Spatio-Temporal Mixed Pixel Analysis of Savanna Ecosystems: A Review

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Abstract: Reliable estimates of savanna vegetation constituents (i.e., woody and herbaceous vegetation) are essential as they are both responders and drivers of global change. The savanna is a highly heterogeneous biome with high variability in land cover types while also being very dynamic at both temporal and spatial scales. To understand the spatial-temporal dynamics of savannas, using Earth Observation (EO) data for mixed-pixel analysis is crucial. Mixed pixel analysis provides detailed land cover data at a sub-pixel level which are essential for conservation purposes, understanding food supply for herbivores, quantifying environmental change, such as bush encroachment, and fuel availability essential for understanding fire dynamics, and for accurate estimation of savanna biomass. This review paper consulted 197 studies employing mixed-pixel analysis in savanna ecosystems. The review indicates that studies have so far attempted to resolve the savanna mixed-pixel issues by using mainly coarse resolution data, such as Terra-Aqua MODIS and AVHRR and medium resolution Landsat, to provide fractional cover data. Hence, there is a lack of spatio-temporal mixed-pixel analysis for savannas at high spatial resolutions. Methods used for mixed-pixel analysis include parametric and non-parametric methods which range from pixel-unmixing models, such as linear spectral mixture analysis (SMA), time series decomposition, empirical methods to link the green vegetation parameters with Vegetation Indices (VIs), and machine learning methods, such as regression trees (RT) and random forests (RF). Most studies were undertaken at local and regional scale, highlighting a research gap for savanna mixed pixel studies at national, continental, and global level. Parametric methods for modeling spatio-temporal mixed pixel analysis were preferred for coarse to medium resolution remote sensing data, while non-parametric methods were preferred for very high to high spatial resolution data. The review indicates a gap for long time series spatio-temporal mixed-pixel analysis of savannas using high resolution data at various scales. There is potential to harmonize the available low resolution EO data with new high-resolution sensors to provide long time series of the savanna mixed pixel, which, according to this review, is missing.

Keywords: spatio-temporal; mixed pixel analysis; savanna; fractional cover; Earth Observation (EO)

1. Introduction

Savanna ecosystems are heterogenous landscapes composed of a mixture of discontinuous patches of woody vegetation (i.e., trees and shrubs) and a continuous grass layer, governed by key local and global drivers (Figure 1) [1]. Globally, savannas cover about one
fifth of the earth’s surface and over half of the area of Africa [1,2]. About 20% of the world’s population live in savannas. Savannas are pivotal and play a crucial role in the global carbon cycle; they store about 15% of the global carbon stock and contribute about 30% to the global terrestrial net primary productivity [2,3]. At continental level, such as in Africa, savannas are critical to wildlife biodiversity and contribute immensely to environmental conservation, economic, and livelihood gains in form of nature-based tourism, food supply, livestock grazing, and firewood for populations who live within these ecosystems [3–5].

**Figure 1.** Global, regional, and local factors influencing the tree-grass co-existence and the dynamics of savanna transitional zones of cover types over time. MAT, MAP, and CO$_2$ represent Mean Annual Temperature, Mean Annual Precipitation, and Carbon dioxide, respectively. The savanna map is based on biome classification according to Hengl et al., 2018. The South American savannas, the Caatinga, and the Cerrado boundaries were updated using the National Institute for Space Research (INPE) products developed by Aguiar et al., 2016. Key drivers are derived from Sankaran et al., 2005, 2008; and Scholes and Archer, 1997.

Human population growth increasingly poses a threat to savanna ecosystems due to land use, land cover changes, and management policies [6] Climate change, such as prolonged droughts and erratic rainfalls, along with government policies for reforestation and afforestation, continue to threaten the resilience of savanna ecosystems [7,8]. As such, savannas have witnessed extended land clearing in the past three centuries which threaten the ability of savannas to continue serving as a carbon sink [9]. In South American savannas, about 48% of the Caatinga and 53% of the Cerrado savannas are reported to be impacted by humans due to agricultural expansion, which leads to the fragmentation of these savanna
biomes [10]. To keep savanna ecosystems sustainable, and to monitor, manage, and better understand the spatio-temporal and the ecological variations in the savanna, accurate representation and quantification of the savanna ecosystem is essential. Estimation of savanna vegetation physiognomies is crucial for habitat quality assessment, understanding earth’s energy exchange, carbon and nutrient fluxes, and for better conservation management of savanna ecosystems.

Earth Observation (EO) information provides a suitable tool for the monitoring of savanna ecosystems [11–14]. However, due to the nature of savanna, it is one of the challenging biomes to monitor using EO data [11,15], particularly because of the difficulty to distinguish between woody and herbaceous components. The savanna landscape is shaped by complex interactions of top-down and bottom-up processes, resulting in heterogenous woody and herbaceous layers with plant density, height, and canopy cover varying over space and time [1,2,15]. Rainfall, fires, herbivory, and human activities are major drivers of the complex savanna landscape [1,2,16]. At a global level (Figure 1), savannas are reported to be influenced by climate, specifically mean annual temperature (MAT), mean annual precipitation (MAP), rainfall seasonality, fire regime and soil type [2,17], and atmospheric CO$_2$ levels [18–20]. At a local level, fire regime, such as fire recurrence, fire behavior, soil properties, such as fertility, water availability, herbivory, and micro-climate factors, play a major role in influencing savanna cover types (Figure 1) [1,2,17,21,22]. Fire and herbivory and their interaction serve as disturbance mechanisms that affect the structure of the savanna and result in a variable and dynamic mixture of tree, shrubs, and grasses [16,22–24].

