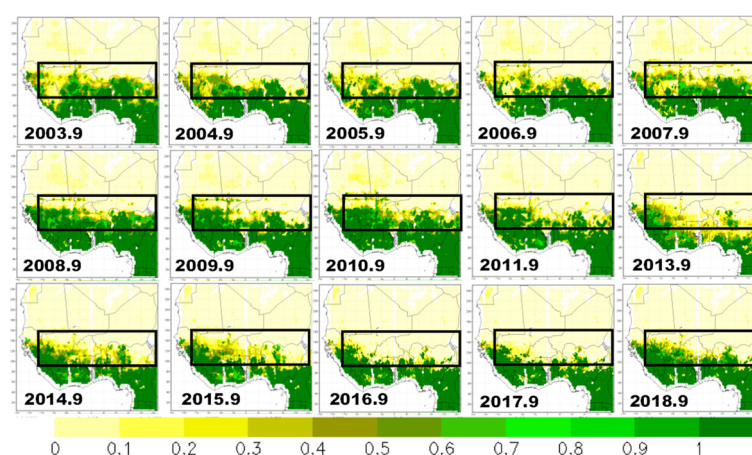
where x_i is a variable (i.e., near-surface soil moisture content, root-zone soil moisture content, vegetation water content, pearl millet yield, and number of days with a locust outbreak) on arbitrary date (i) in a year, and μ and σ are the average and standard deviation for x_i on arbitrary date (i) in all years (2003–2018). Values of x_i for near-surface soil moisture content, root-zone soil moisture content, and vegetation water content were calculated for each grid by CLVDAS, as shown in Figure 3. Therefore, μ and σ were also calculated for each grid. Using these values of x_i , μ , and σ , the normalized index (NI_i) based on the z-score theory was calculated for each grid, as shown in Figure 4. Subsequently, the normalized index (NI_i) values were averaged spatially for the Sahel-inland region. Finally, the normalized index (NI_i) values were averaged temporally for September, as shown in Figure 5. Values of x_i for the pearl millet crop yield represent the annual total yield in the Sahel-inland region (i.e., Chad, Niger, Nigeria, Benin, Burkina Faso, and Mali) in all years (2003–2018). Therefore, μ and σ were calculated using the x_i value for each year. Finally, the annual normalized index (NI_i) values for the pearl millet crop yield were calculated, as shown in Figure 6. The number of days with a locust outbreak were calculated as follows. The number of days (x_i) in each year (2003–2018) were counted when more than 10 locust plagues occurred in the Sahel-inland region, according to the Locust watch of the Food and Agriculture Organization (FAO) of the United Nations. Then, the average (μ) and standard deviation (σ) were calculated using these numbers (x_i) for each year. Using these values of x_i , μ , and σ , the normalized index (NI_i) based on the z-score theory was calculated, as shown in Figure 7.



(a)



(b)



(c)

Figure 3. Spatial distribution of (a) near-surface soil moisture content (m^3/m^3), (b) root-zone soil moisture content (m^3/m^3), and (c) vegetation water content (m^3/m^3) from CLVDAS (September monthly averages in the period 2003–2018; spatial resolution is $0.25^\circ \times 0.25^\circ$). Black rectangle outlines the Sahel-inland region. In the Sahel-inland region, vegetation water content has shown a trend of decrease from the north since 2011 (c). This trend has also shown in the root-zone soil moisture content (b) although not clearly in the near-surface soil moisture content (a).

