Progress in Remote Sensing of Grass Senescence: A Review on the Challenges and Opportunities

Lwando Royimani, Onisimo Mutanga, and Timothy Dube

***Abstract*—Grass senescence estimation in rangeland is particularly important for monitoring the conditions of forage quality and quantity. During senescence, grasses lose their nutrients from the leaves to the root and thereby affecting forage productivity. Studies on the remote sensing of grasslands have been conducted during the senescent phenological stage. However, despite the efforts made in previous remote sensing studies on grass senescence, its role in estimating grass senescence is rudimentary. More so, the strengths and limitations presented by the newly developed remote sensing instruments in grass senescence estimation are not well documented. This work, therefore, provides a detailed overview on the progress of remote sensing applications in characterizing grass senescence. The review further highlights the challenges and opportunities presented by these techniques. Overall, the review indicates that studies on remotely sensed grass senescence are focused on understanding biophysical and biochemical properties, and these studies identify the leaf area index, biomass, and chlorophyll content, among others, as the key indicators of grass senescence. Nonetheless, recent scientific research highlights a mismatch between studies on the grass senescence and the development in remote sensing technologies. The use of sophisticated and robust time-series analysis techniques together with improved sensing characteristics from the new generation sensors seem to present new opportunities for the optimal quantification of grass senescence at resolutions complementary to the spatial extents of the rangelands. We, therefore, recommend further research in this field through the adoption of new satellite technologies and advanced spatial data analytics to enhance the monitoring of rangeland resources.**

***Index Terms*—Forage resources, grass quality and quantity, rangelands, remote sensing, senescence.**

I. Introduction

THE understanding of grass senescence in rangeland environments is of great importance as it informs the knowledge on availability status, condition, distribution, and allocation of forage [29], [54], [65]. By definition, senescence is generally described as the last phase in the plant's lifespan [40]. In the process, plant components such as the leaves and stems individually or collectively deteriorate through time as a result of either internal or external factors [30], [43], [51], [62]. Highlighting the impact of external factors in senescence, Castro and Sanchez-Azofeifa [14] noted that the autumn senescence of deciduous vegetation in temperate regions is strongly influenced by the day-length of the region during this particular period. Buchanan-Wollaston *et al.* [12] also noted that the process of grass senescence is invaluable for livestock production as it helps to promote the growth and development of new and, often, nutritious feed. Nonetheless, many other studies have also highlighted the ecological relevance of grass senescence [5], [8]. For instance, senescence reduces the leaf area of the leaves, thereby minimizing the stomatal pores of the associated grass foliar, and this, in turn, lowers the evapotranspiration fraction [20]. Also, the senescent grass leaves are known for their low absorptive capacity of the atmospheric carbon, thus decreasing the amount of sequestrated carbon [5], [8]. In addition to the common stressors of foraging resources like rangeland degradation [54], climate change [3], and the undesirable anthropogenic activities, grass senescence also presents extra pressure on ranch and forage productivity. Therefore, this emphasizes the need for understanding grass senescence, especially in developing countries where their gross domestic products are largely dependent on livestock farming. Such information will not only provide insightful baseline knowledge on grass-production budgets but also boost awareness on the value of livestock farming toward poverty alleviation which addresses the sustainable development goals 1 and 2.

Traditionally, grass senescence estimation has been achieved, largely, by means of visual inspections and handheld field spectrometers (Liu *et al.* 2013, [6], [45]). However, the major drawbacks of such methods in vegetation assessment are well detailed in the literature and they include, among others, the limited spatial extents, compromised repeatability, and excessive time and labor required [57], [58]. Contrastingly, remote sensing allows for reliable, cost-effective, and repeated assessments of grass senescence at various landscape scales. Its ability to acquire spatial data over the same locations, repeatedly, provide multitemporal data required for detecting subtle changes in the physiology and phenology of grass canopies over time. In light of these benefits, scholars have explored the contributions of remote sensing techniques in estimating grass senescence using different sensing instruments, ranging from local [6] to regional [5], [55] scales of application. Local scale assessment of grass senescence with remotely sensed data has often been done, using