The rates of changes in fire regimes in savannas are increasing over time [25]. The pressure on land clearance and the tampering of fires and grazing regimes, along with climate change and increasing CO$_2$ and how they contribute to the degradation of savanna, are not yet fully known at continental scales [26]. However, regional differences are suggested for those factors in Africa, South America, and the Australian savannas. Brazilian savanna, for example, which experience the highest rate of land clearing and fire suppression, are reported to have the highest rates of woody encroachment. This may suggest that fragmentation and fire suppression can have regional consequences on the response of spatio-temporal mixed pixel analysis [26]. Land clearance can limit fire and herbivory by fragmenting the landscapes and reducing their connectivity, which can potentially lead to increased woody cover in the uncleared areas [26]. Droughts may kill woody cover directly; however, the effect of drought on fire may also depend on the rainfall regimen. Fires and browsing are limitations for tree recruitment into the grass layer, which may lead to escape heights issues [27]. When trees surpass the escape height, they can no longer be suppressed by fire or browsing, making trees mature, and this possibly may lead to increased woody cover [27]. Additionally, C$_4$ grasses are intolerant to shading of closed canopies, and the absence of understory grass can lead to fire suppression [26].

Using EO information for savanna monitoring has advanced in previous decades, and several approaches have been used to characterize the savanna [15]. Remote sensing approaches for savanna monitoring include utilizing vegetation indices, such as the Normalized Difference Vegetation Indices (NDVI) based on phenological differences between trees and grasses, photosynthetic and non-photosynthetic differences of the vegetation using low spatial resolution EO data [11,28], time series methods, combinations of vegetation indices with Spectral Mixture Analysis (SMA) methods, or SMA methods alone [29–33], to derive fractional cover for spatial temporal dynamics of the savanna. EO applications in savannas have also applied traditional hard and discrete classifications, as well as object-oriented methods, for distinguishing between the woody and herbaceous components of the savanna [34–39].

Hard classification methods, however, assume that pixels are pure, that is to say, they represent a single homogenous cover of the land cover class (e.g., in the context of savannas, pixels of homogenous woody vegetation, or homogenous herbaceous vegetation) [36,40,41]. The savanna indeed is a highly heterogeneous landscape which leads to a mixture of more...
than one land component within the pixel, a concept known as mixed pixel. The concept of mixed pixel is common in ecosystems with high cover dynamics and variability \[40,42,43\], and it arises as a result of the spatial, temporal, and spectral variability in the landscape of the savanna, often compounded by the relationship between a sensors’ spatial resolution and the cover dynamics, which lead to a pixel being a product of many land cover spectral responses instead of a single homogenous spectral response in the EO pixel \[40\].

In addition to the mixed pixel problem in the savanna, studies over the savannas have mainly utilized medium to low spatial resolution (ranging from 15 m–1 km) EO data, such as MODIS, Advanced Very High-Resolution Radiometer (AVHRR), and Landsat \[44–49\]. This, along with hard classifications, lead to the inadequate capturing of savanna environments and tendency to overestimate or underestimate vegetation cover \[50\]. Few studies have employed high spatial resolution (<15 m) EO data for separating between savanna vegetation components and tend to be confined to local and regional scales. A few studies have sometimes fused between either medium and high resolution or low and high resolution EO data to improve mixed-pixel classification \[28,51,52\].

Due to weaknesses in hard categorical and discrete mapping approaches, fractional vegetation estimates, such as Vegetation Continuous Fields (VCF) methods, have gained a momentum \[53–55\]. Vegetation Continuous Fields (VCF) methods are based on quantifying sub-pixel proportions in a single pixel. However, although the VCF concept does compensate for errors in discrete approaches, the existing VCFs are mainly only available at global scales and are popularly available for low spatial resolution EO data and focused mainly to estimate tree cover. Global VCFs products are generated from MODIS \[56–62\]; AVHRR \[44,53,63–66\]; Landsat \[59,67–69\]; Visible Infrared Imaging Radiometer Suite (VIIRS) \[58,70\]; or from a combination of some of these EO data \[65\]. VCF are widely applied in environmental change, forestry monitoring and estimation, such as deforestation and forest degradation \[71,72\], atmosphere-biosphere models \[73\], prediction of forests vegetation biodiversity and species diversity \[74\], and environmental resources monitoring, such as estimating stock volume \[56\]. Although VCF have a wide environmental application, they have limited local focus and less validation, especially at local scales in savanna environments. Where VCF products have been validated for savannas, they are reported to present a challenge in areas with low and sparse tree cover between 20–30% \[75,76\]. MODIS VCF, for example, are reportedly not well resolved below 20–30% tree cover \[77\], especially for African savannas where the mean VCF tree cover is around 20% \[5,77–79\]. Besides, the MODIS VCF product has defined woody cover as larger than 5 m tall, and most of the savanna vegetation may fall below that threshold \[80\].

Accurate fractional cover of savannas is required as they are essential to produce reliable vegetation parameters for forest assessments, environmental change, monitoring of bush encroachment, monitoring fuel load for fire dynamics, biomass for wildlife, for climate models, and modeling of trees-grass interactions \[12\]. Current sub-pixel data in savannas have focused primarily on woody fractional cover \[5,81–85\]. Fewer studies focused on separating between the woody vegetation cover and the herbaceous vegetation cover \[12,86,87\], and very few estimated full vegetation cover fractions, such as to resolve between trees, shrubs, and the herbaceous cover altogether. Therefore, high spatial resolution fractional cover at localized levels is required to circumvent the weaknesses of the available data.

For the reasons outlined above, this paper reviews the existing literature on the topic of spatio-temporal mixed pixel analysis of the savanna ecosystems. The literature review focused on publications which have investigated the savanna mixed pixel problem to resolve either single or multiple fractional cover. We focused only on the publications which have used EO data as input data for modeling mixed pixel. To the best of our knowledge, there is no existing comprehensive review paper on the use of EO data for spatio-temporal mixed pixel analysis of the savanna. However, a few reviews that were not necessarily focused on savanna ecosystems but on fractional cover estimation were identified. Gao et al. \[88\] reviewed remote sensing algorithms for estimation of fractional
vegetation cover using vegetation indices, and Zhang et al. [89] reviewed the progress and summary of methods for crop residue fractional cover estimation, while Somers et al. [90] reviewed and summarized the methods for mitigating variability in endmembers. These three reviews differ from our focus in the sense that they focused on crops, and on pure index values, and on the mitigation of endmembers variability in the spectral mixture analysis. All three of the reviews placed no specific emphasis on the savanna biome.