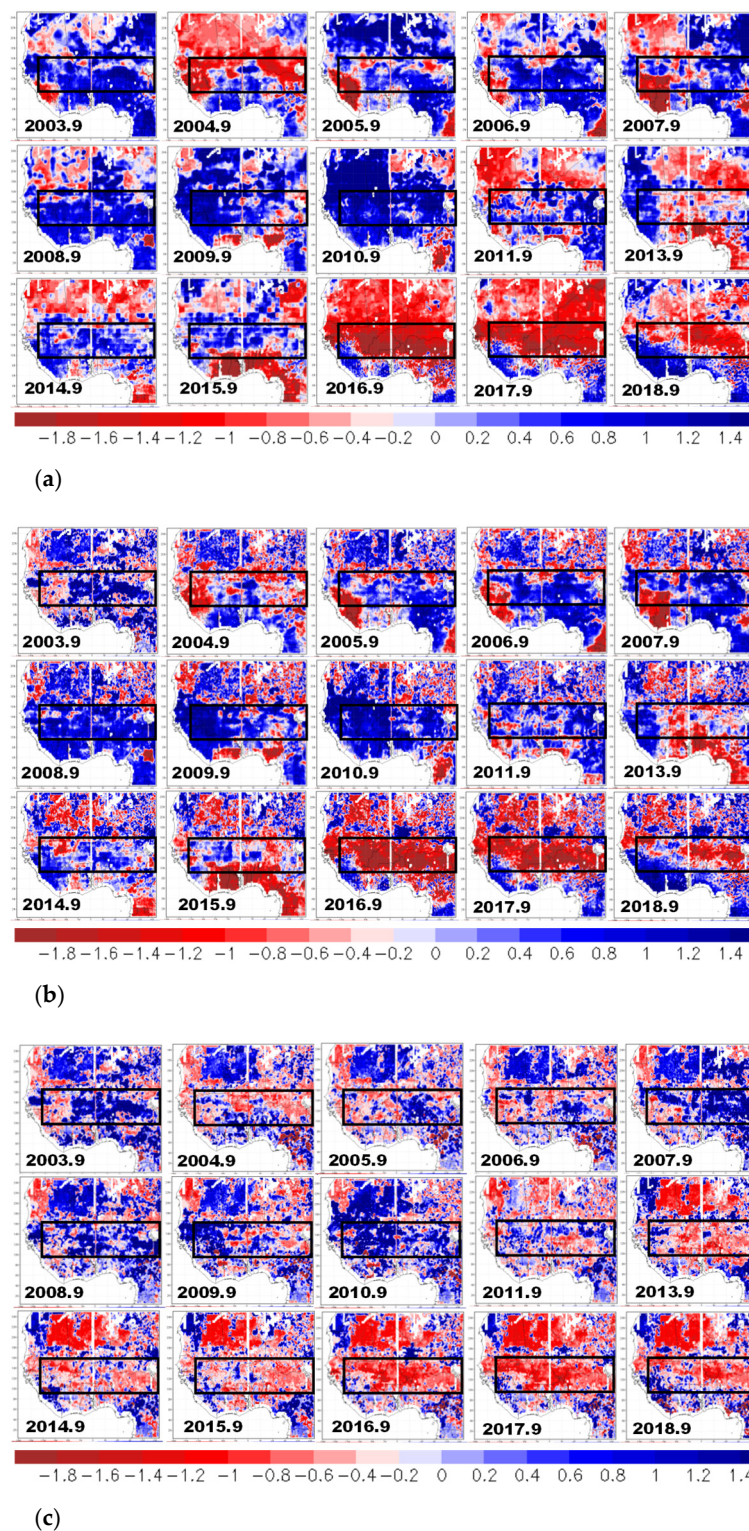


Figure 4. Spatial distribution of NI_i for (a) near-surface soil moisture content (m^3/m^3), (b) root-zone soil moisture content (m^3/m^3), and (c) vegetation water content (m^3/m^3) from the CLVDAS (September monthly averages in the period 2003–2018; spatial resolution is $0.25^\circ \times 0.25^\circ$). Black rectangle outlines the Sahel-inland region. Although variation in vegetation water content itself is slightly unclear (Figure 3c), its normalized index (NI_i) based on the z-score theory clearly shows the decrease since 2011(c). Furthermore, this trend is also shown in the near-surface and root-zone soil moisture content (a) and (b), respectively.