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the analytical spectral devices (ASD) and other hyperspectral radiometers [6], [10]. Although these instruments yield adequate estimation accuracies, their limited coverage coupled with excessive acquisition cost often impedes their adoption, especially for forage monitoring efforts at the landscape scale. Remote sensing multispectral sensors like the Landsat 5 Thematic Mapper (TM), Sentinel-2, and Landsat 7 Enhanced Thematic Mapper Plus (ETM+), on the other hand, have dominated grass senescence monitoring at an operational scale (Liu *et al.* 2013, [5], [10], [33], [55]). With improved spectral, spatial, and temporal properties of these sensors, reasonable estimation accuracies of grass senescence in geographical scales that are complementary to the spatial extents of rangelands are achievable. Also, the free provision of quality data from these sensors is a huge advantage for rangeland resource monitoring, especially in resource constrained regions such as the southern Africa. Nonetheless, the success of remote sensing techniques in characterizing grass senescence relies on the use of biochemical, physiological, and phenological properties of the foliar as surrogates. Commonly used biophysical indicators that have aided the remote sensing estimation of grass senescence include the lean area index (LAI) [6], fractional photosynthetically active radiation (fAPAR) [13], chlorophyll content (Liu *et al.* 2013), and aboveground grass biomass [5], [13], [33], among others.

Despite this knowledge, only a handful of studies have reviewed remote sensing applications of vegetation with an element of senescence in general. For instance, Bradley [11] reviewed remote sensing techniques for detecting invasive plants using phenological, spectral, and textural attributes. Moore *et al*. [47] gave a synthesis of remote sensing approaches for monitoring changes in the phenology of the Australian vegetation. Although the potential of remote sensing in characterizing senescence has been noted, however, such studies have largely focused on croplands or forested vegetation instead of grass species. This highlights the need for the state-of-the-art review in the literature to understand the contributions of remote sensing methods in estimating grass senescence. Also, this information will serve as a baseline for highlighting critical knowledge gaps for future improvements. Such a synthesis is even more relevant owing to current developments in remote sensing technology. For instance, the recent introduction of broadband multispectral remote sensing instruments (e.g., Sentinel-2 and Landsat 8) with improved spatiotemporal and spectral properties provides new options for grass senescence assessment and estimation. Therefore, the current study provides an overview of remote sensing techniques and their applications in characterizing grass senescence with associated challenges and opportunities. Primarily, the study gives a detailed discussion of the methodology followed in searching and identifying relevant literature for the review process. Further, the study explored the process of grass senescence jointly with the subsequent impact on forage productivity across various veld types. In addition, the review examined the differences in spectral reflectance of green versus senescent grass species. The study also interrogated the commonly used remote sensing techniques and vegetation indices for characterizing grass senescence. Finally, the study highlighted the common challenges in remote sensing of grass senescence together with possible directions for future studies in remote sensing of grass senescence.

II. Literature Search and Selection of Source Articles

To achieve the objective of the present study, relevant literature from selected peer-reviewed journals were gathered and reviewed. The selected articles were identified using key search words from the web of science, Google scholar, and other revered scientific databases. These repositories or scientific databases are believed to be among popular databases, which are rich in terms of peer-reviewed scientific work of this nature. The key search words included the following: "remote sensing of grass senescence," "remote sensing of dry grass biomass," "grass senescence," "sour veld grass development," "livestock forage quality," "remote sensing of grass phenology," and "pasture production." Additional journal articles were found from the reference lists of included studies through a process known as backward reference list checking [37]. Studies were, therefore, included or excluded from this work based on the above-mentioned criterion.

III. Grass Senescence and Its Impact on Forage Productivity Across Various Veld Types

Senescence is an important phenological stage in the life cycle of grasses which marks the end of the older life and paves a way for the beginning of a new one [23], [40]. In the process, fundamental changes are notable in the gene expression, metabolism, and structure of various grass components such as the leaves and the stem [39]. The earliest and the most common form of senescence in grasses is the leaf senescence, in which the individual green leaves of the grass gradually turn yellow to brown in color as a result of breakdown and loss of chloroplast [12], [19], [32]. The progressive loss of green color in grass foliage often coincides with the migration of associated nutrients from the tiller parts to the root systems [21]. Broadly, the leaves can senesce as a result of poor plant health status, strenuous environmental conditions, and/or old age [15], [59]. The process whereby plant leaves uniformly go through senescence due to their old age, like the autumn senescence, at the landscape scale is called natural senescence [30], whereas induced senescence is consequent to actions of particular agents like diseases, extreme weather conditions, or physical disturbances, among others.