The aim of this review paper is to give a comprehensive overview on the application of remote sensing data for spatio-temporal mixed pixel analysis with emphasis on the savanna ecosystems and to identify possible research gaps. We aim to do this by addressing the following questions:

- What types of savanna land cover dynamics have been estimated?
- In which geographic locations are the studies conducted?
- What is the geographic extent of the study sites?
- Which mixed pixel estimation methods have been applied?
- Are there any emerging trends pertaining to the estimation methods?
- What are the most preferred remote sensing systems, platforms and resolutions?
- What are the characteristics of the temporal data used as input for modeling the mixed pixel?
- What is the outlook on the validation and accuracy of the reviewed studies?

The approach and methods used in this review is outlined in Section 2. The result from the review is presented in Section 3. Discussions are presented in in Section 4, and conclusion is given in Section 5.

2. Review Methodology

For relevant literature to be identified, the Web of Science and Google Scholar were searched using the following singular or set of combined key words: “savanna mixed pixel”, “spectral mixture analysis”, “pixel mixture analysis”, “semi-arid mixed pixel”, “dryland mixed pixel”, “mixed pixel”, “sub-pixel”, “pixel-unmixing”, pixel decomposing”, “fractional cover”, “vegetation fractional cover”, “fractional vegetation”, “fractional cover analysis”, “vegetation continuous fields”, “VCF”; “continuous fields”, “spatio temporal savanna dynamics”, “remote sensing”, “multi-spectral”, “multi-temporal”, “earth observation”, using “OR” to combine the terms. A wide range of key words were selected as the problem of mixed pixel is addressed by different, inconsistent, and interchangeably used terminologies. The search range time is between 1990 to 2020. This resulted in an initial total number of 4079 journal articles. The 4079 journal articles were screened further to form part of the final review according to the following criteria:

- The journal article must be focused on mixed pixel analysis.
- The journal article study area is located in a savanna biome.
- The journal article is fully or in parts using EO as input data to derive single or multiple fractional land cover.
- A number of global VCF articles and very few articles with focus on semi-arid or dryland biomes, such as grasslands and savanna desert ecotones, were considered. Vegetation Continuous Fields methods are fundamental to the development of fractional and sub-pixel mapping, although not entirely focusing on the savanna most of the time.

After the screening process, 197 publications were retained for the final review process (Supplementary Materials Table S1). The retained papers were further analyzed and their pre-defined parameters and attributes extracted to form part of the in-depth analysis. The parameters extracted and analyzed are the year of publication, journal name, geographic location of the study area, spatial extent of the study area, type of EO data used (i.e., sensor mission name, sensor platform type, spatial resolution, temporal resolution), method of estimation, type of biophysical parameters estimated, characteristics of the input data, EO
data used for validation data, and the overall accuracy of the EO data used for mixed pixel analysis.

3. Results

Figure 2 illustrates the list of journals included in the literature review. Majority of the papers were published across 10 high impact journals, with the journal of Remote Sensing of Environment having the highest number of published manuscripts. The “Others” category of journals is made up of journals containing only one publication.

![Journal List](image)

**Figure 2.** The overview of the final retained 197 papers, their publishers and the number of papers per journal.

3.1. Geographic and Spatial Scale

The geographic locations of the reviewed publications study areas are depicted in Figure 3. About 47% of the papers have a study area located in Africa, followed by South America with 18%. This is possibly because more than 50% of Africa is covered by savanna, concentrated in different parts of the continent and made up of varying savanna ecosystems.

The African savannas range from the Serengeti grassland savannas with scattered trees in East Africa (Kenya and Tanzania), to humid savannas in West Africa, dryland savannas of the Sahel region which are savanna desert ecotones, Miombo savanna woodlands, and semi-arid savannas in Southern Africa. The second highest number of studies focusing on Southern America can be justified by the fact that the continent is home to the Cerrado and Caatinga grasslands. The Cerrado, for example, is considered one of the global biodiversity hot-spots and one of the most diverse tropical savannas in the world [91]. These two biomes are recognized as biosphere reserves due to high level of species biodiversity, but, at the same time, they both have a high rate of fragmentation and are reported to be highly endangered due to high rates of deforestation and habitat fragmentation due to agriculture [10]. About 55% of the Cerrado’s original vegetation has been estimated by remote sensing to have been already converted by human actions [10]. The Caatinga biome, on the other hand, is reported to be one of the most threatened tropical ecosystems, with a greatest destruction rate [10]. Between 30.4% and 51.7% of the Caatinga is reported to be altered by human activities, making it as the third most heavily impacted biome in Brazil [92]. The Chaco and the Caatinga are considered to the most endangered biome in Brazil, at a risk of disappearing, which highlights an urgent priority for conservation due to great deforestation there [93]. About 8% of study sites were based in Australia. Only about 1% of the retained papers focus on Central America. The global category includes mainly the VCF literature, which are widely applied for estimation of global trees fractional cover.
by Hansen et al. [60,66,67,76,94–96]. Vegetation Continuous Fields are crucial in showing development and progress for fractional cover estimation but are mainly presented at a global scale and are derived from low spatial resolution remote sensing and are not necessarily focusing on savanna biomes alone [65,66].