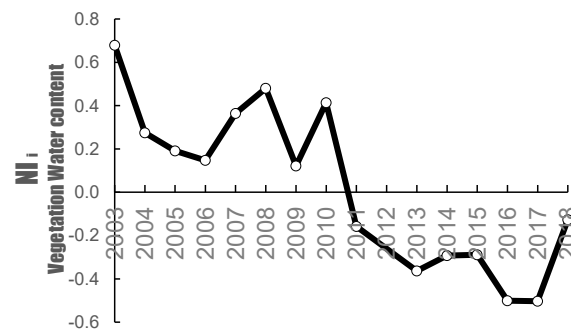


Figure 5. Annual variation in NI_i for vegetation water content in the Sahel-inland region (September monthly averages in the period 2003–2018; spatial average of entire Sahel-inland region: resolution is $0.25^\circ \times 0.25^\circ$). A substantial decrease in the normalized index (NI_i) of the vegetation water content since 2010 is shown.

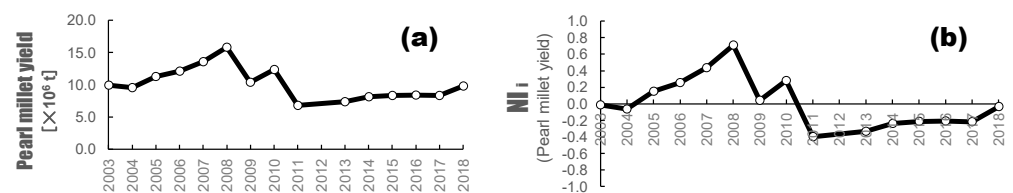


Figure 6. Annual variation in the pearl millet yield in the Sahel-inland region consisting of Chad, Niger, Nigeria, Benin, Burkina Faso, and Mali: (a) pearl millet yield, and (b) its normalized index (NI_i), decrease in pearl millet yield since 2011 is clearly shown.

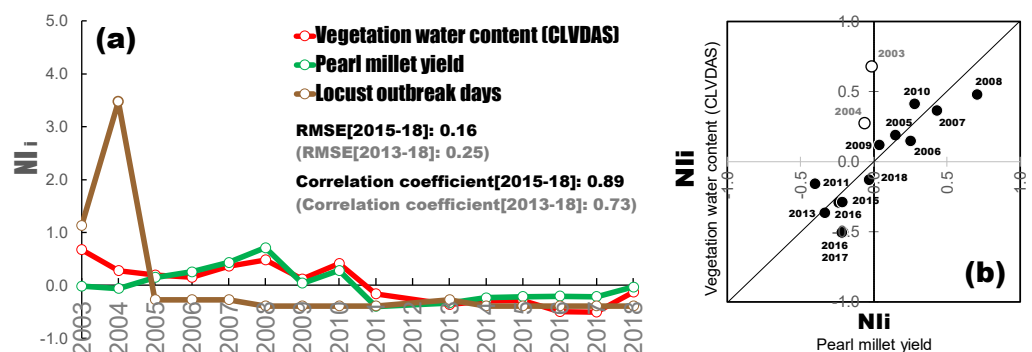


Figure 7. (a) Comparison of the normalized index (NI_i) for the vegetation water content (CLVDAS) (blue line), pearl millet yield (red line), and number of locust outbreak days (brown line), and (b) scatterplot between the NI_i for vegetation water content and the NI_i for pearl millet yield of the Sahel-inland region. The number of locust outbreak days was calculated as follows. The number of days (x_i) in each year (2003–2018) were counted when more than 10 locust plagues occurred in the Sahel-inland region according to the FAO Locust watch. Then, the average (μ) and standard deviation (σ) were calculated using these numbers (x_i) for each year. Using these values of x_i , μ , and σ , the normalized index (NI_i) based on the z-score theory was calculated. In this study, we assessed agricultural drought for the period 2005–2018, excluding 2003–2004. For this period, the RMSE between the NI_i for pearl millet yield and the NI_i for vegetation water content was 0.16 and the correlation coefficient was 0.89, indicating strong agreement.