According to Lim *et al*. [39], Fig. 1 illustrates the phenology of the vegetation with a particular focus on the senescent stage with internal and external casual factors, on the left and right hand sides, respectively. It can be seen that the internal factors are largely defined by the biochemical constituents of the plant itself while the external causes are more of an outside agent, like the microclimate, pathogens, etc. Under the influence of internal factors, grasses can senesce earlier than their natural expected time, mainly due to the excess or shortage of particular hormones or ill health. However, in external factors, grasses senesce because of limited sunlight, water, and nutrients, among

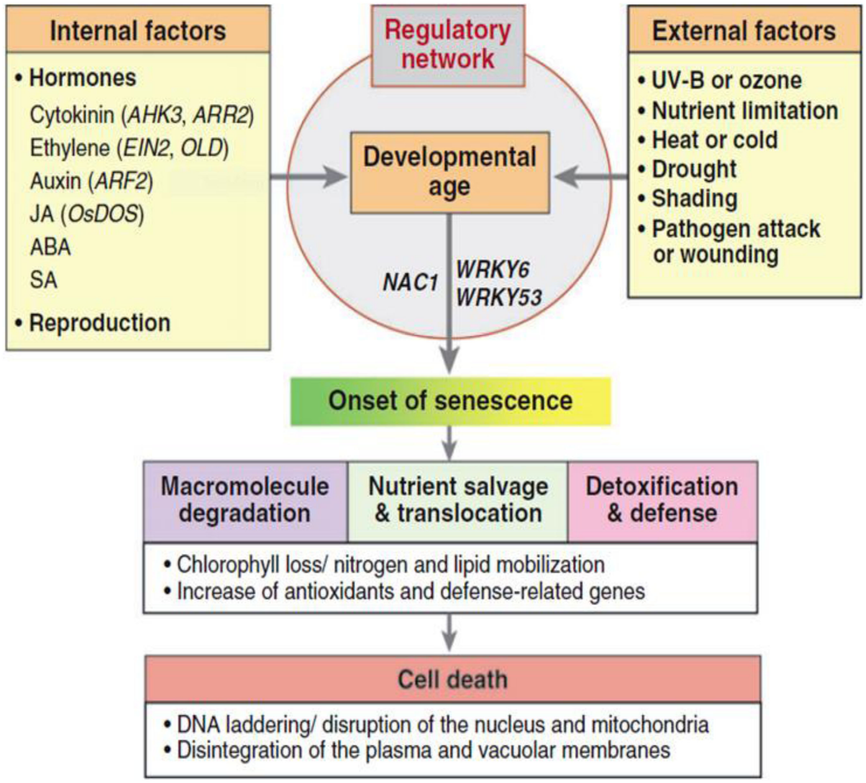

Fig. 1. Schematic representation of the process of leaf senescence as a result of, both, internal and external factors (Source: [39]).

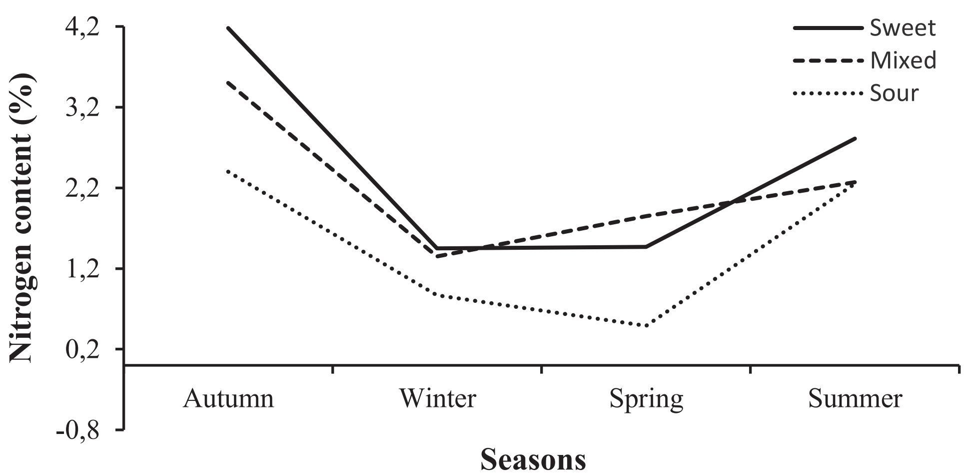

Fig. 2. Seasonal dynamics in percentage nitrogen (N) concentration in sweet, mixed, and sour veld grasses (Source: [66]).