Figure 3. Global distribution of savanna biomes, study sites, and number of studies per geographic area (Terrestrial ecoregions of the world map is modified from Hengl et al., 2018, and incorporated with updated boundary maps of Cerrado and Caatinga derived from the National Institute for Space Research (INPE) products from Aguiar et al., 2016. Some of the study locations seem to be outside of the savanna biome because of scale mismatches (the global mapping scale versus savanna patches occurring at smaller and local scales). This is evident in areas with smaller savanna patches with a high number of reviewed papers, such as the California oak savannas. Another reason is because of the variable definition in the biome classification used, as it does not account for the oak savannas in North America, such as the California oak savanna and the southwestern oak savanna.

The number of published mixed pixel studies in the savannas have increased in recent years. There is a peak in the number of studies in 2019, representing 11% of the total number of studies, and 10% of the studies were conducted in 2020 (Figure 3). The trend of increasing studies is less clear between 1994 and 2010; however, it is more pronounced between 2010 and 2020. Approximately 63% of the reviewed papers fall in the last 9 years of the 27 years length of the review period. This may be due to the increased availability and free accessibility of remote sensing data and the introduction of machine learning algorithms to successfully process big data reported in the last decade. A review on machine learning applications to land cover classification based on multispectral earth observation found more or less the same trend of number of publications doubling between 2015 to 2020 [97]. In addition, Wulder et al. [98] reported the emergence of a new era of land cover analysis, which is made possible by free access data and ready-to-analyze EO data along with the availability of high-performance computer processing capabilities to enable rapid data processing.

The vast majority of the studies (~63%) were conducted at a local scale (Figure 4). Approximately 24% of the reviewed publications were conducted at a regional scale.
Regional scale represents studies with a study area located in more than one neighboring country or where more than one country is included in the study area. Only about 6% of studies were conducted at a global scale, 5% at a national scale, and 2% at a continental scale (Figure 4). Data processing and storage power has increased, but it seems that working with EO data at continental and global scale remain a challenge [99]. Another reason could also be because savannas are so variable at large scales, and, hence, methods must be developed and calibrated at smaller scales. Savanna mixed-pixel analysis of vegetation components often requires multi-temporal images spanning over several seasons to capture phenological differences in order to increase accuracy [5]. These multi-temporal images are required to go through pre-processing, which increases the computational demand [99]. At a global scale, generating and collecting reliable and geographically representative validation data tend to be a challenge. Besides the MODIS VCF studies which offer global fractional tree cover products [59,100], we identified only one study which conducted mixed pixel analysis of savannas at a global scale. Hill and Guerschman [11] used MODIS to characterize vegetation fractional cover with a focus on grasslands and savannas at a global scale. In addition, Jia et al. [101] used a general regression neural networks algorithm on MODIS data to estimate land surface fractional vegetation cover on a global scale. There was no study found at a sub-national regional level to qualify as regional at a single country level. A few of the regional scale studies were conducted in African savanna mosaics along the Sahel drylands of West Africa with several countries, such as Mali and Niger, included in the study area [102–104]. For example, Souverijns et al. [105] estimated fractional land cover over a period of 30 years at a regional scale in Senegal, Burkina Faso, Nigeria, Niger, and Sudan. In other regions, Guan et al. [106] estimated vegetation fractional land cover over tropical savanna regional areas covering Ethiopia, Kenya, Tanzania, Malawi, Zambia, Zimbabwe, and Botswana.

3.2. Estimated Mixed-Pixel Parameters

The majority of the reviewed studies (62%) estimated multiple fractional covers when analyzing mixed pixels (Figure 5). Multiple cover estimation means that the authors did not just focus on estimating one type of cover but estimated multiple fractional covers, such as grass, trees, shrubs, and bare ground, or various combinations of these. Theseira et al. [107] estimated multiple fractional covers by applying a spectral mixture model to derive grassland, areas of low and high savanna trees, grassland, savanna shrub, and bare ground; Xian et al. [108] used non-parametric regression trees to characterize a shrubland environment into continuous fields of herbaceous, litter, shrub, and bare ground; and Bauman et al. mapped continuous fields of tree and shrub cover in the Gran Chaco savanna ecosystem in South America [109]. Trees were the most estimated single fractional cover. Approximately 20% of the reviewed studies estimated tree cover (Figure 5). Hansen
such as grass, trees, shrubs, and bare ground, or various combinations of these. These
not just focus on estimating one type of cover but estimated multiple fractional covers.

3.2. Estimated Mixed-Pixel Parameters

African savanna. In other regions, Yang and Crew [48] used Landsat data to estimate
fractional woody cover in the Texas savannas in North America. Roughly 13% of the reviewed
papers estimated woody fractional vegetation cover, which typically includes both tree and
woody cover (Figure 5). Many studies estimated woody cover in African savannas [84,110].
For example, Higginbottom et al. [111] and Naidoo et al. [83] used a fusion of optical
data with SAR to estimate fractional woody cover in African savanna. In other regions,
Yang and Crew [48] used Landsat data to estimate woody cover in the Texas savannas in
North America.

![Figure 5. Biophysical parameters estimated.](image)

3.3. Type of Earth Observation Data Used

In many scenarios, there are multiple EO data types employed by a single paper. For example, Gessner et al. [112] employed a multi-resolution approach that included
different sources of remote sensing data (Quickbird-2, IKONOS-2, Landsat TM, and
MODIS) to derive fractional cover at a regional scale in an African grassland, savanna, and
shrubland biome.

Additionally, the overview shows the employed EO sensor systems classified according
to optical, radar, LiDAR, or LiDAR and hyperspectral (Figure 6). Spatial resolution is
classified from very high to low resolution.