4. Results and Discussion

In passive microwave remote sensing, the low-frequency band with the longest wavelength is used by AMSR-E and AMSR2 because the microwaves emitted from the soil must be scanned through the atmosphere and vegetation. However, a passive microwave sensor can generally detect only the near-surface soil moisture content because even microwaves in the low-frequency band are absorbed by soil moisture [23]. This is the reason why the AMSR-E and AMSR2 soil moisture product targets only the near-surface soil moisture

content [23]. To overcome this shortcoming, as described in Section 1, the following processing is implemented in CLVDAS. Eco-HydroSiB evaluates the ecohydrological water cycle, which expresses the penetration of precipitation, water storage in the root-zone, and water absorption by roots and vegetation growth, and simulates the ecohydrological variables (e.g., soil moisture profile, evapotranspiration, and biomass). Furthermore, the RTM calculates the microwave brightness temperatures emitted from the land surface using the simulated ecohydrological variables. Additionally, changes in the ecohydrological variables and assimilation of the microwave brightness temperatures are repeated until the difference between the simulated and satellite-observed microwave brightness temperatures of the ground surface is minimized. Hence, an accurate estimation of the ecohydrological water cycle is derived using this process. This represents the major advantage of this system. Hitherto, the CLVDAS outputs of estimated soil moisture content and LAI were validated by comparison with the following observations: ground-based observed soil moisture content and LAI observed at the Yanco Flux Tower site located in New South Wales (Australia) [12], ground-based observed soil moisture content from the African Monsoon Multidisciplinary Analyses, Vaira Ranch (USA), Bayantsagaan (Mongolia) [11,13], and the Moderate Resolution Imaging Spectroradiometer LAI in West Africa and Northeast Brazil [14]. The following estimation accuracy was achieved: (1) root mean square error (RMSE) of $0.05 \text{ m}^3/\text{m}^3$ or less and bias of $0.045 \text{ m}^3/\text{m}^3$ or less in terms of soil moisture content, and (2) RMSE of $0.12 \text{ m}^2/\text{m}^2$ or less and bias of $0.14 \text{ m}^2/\text{m}^2$ or less in terms of LAI.

For the period from 1 January 2003 to 31 December 2018, the near-surface soil moisture content (m^3/m^3), root-zone soil moisture content (m^3/m^3), and vegetation water content (m^3/m^3) were simulated using CLVDAS and used to create a gridded dataset (temporal resolution: daily, spatial resolution: $0.25^\circ \times 0.25^\circ$). Figure 3 shows the spatial distribution of the averaged ecohydrological variable in September. In the Sahel-inland region, vegetation water content has shown a trend of decrease from the north since 2011 (Figure 3c). This trend has also shown in the root-zone soil moisture content (Figure 3b) but not so clearly in the near-surface soil moisture content (Figure 3a). Furthermore, NI_i for each ecohydrological variable was calculated for each grid using Equation (2). Figure 4 shows the spatial distribution of each normalized index of the averaged ecohydrological variables in September. Although variation in the vegetation water content itself is slightly unclear (Figure 3c), its normalized index (NI_i) based on the z-score theory clearly shows a decrease since 2011 (Figure 4c). Furthermore, this trend has also shown in the near-surface and root-zone soil moisture content (Figure 3a,b). Figure 5 shows the annual variation in the normalized index (NI_i) based on the z-score theory for vegetation of water content in the Sahel-inland region, calculated using Equation (2) (September average in the agricultural drought assessment period from 2003 to 2018, regional spatial average). We calculated the annual total yield of pearl millet, in the Sahel-inland region consisting of Chad, Niger, Nigeria, Benin, Burkina Faso, and Mali from 2003 to 2018 (Figure 6a), which revealed that the annual yield since 2011 has been approximately half that in 2008. Furthermore, we calculated the normalized index (NI_i) based on the z-score theory of the total yields of pearl millet using Equation (2) (Figure 6b). Figure 7 shows the annual variation in NI_i for both pearl millet yield and vegetation water content in the Sahel-inland region (temporal average in September and regional spatial average). The NI_i values for the pearl millet yield are negative during 2003–2004, whereas the concurrent NI_i values for vegetation water content are positive, and the difference between the two sets of NI_i values is large. We investigated external factors other than droughts by considering previous studies [24,25] and the FAO Locust watch (<http://www.fao.org/ag/locusts/en/archives/briefs/index.html> accessed on 30 September 2021), which revealed that serious locust outbreaks occurred during 2003–2004 in West Africa. The number of days (x_i) in each year (2003–2018) was counted when more than 10 locust plagues occurred in the Sahel-inland region using the FAO Locust watch. The average (μ) and standard deviation (σ) were calculated using these the numbers of days (x_i) in each year. Using x_i , μ , and σ , the normalized index (NI_i) based on the z-score