others [12]. Research reveals that after senescence, the fallen grass material is decomposed to improve soil structure and water holding capacity, which also reduces soil erosion [1], [38]. Likewise, the decomposed grass material activates soil nutrient turnover and primary production, which is necessary for livestock grazing purposes [34], [50]. Clearly, grass senescence is not a completely undesirable process, especially for livestock production as it activates the development of new and mostly high nutrient forage [12]. A detailed scientific report of this process is presented in the works of Gepstein *et al*. [30], Lim *et al*. [39], Lim and Nam [40], Woo *et al*. [64], etc.

In addition, experimental studies showed that senescence is a major determinant of grass quality and quantity [22], [36], [43], especially for grazing purposes. This is particularly the case in sour veld grazing areas, whereby grasses are subjected to a process of "leaf-to-root" nutrient translocation as a result of senescence [62], and this significantly degrades grass leaf nutrients [21]. A clear demonstration of this process has been made in Fig. 2 using data extracted from the work of Zacharias [66]. This author used nitrogen content as an indicator of grass quality to compare nutrient holding capacities between sweet,

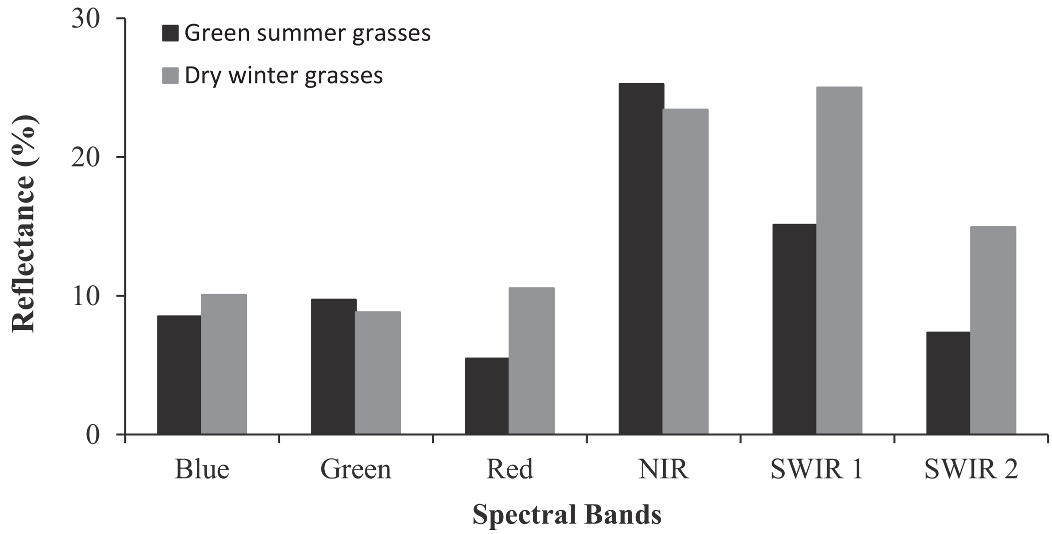

Fig. 3. Averaged spectral reflectance of green versus senescent *Aristida junciformis* grasses extracted from the visible, NIR, and SWIR bands of the Landsat 8.