A total of 39 EO data types were used in the reviewed studies. This reflects a wide
range of EO applications for savanna mixed pixel analysis [47,105,113–118]. Of these,
26 (89%) were optical, 11 (7%) radar, 2 (3%) LiDAR, and 1 (1%) were a combination of
optical hyperspectral and LiDAR. The most frequently used EO data were optical Landsat
(n = 94), MODIS (n = 83), AVHRR (n = 26), and Google earth (n = 22). These EO systems
have a short return period, long time series, and are freely available. For example, Landsat,
MODIS, and AVHRR have been in operation for more than 20 years, providing freely
available and continuous EO data. Landsat has been providing data for thematic Land
Use and Land Cover (LULC) mapping for more than 30 years now. Google Earth is not
necessarily a sensor fleet but is included in the list of EO data used because, as a very high
spatial resolution data, it has been used in many of the reviewed papers as a reference data
for validation and accuracy assessments. Both MODIS and AVHRR datasets are well suited
for large study area scenarios, as well as for applications where a long time series is most
crucial. The major advantage of AVHRR in the spatio-temporal dynamics of the savanna
mixed pixel analysis is that it offers long time series spanning as far back as 1981. AVHRR,
regardless of it being known for its broad channels and that AVHRR Vegetation Indices
(VIs) products are reported to be less accurate when compared with MODIS VIs, long-term
NDVI time series, AVHRR Global Inventory Modeling and Mapping Studies (GIMMS),
have been found to be suitable for long-term vegetation studies in dry areas [119]. The long
time series and high revisiting times of these low-resolution remote sensing data is effective
to limit gaps in the time series as a result of cloud cover issues [120]. Creating consistent time series from very high and high spatial resolution data, however, is often not easy. This is because of their low revisiting and smaller area coverage. This probably explain why high and very high spatial resolution images are under-represented in the analysis of mixed pixel compared to low and medium spatial resolution with high revisiting time.

Figure 6. Count of sensor fleets and type of earth observation data mission types employed by the 197 studies, organized according to the spatial resolution (low > 30 m, medium (15–30 m), high (5–15 m and very high (<5 m). Studies were counted several times, where multiple sensors were used. UAV, Google Earth, and Optical Aerial Photographs are not necessarily sensor fleets but are included because of their importance as high and very high spatial resolution, although their missions are not re-constructible as such. The overview shows the frequency of use of different sensors, highlighting whether the data is optical, radar, LiDAR, or a combination, as well as the acquisition platforms (aircraft, satellite, or UAV).

High spatial resolution (HR) and very high spatial resolution (VHR) sensors, such as IKONOS-2, Quickbird, GeoEye, and SPOT 5-6, have been applied less often. This is likely due to the low revisiting time and high data costs [121]. Historically, VHR and HR tend to have smaller swath coverage to be considered for large spatial scale studies compared to coarse and medium resolutions. Low temporal resolution tends to be less suitable for tracking seasonal dynamics in the vegetation [121]. The aspect of seasonal variation is often influential in the separability of vegetation components in the mixed pixel analysis of the savanna [11].

Synthetic Aperture Radar (SAR) played a very minor role in the type of EO sensor data used. This is despite the fact that SAR data tends to be a better option for multi-temporal mixed pixel analysis because it is not severely affected by most weather conditions and is unaffected by cloud cover. Furthermore, the limited application of SAR may also be due to computational challenges given the spatial and spectral distortions and geometric distortions as a result of the complex nature of processing SAR [122]. Within the reviewed publications, there were fewer scenarios of fusion between SAR and optical EO data. This is despite the fact that studies that combined SAR with the optical reported higher accuracies compared to when SAR or optical were used alone. For instance, Baumann et al. [109] developed a novel approach to map continuous fields of tree cover and shrub cover across the South American Gran Chaco, using Landsat-8 optical and SAR Sentinel-1. The study
found that the best model for VCF estimation was the one which fused optical and SAR, performing far better than models using data from only one sensor. Borges et al. [123] used Sentinel-1 and Sentinel-2 to map savanna land cover, and Naidoo et al. [83] tested the utility of multi-seasonal and multi-sensor use of Landsat TM/ETM and ALOS PALSAR to map woody fractional cover over South Africa’s semi-arid savannas. All three studies reported higher and improved accuracies for models which integrated SAR with optical data [109, 113].

3.4. Methods Used for Estimation of Mixed Pixel Parameters

Categorization of Savanna Mixed Pixel Estimation Methods

Table 1 shows that various methods were used to estimate mixed pixel parameters using EO data. The identified methods were categorized into parametric and non-parametric approaches (Table 1). Maximum Likelihood (ML) classification is one of the parametric methods for categorical classification. Here, a gaussian normal distribution is assumed. For example, supervised classification is a parametric classification which assumes a multi-variate gaussian distribution of each class that is extracted from the training data by estimating the central tendency statistics, such as the mean and covariance matrix, which are used as the parameters for discrimination between land covers [124]. Parametric methods for categorical and discrete classifications include Step-wise Discriminant Analysis (DA) and Minimum Distance (MD). However, because these classifications only use decision boundaries, they tend to be prone to noisy classifications when applied in regions with high heterogeneity. Parametric classifications are reported to lack robust capabilities and tend to be unsatisfactory in characterizing land cover in large areas with complex environments, such as the savannas [124].

However, non-parametric classifiers side-step the parametric issues. Non-parametric methods use an iterative process. Examples of non-parametric classifiers include Nearest Neighbor (1-NN and k-NN), kernel methods [125], neural networks, and classification trees, Random Forest (RF) and Regression Trees (RT) [94]. Non-parametric methods, however, require more training data and are computationally intensive due to large sets of training data. Non-parametric methods are postulated to circumvent the issues of arbitrary boundaries. These issues are common in parametric methods. Non-parametric methods are reported to offer computational flexibility and are more robust to apply to processing of large areas data and well suited to areas where the distribution of the land cover is not well known [53]. Parametric methods, on the other hand, are unsatisfactory in large areas and, especially, in complex environments with no obvious land cover class gradient. Some publications employed both parametric and non-parametric methods (indicated as “Both” in Figures 7–9 and Table 1).