theory is calculated by using Equation (2) (brown line). The NI_i values for locust outbreaks (brown line in Figure 7; calculated as described in Section 3.3) in 2003 and 2004 are 1.31 and 3.37, respectively; although, all NI_i values after 2005 are negative. We recognize that crop yields of the Sahel-inland region were likely to be adversely affected by the external impact of locust plagues in 2003–2004. Therefore, we assessed agricultural drought in the period from 2005 to 2018. For this period, the RMSE between the NI_i for pearl millet yield (green line in Figure 7a) and the NI_i for vegetation water content (red line in Figure 7a) was 0.16 and the correlation coefficient was 0.89, indicating a strong agreement. As an aside, the RSME and correlation coefficient values when including the period 2003–2004 were 0.25 and 0.73, respectively).

The variation in NI_i for precipitation and the simulated ecohydrological variables (near-surface soil moisture content, root-zone soil moisture content and vegetation water content) were investigated for the Sahel-inland region during the agricultural drought assessment period (2005–2018) (Figures 8 and 9). In the first half of the agricultural drought assessment period (Figure 8), the NI_i of vegetation water content was mostly positive, except in 2005, 2008 and 2009, which indicates that the effect of drought on vegetation water content is small. We also found that each peak had a time lag when focusing on the negative peak for precipitation, soil moisture content, and vegetation water content in 2005, 2008, and 2009 (yellow marks and lines in Figure 8). This is attributable to the following process: (i) the land surface soon dries because of the shortage of precipitation, (ii) the root-zone soil moisture decreases after a further amount of time because water is not supplied from the land surface, and (iii) vegetation water content declines after an even further amount of time because of the lack of root-zone soil moisture available for absorption by roots. In the second half of the agricultural drought assessment period (Figure 9), the vegetation water content gradually became negative after 2014. As in the first half of the agricultural drought assessment period (Figure 8), the shortage of precipitation gradually propagated to the lack of vegetation water content (yellow marks and lines in Figure 9). Although the NI_i values of precipitation became positive in April 2016, negative values remained in the growth and early harvest seasons (May–October), leading to negative NI_i values of soil moisture and vegetation water content simultaneously (green line in Figure 9). The NI_i values of precipitation became positive in the second half of December 2016 owing to the occurrence of heavy rainfall; however, they reverted to negative values in the beginning of January 2017. The surface soil moisture content showed the same behavior. In contrast, the root-zone soil moisture content was positive in the period from January–April because the water associated with the heavy rainfall was stored in the rootzone. The vegetation grew by absorbing the stored root-zone soil moisture, as indicated by the positive peak of vegetation water content at the beginning of April (blue line in Figure 9). This indicates that storage of root-zone soil moisture is important for vegetation growth, and that CLVDAS can evaluate such a mechanism. In 2017, soil moisture was not stored in the near-surface soil because precipitation amounts were low. Following subsequent rainfall events, the NI_i values of near-surface soil moisture recovered (became positive) in March 2018; however, the NI_i values of root-zone soil moisture and vegetation water content did not recover (remained negative). Thus, both the root-zone soil moisture content and vegetation water content remained negative in the long term because they have a long retention period of the memory of past water shortages (red line in Figure 9). By investigating the daily variation in precipitation, soil moisture content, and vegetation water content using CLVDAS, we were able to evaluate the following land surface hydrological water cycle and vegetation growth dynamics mechanism. (i) Reduced precipitation causes aridity of the land surface, which affects the condition of the root-zone soil moisture. (ii) Plants cannot retain sufficient water within their structures because of the lack of soil moisture available for absorption in the root-zone layer. (iii) Near-surface soil moisture content can change rapidly in response to temporary rainfall events. In contrast, both the root-zone soil moisture and the vegetation water content tend to remain in long-term drought conditions because they have a long retention period of the memory of past water shortage. The major finding of this

study was establishing that CLVDAS can be used to evaluate the hydrological water cycle (penetration of precipitation to the root-zone soil layer and its absorption by roots) and vegetation growth dynamics. Additionally, we confirmed that vegetation water content output by CLVDAS can be used to assess agricultural drought through comparison with major crop yields and investigation of external factors in the target region.