mixed, and sour veld grasses over different seasons. The results of this experiment reveal that sweet veld grasses can hold their nutrients constantly high throughout the year, whereas the quality of mixed veld grasses is highly variable mostly with seasons. On the other hand, grasses from sour veld have low nutritional content for most of the year, with the lowest (0.5%) nitrogen value reported in the transition period from winter to spring. Evidently, the sour veld grasses are mainly effective during summer as far as the livestock grazing purposes are concerned. Although grasses from the sweet and mixed veld are subjected to senescence, the ability of their leaves not to drastically lose nutrients makes them a better choice for the livestock production. It is also assumed that the yellow to brown leaves of sour veld grasses, following senescence [40], are not adequate or even nutritious for the livestock consumption. Even though sour veld grazing areas are considered to be rich in terms of species diversity, Hardy *et al*. [35] and Pickup [54] maintain that not all the herbage produced from rangelands are palatable. This further perpetuates the selective grazing that has been reported in sour veld areas [52]. Likewise, the selective grazing increases fuel loads [28], [41], thereby promoting veld fires [41]. The remaining grass stems as a result of cold fires or senescence are often less likely to regrow their leaves until the next rainy season, mostly spring, occurs. This is precisely because grass production processes in sour veld are strongly influenced by seasonality and rainfall [35]. The subsequent impact, thereafter, is expected to be felt mostly by rural livestock farmers who can afford the expensive supplementary forage [56]. This argument shows the need for forage assessment studies that prioritize not the investigation of grass senescence in general but rather in grasses that are situated in sour veld communal grazing areas. Although previous experiences have proved that data collection for rangeland assessments can be laborious, resourceful, and time-consuming, remarkable progress has been made, using recent methods, which rely on spectral properties of the vegetation observed through remote sensing platforms.

IV. Spectral Properties of Green Versus Senescent Grasses

A large body of evidence [2], [16], [17] suggests that the spectral signals of grasses, like any other vegetation, is governed by its internal and external factors, such as the structural and surface features of the leaves along with distribution and concentration of pigments. Cole *et al*. [18] and Clark *et al*. [17] noted that these internal and external factors have measurable and known absorption and reflectance features in the electromagnetic spectrum. Certainly, variation in the distribution and quantities of these constituents among senescent and green grass leaves promotes their spectral distinctiveness in different regions of the electromagnetic spectrum as shown in Fig. 3. Specifically, Fig. 3 shows the averaged spectral reflectance of green and senescent *Aristida junciformis* grasses extracted from the visible, near infrared (NIR), and shortwave infrared (SWIR) bands of the Landsat 8 (Operational Land Imager and the Thermal Infrared Sensor) to understand the behavior of the spectral response of the grass between these two phenological periods. In the process, two preprocessed Landsat 8 images covering the uMsunduzi Municipality of KwaZulu-Natal, South Africa were downloaded from Earth-Explorer, and each image corresponded to summer and winter to represent green versus senescent grasses, respectively.

It could be observed that the spectral signatures of green grasses were dominant in the visible green and the NIR regions, whereas those of the senescent grass leaves were superior in the visible blue, red, and SWIR sections. Based on Peñuelas and Filella [53], the high chlorophyll content in the leaves of green grasses is responsible for the increased reflectance in the visible green and the NIR while remaining low in the other regions because of increased absorption. These results also concur with findings by Adam *et al*. [2] who reported that a typical spectrum of green leaves is characterized by increased reflected and absorbed spectra in the NIR and the mid infrared (MIR) due to pigment concentration and water content, respectively.

Other studies [6], [44] that have conducted a close comparison between green and dry plant spectra confirm the results presented in Fig. 3 that the spectral reflectance of senescent vegetation dominates the visible and the SWIR regions of the spectrum. However, Elvidge [27] emphasized that remote sensing works of vegetation assessment have been limited to green leaf spectra as opposed to the nongreen canopies.

Contrary to the green leaves, the spectral properties of senescent vegetation are not easily discernable due to many factors including the soil background promoted by the decrease in foliar cover and LAI, among others. Similarly, spectral reflectance of senescing flora is often mixed and confused with fractions of adjacent green leaves, and this is particularly the case when using measurements taken at the canopy level. However, with the understanding of the influential internal and external constituents, Asrar *et al*. [7] showed that the spectra of senescing leaves can also be detected from various regions of the electromagnetic spectrum. As opposed to the high chlorophyll content of green leaves, which induces the spectral signatures at 450 and 550 nm, the low chlorophyll content of senescent leaves increases the subsequent spectra at 675-nm wavelength [53]. It is further noted that senescing leaves exhibit increased spectral reflectance in the red and SWIR regions of the spectrum due to decreased chlorophyll and water content [44]. The variation in water content between senescent and green leaves is further expected to induce their spectral distinctiveness in the MIR region of the electromagnetic spectrum [2].