Figure 7. Methods category used to estimate the mixed pixel analysis parameters.
From a geographic perspective (Figure 8), non-parametric methods have the highest percentage of application in Africa, with more than 50% of the studies having used non-parametric methods located in Africa. When it comes to Australia, studies conducted in Australia have a slightly higher preference of parametric methods of ca. 11% use compared to ~2.5% application of non-parametric methods there. Due to Africa having a range of savanna ecosystems with high cover variability due to variable fire regimes and land uses (e.g., livestock grazing and wildlife conservation), the high variability in cover may prompt researchers to opt for methods which are capable of dealing with high spatial heterogeneity in land cover [15].

Table 1. Examples of methods used for spatio-temporal mixed-pixel analysis. The methods are categorized as parametric, non-parametric, and both (a combination of parametric and non-parametric methods).

| Reference | Method Name | Method Type | Estimated Biophysical Parameter |
|-----------|-------------|-------------|-------------------------------|
| [75]      | Regression Tree | (Non-parametric) | Tree Cover |
|           | Spectral Mixture Analysis (Pixel Unmixing) | Parametric | Percent vegetation cover per pixel (% woody vegetation, % herbaceous vegetation, % bare ground), leaf type (% needleleaf and % broadleaf) and leaf duration (% evergreen and % deciduous) and % bare |
| [39]      | Object-Based Image Analysis | Parametric and Non-parametric (Both) | Multiple Cover: Trees, Shrubs, Bare Soils, Grass |
| [105]     | Random Forest | Non-parametric | Multiple Cover: Shrubland, Forest, Urban, Cropland, Seasonal water, Bare Soil, Permanent water |

In Figure 7, the literature review shows the percentage of applications for each method categorization. The review shows that 93 (~47%) of the reviewed publications used non-parametric methods, while 92 (~47%) used parametric methods, and only 12 (~6%) used a combination of parametric and non-parametric methods.
3.5. Temporal Characteristics of the EO Input Data

Figure 10 represents the type of input EO data attributes for spatio-temporal mixed pixel analysis of savannas. The two most widely used EO input data attributes are band statistics (40%) and spectral indices (28%) (Figure 10a). For this review, band statistics consists of metrics from spectral bands and metrics from indices, such as maximum band value, mean of NDVI, mean of reflectance, maximum NDVI value, mean band value, standard deviation NDVI value, and amplitude band value. Vegetation indices are used as a proxy for vegetation cover in spatio-temporal mixed pixel studies. Many of the
normalized indices used red reflectance and NIR and applied parametric linear regression methods, SMA, non-parametric time series decomposition trend methods, such as harmonic analysis or machine learning methods, for mixed pixel parameters estimation [127–130]. The third most used data input is seasonal metrics (14%). Seasonal metrics correspond to those input data whose spectral values correspond to phenological cycles and stages in the spectral or reflectance metrics or indices, for example, NDVI peak greenness, value rate of green up, total length of growing season, the timing of the onset of green up, and the onset of the maximum NDVI.

The majority of the studies used inter-annual (68%) temporal data, which means the time series enabled the modeling of inter-annual differences of multiple years (Figure 10b). The majority of the temporal EO data used in the mixed pixel analysis are multi-temporal time series (77%) (Figure 10c). A larger part of the studies applied shorter time series (~61.4%) EO data with a length of 1–5 years in (Figure 10d).

The length of investigation for each reviewed paper was examined (Figure 11). The starting year and the ending year analysis are considered to derive the paper’s study period (x-axis) and the publication year (y-axis). The results show that many studies have used multiple years to understand the spatio-temporal dynamics of the mixed pixel. More than 60% of the reviewed papers used data spanning over multiple years to look into the spatio-temporal dynamics of the mixed pixel. However, the majority of those studies have a length of investigation between 1 to 5 years, which indicates a leaning towards use of shorter time series. The longest study period is 59 years, which analyzed long archives of optical aerial photographs combined with satellite data to assess woody vegetation spatio-temporal dynamics in South Africa [131]. Blentlinger and Herrero [132] also characterized woody cover in a protected area for over 44 years in a neotropical savanna ecosystem in Belize, Central America.
Figure 11. The length of analysis in years for the reviewed publications. Studies’ length of investigation is shown on x-axis with the publication year shown for every publication on y-axis. Inter-annual studies which represent investigating periods covering multiple years are illustrated by a line with orange square at the ends, while multiple images spanning over a single year (intra-annual) are represented by blue diamond shape point, and single images which represent a mono-temporal single date are indicated by single round green point symbol. The graph was generated with courtesy of a Python code generated by Sophie Reinnerman of German Aerospace Center (DLR).

3.6. Accuracy and Validation of the Reviewed Publications
3.6. Accuracy and Validation of the Reviewed Publications

In Figure 12, the accuracy of the reviewed studies which reported a clear overall accuracy is summarized. Overall accuracy considered for the analysis means the study reported a standard accuracy metric of either confusion matrix overall accuracy, kappa, or a $R^2$ from a regression model. About 85% of the reviewed studies reported a clear overall accuracy. For the papers which reported an overall accuracy, the majority (46%) have an accuracy class between 80–100% (Figure 12a). For the studies which reported an overall accuracy, EO datasets used as reference data for accuracy assessment are shown (Figure 12b).

![Percentage of studies](image)

**Figure 12.** The percentage of studies per overall accuracy class (a) is shown only for those publications with overall accuracy clearly indicated, and (b) remote sensing data used in the validation process for those studies that reported an accuracy are shown.
In order to find out which EO datasets achieved a better accuracy, a comparison is made between the four accuracy categories (Figure 13) across the spatial resolutions (very high, high, medium, and low) of those EO datasets utilized by the studies. The EO dataset types which have the highest percentage of studies achieving a >60% accuracies are those which have used medium spatial resolution (88%), followed by 84% of studies which have used the HR spatial resolution EO data. Studies which used VHR EO data have the lowest (74%) number of studies, which achieved accuracies of >60%, followed by those studies which have used low spatial resolution EO data (82%). The majority of studies have used low spatial resolution compared to others, with HR EO datasets being the least used across those studies which reported an overall accuracy. Although less frequently used, HR studies achieved better accuracies compared to VHR and low resolution. Medium resolution studies which have the highest percentages of studies (88%), with high accuracies (>60%), is the second most used type of EO datasets across the 159 studies that have reported an overall accuracy and the most used EO data type among all the 197 reviewed studies.