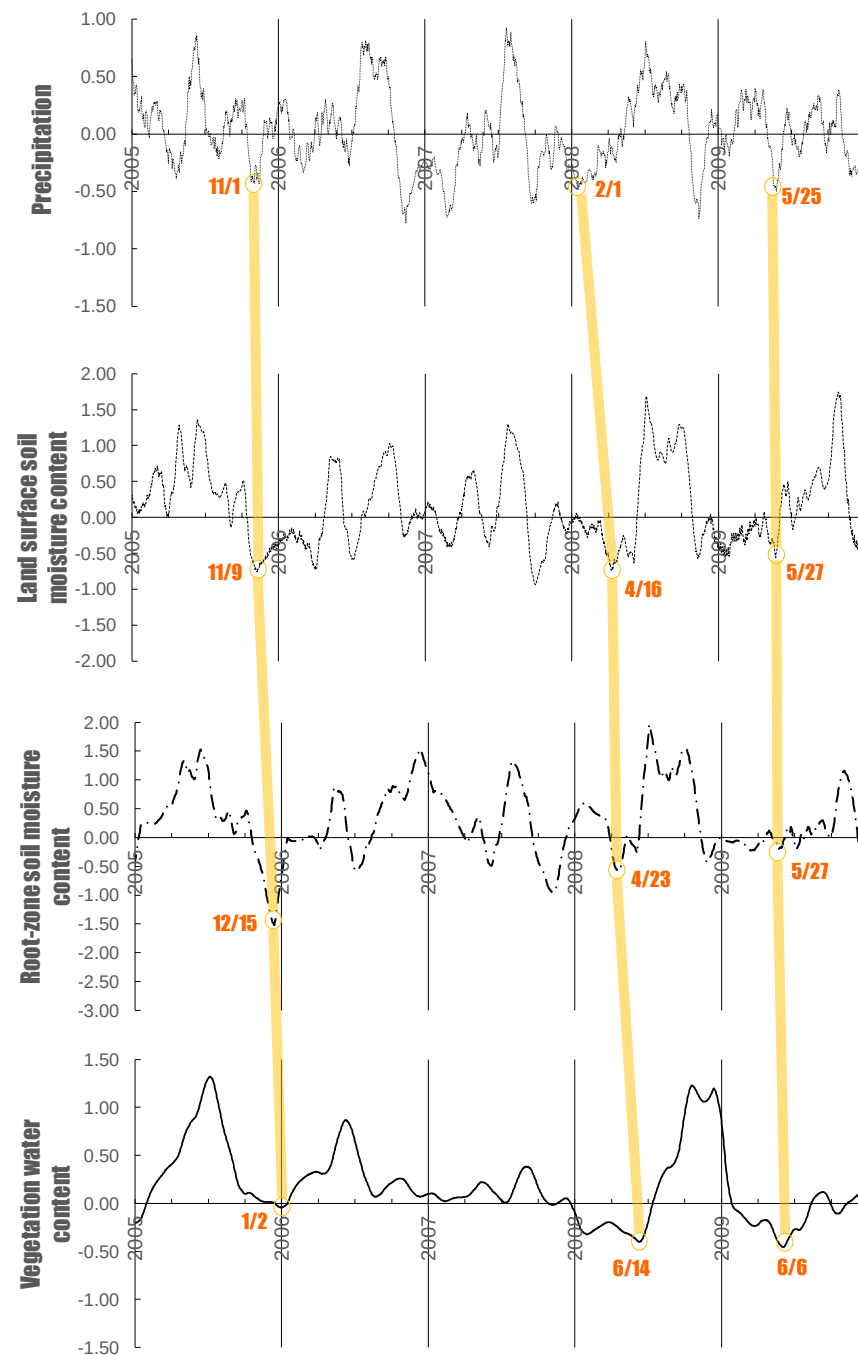


Figure 8. Normalized index (NI_i) for precipitation and ecohydrological variables in the first half of the agricultural drought evaluation period (2005–2009). Spatial averages for the Sahel-inland region. From the top, the graphs present precipitation, near-surface soil moisture content, root-zone soil moisture content, and vegetation water content. Dates in orange indicate the middle day of each negative peak period. We found that each peak had a time lag when focusing on the negative peak for precipitation, soil moisture content, and vegetation water content, as shown by the yellow marks and lines.