V. Remote Sensing Techniques and Common Vegetation Indices for Assessing Grass Senescence

Globally, there are only a handful of remote sensing studies that have investigated the subject of grass senescence in rangeland ecosystems. For instance, Qi *et al*. [55] tested the potential of the Landsat 5 TM and Landsat 7 ETM+ images in estimating forage production based on combined fractional cover of the senescent and green leaves of the herbaceous vegetation in the Appleton Whittell Research Ranch, southeast of Arizona, United States of America (USA). The green canopy cover was assessed using the normalized difference vegetation index (NDVI) while the senescent components were characterized based on the normalized difference senescence vegetation index (NDSVI) index and the linear unmixing analysis. The formula for the NDSVI and for other indices commonly used in estimating grass senescence is presented in Table I. Optimal estimates of forage production were obtained with R^2 values of 0.91 and 0.93 and standard errors of 2% and 0.03 (kg) for the senescent fractional cover and the total forage, respectively. In addition, this study observed a poor correlation between the NDVI and the biomass of senescent grasses, something that was also reported by Butterfield and Malmström [13]. The inability of the NDVI to characterize grasses during the senescent phenological stage highlighted the need for an alternation technique (NDSVI) to optimize grass estimation during the senescent stage. On another study, McKean *et al*. [45] investigated the role of the multispectral Thematic Mapper Simulator NS001 (TMS-NS001) datasets and time-series analysis in explaining grass senescence as a result of landslide debris flow across an uneven terrain of the Marin County of California in the USA. The authors derived three vegetation indices from the four TMS-NS001 images acquired, of which two of those indices were based on the simple ratio (SR) calculated using band combinations from various regions of the spectrum while the third being the greenness index. Their findings point out that the greenness index is a crucial indicator of grass senescence estimation with an R^2 value of 0.60. Also, their results showed that the onset of senescence in grasses located in the valley areas was delayed and that could be attributed to the increased soil moisture content in those regions.

In addition, Asrar *et al*. [6] examined the capabilities of the Modular Multispectral (MMR) Model 15-1000 and the Model 100-A radiometers in spectrally separating between bare soils, senescent, and green grass leaves in the Konza Prairie Research Natural Area, Manhattan, USA, using the discriminant and canonical discriminant analysis procedures. Based on their findings, the senesced grass were spectrally discrete from the other land cover classes with a classification accuracy of 99% and 82% for the MMR Model 15-1000 and the Model 100-A, respectively. The strengths of the remote sensing techniques like radiometers in characterizing grass during the senescent stage rely on their ability to detect subtle changes in pigment concentrations. For instance, Merzlyak *et al*. [46] noted that the spectral signal of the vegetation increases by around 550 and 740 nm due to senescence-induced chlorophyll degradation while remaining low at 400 and 500 nm because of carotenoid retention. Additional evidence highlights that at 500 nm, plant spectra are mainly controlled by both chlorophyll *a*/*b* as well as carotenoid, whereas at 680 nm, it is determined by chlorophyll *a* [14], [18], [46]. However, the problem of mixed pixels commonly reported in studies of dry vegetation and soils was also noted in the study by Asrar *et al*. [6] with error rates of 3% and 20% for the MMR Model 15-1000 and the Model 100-A, respectively. Besides the superior spectral properties of the radiometers employed, the success of the results obtained in this study could be attributed to the fact that the analysis was done at an early stage of senescence when the green elements were still evident in the grass as compared to later stages when all the grass was completely dry. Butterfield and Malmström [13] also examined the impact of senescence on biomass of the *Avena fatua* L. *Bromus hordeaceus* L. and *Lolium multiflorum* Lam. grasses in Michigan, USA, using a hyperspectral radiometer. Three models, namely, the NDVI, fAPAR, and the LAI, were used as indicators for grass biomass. The authors further emphasized the poor correlation between the NDVI and grass biomass, particularly when the fraction of senescent grass canopy was more than 50%, and this shows that the NDVI is not a reliable indicator of senescent grass biomass. Instead, the significant relationships between grass biomass and the fAPAR ($R^2 = 0.82$, $p < 0.001$) and the LAI ($R^2 = 0.80$, $p < 0.001$) highlight the suitability of these two indicators in characterizing grass senescence based on remotely sensed data.