Figure 13. Overview of the employed EO datasets for mixed pixel analysis and their accuracies. The EO datasets are grouped according to their spatial resolution. The graph analysis only incorporated EO datasets from the 159 studies which reported an overall accuracy.

For the three method categories used for mixed pixel analysis in Figure 14, 90% of the studies which have used more than one method type achieved >60% accuracy, followed by 87% of studies which used only parametric methods, and 79% of studies which used only non-parametric methods. Although all methods have a high percentage of papers achieving >60% accuracies, those papers which applied more than one method seem to have performed the best by a small margin. This is regardless of the fact that fewer papers have used a combination of methods.
4. Discussion

4.1. Geographic Patterns of Spatio-Temporal Mixed Pixel Analysis in the Savannas

Because of their large spatial extend and since they are a prime target for conversion from their natural states to agriculture, the provision of rangelands for livestock and subsistence for native populations, majority of the studies have been conducted in the African and South American savannas (Figure 3) [3,5,14,28,30,32,36,38,39,46,47,52,86,95,106,112,114,116–118,129,130,133–166]. The African and Southern American savannas have a significant role in vegetation trends as a result of interactions by climate change and increasing carbon dioxide [15]. The Cerrado, along with the Caatinga, is one of the important savanna or dryland biomes of South America which have very rich flora and high endemism but only have each roughly 2.2% and 1% of their area protected for conservation, respectively, by the year 2015 [91]. The Cerrado, due to mechanized agriculture, conversion for human occupation, invasive grasses, and uncontrolled fires, is going through an intensification of anthropogenic processes, which is a major threat to biodiversity [10]. The Caatinga biome, at the same time, is also undergoing human density, replacement of gallery and dry forests due to desertification, charcoal production, timber, and cattle ranching [10].

The majority of mixed pixel analysis of the savanna have been conducted at the local and regional level with very few studies at a global and continental scale (Figure 4). Mixed pixel analysis at larger spatial scales, such as continental and global scale, tend to be a challenge which lead to more studies focusing at local spatial scales [43]. This is due to the fact that land cover trends tend to differ in some ecoregions due to climate and land use [11]. These difference in land cover trends occur in specific ecoregions and will require more detailed analysis at fine spatial and temporal scales for better understanding. Studies on mixed pixels found that regions with high heterogeneity are a challenge for analysis. Accounting for inherent heterogeneity in savannas, areas of transitional zones between major ecosystems, areas with major anthropogenic activities, boreal forests and tundra, and mountain range areas is reported to be a major challenge. When classifying biomes heterogeneity from high to low, the savanna biome is ranked the highest in terms of heterogeneity [43]. Since 64% of the global vegetated areas are reported to be a mixture of vegetation cover types, this is an indication that much of the global land surface is faced with mixed pixel and high heterogeneity. The majority of the mixed pixels are
also composed of cover types with different vegetation heights especially in transitional ecological zones [43]. Land surfaces in savanna biomes at a global scale are not uniform but highly diverse and heterogeneous. This means that robust methods to account for site differences and the mixed nature of covers are required when analyzing savanna at a global and continental scale to account for the variations in cover. It is possibly because of the obstacles in analysis of the savanna at continental and global scale which led to more studies to focus analysis at savanna local spatial scale. At local scales, the complexity may not be as comparable to large area analysis, as there is less probability of different ecosystems occurring at a local scale.

4.2. The Use of EO Technology for Spatio-Temporal Mixed Pixel Analysis in Savannas

Optical EO data were utilized more often with medium spatial resolution (30 m) Landsat being the single majority applied sensor for spatio-temporal mixed-pixel analysis of the savanna (Figure 6) [83,113,114,166]. Landsat as the most commonly used EO sensor offers at least three decades of imagery with medium spatial resolution. Landsat provides consistent measurements of inter-annual variability of vegetation over the entire earth’s surface and the same will be assumed for the savanna ecosystems [120,167]. However, Landsat does not capture adequate intra-annual or phenological variability because of the 16-day interval for image acquisition [52,139].

The wide use of optical data comes with an under-representation of other EO technologies, such as Synthetic Aperture Radar (SAR) and LiDAR, in spatio-temporal mixed pixel analysis of the savanna. For improved classification, long-time series are required and integration of SAR and LiDAR with optical time series to improve classifications in the savanna is highly recommended [15]. SAR offers an added advantage to optical time series because it is largely weather independent. SAR has been used alone [84,85,166,168,169] and sometimes together with optical imagery [83,113,114,118]. Improved accuracies are reported when models use SAR or when SAR and optical are combined in the spatio-temporal mixed pixel analysis of the savanna [83,109]. Radar remote sensing does not depend on sun illumination or cloud condition and, therefore, is a good potential to offer continuous time series of EO data for long term monitoring of the savannas.

Most of the studies used short time series EO data for savanna spatio-temporal mixed pixel analysis (Figures 10d and 11) [28]. Reliable spatio-temporal trends of the savannas require long time series [29,119,130,170]. EO sensors with many years of data archives are already available. This review has highlighted that the most preferred EO systems are those with a long history of existence. However, it seems the potential of long time series are not fully exploited so far in understanding the mixed pixel dynamics of the savanna. The satellite EO systems with long time series tend to be those with medium to low spatial resolution. The solution may be to fuse and harmonize long time series of low and medium spatial resolution (MODIS, AVHRR, and Landsat) with very high spatial resolution EO satellite data, such as the newly launched Sentinel-1 and Sentinel-2, for longer time series exploits; to fuse radar and optical remote sensing data and explore the recently launched HR EO datasets, such as the Sentinel-1 and Sentinel-2, for improved estimation of the savanna mixed pixel. The heterogenous nature of the savanna mixed pixel requires a consideration of high spatial, spectral, temporal, and radiometric resolution for accurate separation between savanna components.