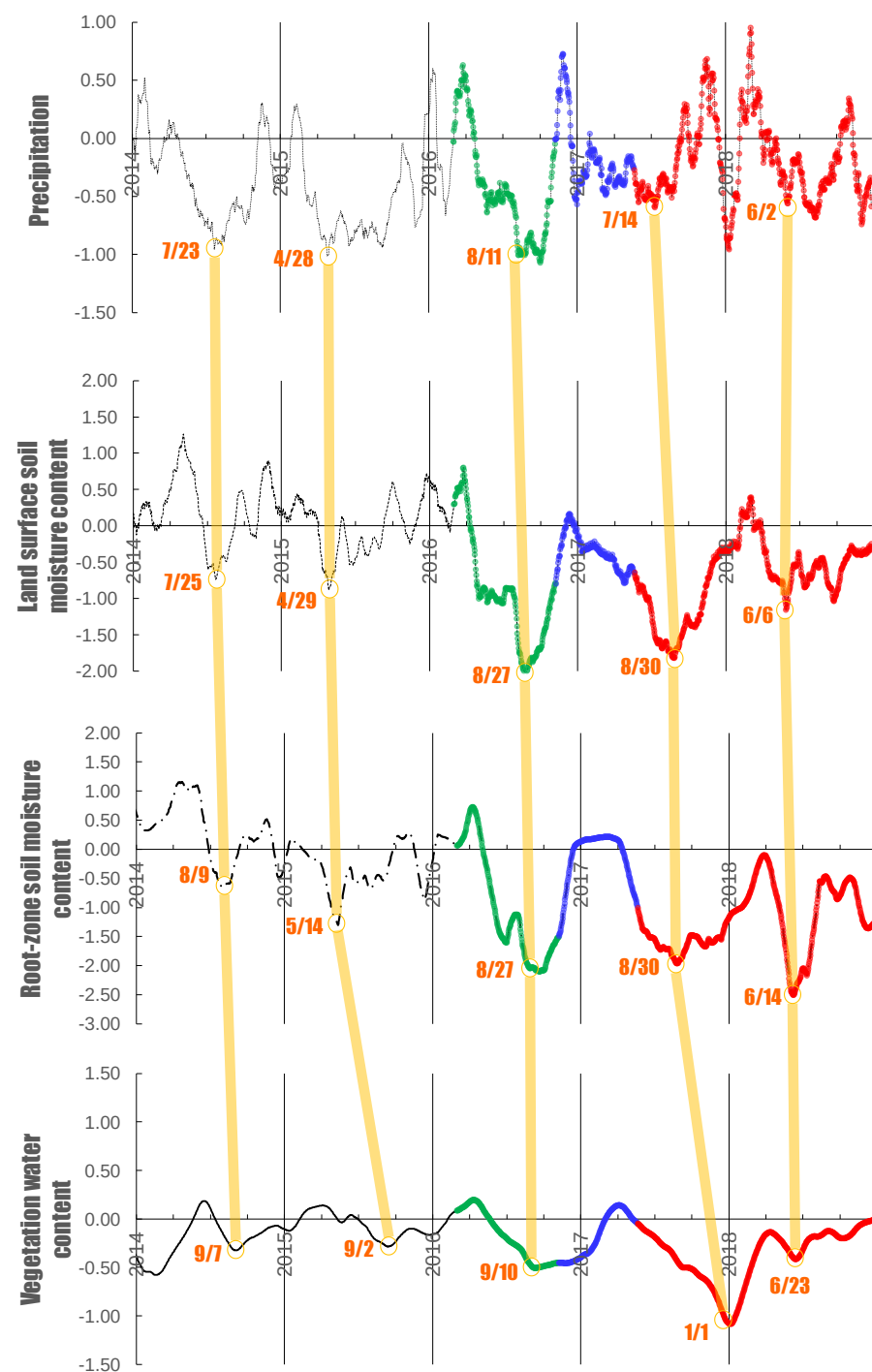


Figure 9. Normalized index (NI_i) for precipitation and ecohydrological variables in the second half of the agricultural drought evaluation period (2014–2018). Spatial averages for the Sahel-inland region. From the top, the graphs present precipitation, near-surface soil moisture content, root-zone soil moisture content, and vegetation water content. Dates in orange indicate the middle day of each negative peak period. We found that each peak had a time lag when focusing on the negative peak for precipitation, soil moisture content, and vegetation water content, as shown by the yellow marks and lines. As shown by the green lines, although the NI_i values of precipitation become positive in April 2016, negative values remain in the growth and early harvest seasons (May–October), which leads to negative NI_i values of soil moisture and vegetation water content simultaneously. As shown by the blue lines, although the NI_i values of precipitation became positive in the second half of December 2016 owing to the occurrence of heavy rainfall, they reverted to negative values in the beginning of January 2017. The surface soil moisture content showed the same behavior. In contrast,

the root-zone soil moisture content was positive in the period from January–April because the water associated with the heavy rainfall was stored in the root-zone. The vegetation grew by absorbing the stored root-zone soil moisture, as indicated by the positive peak of vegetation water content at the beginning of April. As shown by the red lines, both the root-zone soil moisture content and the vegetation water content remained negative in the long term because they have a long retention period of the memory of past water shortage.

5. Conclusions

To fill the gap of the conventional study as described in Section 1, this study used CLVDAS to simulate ecohydrological variables (particularly vegetation water content) for the use of drought indicators, and applied them to the analysis of drought in West Africa during 2013–2018. We found that the Sahel-inland region suffered locust plagues in 2003 and 2004. Because the impact of locust plagues on vegetation growth dynamics cannot be simulated by an ecohydrological model, we excluded the data for 2003 and 2004 from our analysis. The results of our agricultural drought assessment for the period 2005–2018 showed reasonable agreement ($RMSE = 0.16$ in the normalized index NI_i) between the pearl millet yield and the simulated vegetation water content in the Sahel-inland region. The strength of this agreement is attributable to the accurate simulation of the hydrological water cycle and vegetation growth dynamics by CLVDAS, which has great importance regarding agricultural drought assessment. Moreover, the possibility of identifying a relationship between precipitation a few months prior and crop yield was also suggested, although such a relationship also depends on the condition of water retention in the root-zone soil layer. These findings constitute the primary significance of conducting this study. One of the major limitations of the current application of CLVDAS is the spatial resolution of the CLVDAS output ($0.25^\circ \times 0.25^\circ$), which is slightly too wide owing to the assimilation of low-frequency microwave brightness temperatures with a wide observation footprint. Improvement of the spatial resolution of the CLVDAS gridded output is therefore an objective of our future work. Furthermore, the shortage of precipitation has considerable impact on the land surface condition in the rainy season of the following year, as was clarified by the CLVDAS simulation. The importance of deriving accurate initial conditions of soil moisture content and LAI in multi-seasonal drought prediction is therefore another area requiring improvement. In a previous study, a CLVDAS application involving a seasonal meteorological prediction from a general circulation model showed satisfactory performance in predicting the land surface conditions of a drought in the Horn of Africa [13]. Subsequently, a drought monitoring and seasonal prediction system based on CLVDAS was developed for Northeast Brazil [14]. This system can monitor and predict (three months) the soil moisture profile, evapotranspiration, and LAI. By coupling these previous studies with this study of West Africa, it is expected that not only vegetation water content but also crop yield can be predicted by simulating the conditions of the several previous months. Thus, developing CLVDAS for seasonal prediction and crop yield prediction will be addressed in future work.

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