4.3. Future Outlook

The rapid increase in the availability of data for land cover characterization offers great potential for contributing to new land surface cover information. However, this potential requires improved analysis methods beyond the use of vegetation indices and transformation of images. Big data is now more prevalent and open source data mining tools are readily available [171]. The recent launch of sensors with improved spatial and temporal resolutions, such as the Sentinel-1 and Sentinel-2 [118,143]; application of big data processing [143]; and the combination of SAR, LiDAR, and optical data [118] signals
the future direction of remote sensing of savanna environments from space. Multi-sensor, multi-scale imaging is recommended, especially for three-dimensional characterization of the savanna [11].

Cloud computing platforms, such as the Google Earth Engine (GEE), are reported to be a milestone in creating robust reference data to train ML algorithms for analysis in mixed and highly seasonal ecosystems, especially where reference maps for time series classifications are inadequate or unavailable [98,143]. GEE is a powerful tool which brings together multitudes of EO datasets for analysis. The GEE platform offers remarkable computational power with ready-to-analyze data available. Cloud platforms, such as GEE, have the potential to process data that requires high computational power since the process do not take up hard disk space on the computer, thus providing a potential opportunity to perform analysis at continental or global scale and counter-act the issue of data complexities and the lack of studies at large scales (i.e., global and continental) in savanna ecosystems. The GEE platform is especially well suited to large scale analysis in developing countries where access to advanced computational and data processing facilities is a challenge.

5. Conclusions

Estimating mixed pixel parameters in the savanna is essential for long-term understanding of the spatio-temporal dynamics and trends. Mixed pixel vegetation cover is an important biodiversity parameter in savannas where the estimation of the above ground biomass in savanna varies according to fraction of the trees, shrubs, and grasses. The review shows that the spatial focus of the spatio-temporal mixed pixel analysis is on the African and South America savannas due to the size and the importance of biodiversity conservation in the two regions. The majority of the studies are conducted at a local and regional scale which highlights a gap for studies at national, continental, and global scale. The gap in studies at the larger scales (continental and global), in addition, means that robust methods which are capable of large data analysis and handling the complex and highly heterogenous nature of the savanna are required. The preference to use medium (Landsat) and low (AVHRR and MODIS) spatial resolution optical EO datasets highlights the gap in use of high spatial resolution and radar remote sensing to estimate the mixed pixel of the savanna. In addition, the use of short time series of up to 5 years maximum emphasizes that long time series data which are essential for understanding spatio-temporal dynamics of the savannas are required in the estimation of the mixed pixel of savannas.

Although there was no difference in the use of parametric versus non-parametric methods, the preference to apply non-parametric methods when analyzing high spatial resolution EO indicates that more robust non-parametric methods are required to deal with the large scale EO datasets and the required high spatial resolution data to understand the spatio-temporal dynamics of the savanna mixed pixel. The increase in the use of non-parametric methods, for example, Random Forest machine learning methods, mainly used to estimate fractional woody cover in the African savannas, is a good example. Non-parametric methods, such as regression tree methods, are used mainly by the VCF studies which estimated global VCF tree cover probably due to their robustness and ability to handle large volume of data. The most used input data band statistics which are composed of mainly multi-temporal composites which capture phenology to separate savanna vegetation components shows that a multitude of temporal data are required for spatio-temporal dynamics of the savanna. It also indicates that understanding the spatio-temporal analysis of the savanna requires a large volume of data, along with big data infrastructures to handle them. The majority of the time series used are of inter-annual nature, however, consisting of rather short analysis periods. Therefore, the review highlights a research gap for savanna spatio-temporal mixed pixel analysis using high-resolution long time series. This gap can be addressed by increasing the incorporation of active EO, such as SAR. Optical EO data with long time series, such as Landsat, can be harmonized with the recently launched high resolution Sentinel-1 and Sentinel-2 sensors. In addition, exploring the fusion of high-resolution SAR and optical to address the gaps
in time series data due to cloud cover is also a possibility. Satellite data are increasingly becoming available. This creates opportunities for big data and open-source data mining tools to be created, especially to provide fitting methods to monitor complex ecosystems, such as the savanna. The review set out to find out the type of EO datasets and methods used for mixed pixel analysis of the savanna and found a gap for high-resolution EO datasets. This indicate that although satellite data is increasingly available, the processing capabilities of high spatial resolution remote sensing data to monitor long term changes for savannas may be a challenge, especially at global and continental scales. When it comes to EO datasets and what type of methods they recruit for mixed pixel analysis and how accurate they tend to be, it seems that combinations of parametric and non-parametric methods are recommended, along with medium and high spatial resolution long time series EO datasets, for a more accurate spatio-temporal mixed pixel analysis of the savanna.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/rs13193870/s1, Table S1: List of all reviewed research articles.

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Abbreviations

AVHRR Advanced Very High-Resolution Radiometer
EO Earth Observation
GEE Google Earth Engine
GIMMS Global Inventory Modeling and Mapping Studies
HR High Resolution
INPE National Institute for Space Research
1/k-NN Nearest Neighbor
LULC Land Use Land Cover
MD Minimum Distance
MAP Mean Annual Precipitation
MAT Mean Annual Temperature
ML Machine Learning
MODIS Moderate Resolution Imaging Spectroradiometer
NDVI Normalized Difference Vegetation Index
RF Random Forest
RT Regression Tree
SAEON South African Environmental Observation Network
SAR Synthetic Aperture Radar
SDA Step-wise Discriminant Analysis
SMA Spectral Mixture Analysis
VCF Vegetation Continuous Fields
VHR  Very High Resolution
VI  Vegetation Indices
VIIRS  Visible Infrared Imaging Radiometer Suite

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