Furthermore, Asner *et al*. [5] evaluated the temporal dynamics in the biophysical and ecosystem biogeochemical features of meadow during the senescent stage in the south of Santarém,

TABLE I
SUMMARY OF COMMONLY USED VEGETATION INDICES IN ESTIMATING GRASS PHENOLOGY AND SENESCENCE

Index name	Formula	Reference
Enhanced Vegetation Index (EVI)	2.5(NIR - Red)/(NIR + C1 * Red – C2 * Blue + L)	Gómez-Giráldez *et al.* (2020)
Simple Ratio (SR)	(NIR/red)	McKean *et al.* (1991)
Enhenced Vegetation Index 2 (EVI2)	2.5(NIR – Red)/(NIR + 2.4 * Red + 1)	Gómez-Giráldez *et al.* (2020)
Simple Ratio (SR)	(MIR/IR)	McKean *et al.* (1991)
Sentinel-2 Red Edge Position (S2REP)	705 + 35 * ((((NIR + R)/2) − RE1)/(RE2 − RE1))	Gómez-Giráldez *et al.* (2020)
Greenness Index	Karhunen-Loeve Transformation (KLT)	McKean *et al.* (1991)
Green Chromatic Coordinate (GCCs)	G/(R + G + B)	Gómez-Giráldez *et al.* (2020)
Meris Terrestrial Chlorophyll Index (MTCI)	(NIR − RE)/(RE − R)	Gómez-Giráldez *et al.* (2020)
Normalized Difference Vegetation Index (NDVI)	(NIR – R)/(NIR + R)	Butterfield and Malmström (2009); Di Bella *et al.* (2004)
Green Normalized Difference Vegetation Index (GNDVI)	(NIR - Red)/(NIR + Red)	Gómez-Giráldez *et al.* (2020)
Normalized Difference Senescence Vegetation Index (NDSVI)	$(R_{\mathrm{SWIR}} - R_{\mathrm{red}})/(R_{\mathrm{WSIR}} + R_{\mathrm{red}})$	Qi *et al.* (2002)
Inverted Red Edge Chlorophyll Index (IRECI)	(NIR − R)/(RE1/RE2)	Gómez-Giráldez *et al.* (2020)
Soil Adjusted Vegetation Index (SAVI)	1.5(NIR − Red)/(NIR + Red + 0.5)	Gómez-Giráldez *et al.* (2020)

Note: R = wavelength.

Brazil, using the Landsat TM and spectral mixture analysis. Specifically, these authors tested the relationship between the aboveground biomass of the *Brachyaria brizantha* and *Pennesetum clandestinum* grasses and the soil organic carbon across two different soil types (clayey Oxisols and sandy Entisols) during the senescent stage and linked the resultant correlations to short- and long-term signs of nutrients in the grasses. Their findings exhibited a dual decrease in both the aboveground grass biomass and soil carbon storage with progress in senescence across the two soil types. Equally, the analysis of nutrients showed that phosphorus (P) concentration was low in all grasses situated in both soil types and it further decreased with advancements in the stage of senescence while nitrogen (N) content varied and correlated less with either the aboveground biomass or soil organic carbon. In a multitemporal study, Bork *et al*. [10] also examined the potential of simulated eight broadband Landsat TM and 52 narrowband ASD spectral signals in characterizing rangeland cover components, including grasses, in the north of Dubois, Idaho, USA. The results showed that optimal estimation of grass cover was achieved during the later stage of summer (August) due to the effect of senescence with correlation coefficients (r) of 0.4 and 0.54 for the broadband (NIR) and narrowband ($AR_{\mathrm{green/blue}}$) instruments, respectively. Guerini Filho *et al.* [33] explored the robustness of the Sentinel-2 data jointly with subsequent vegetation indices and the multiple linear regression model in estimating green, senescent, and the total biomass of the natural grasslands of the Federal University of Santa Maria in southern Brazil. Based on the findings obtained, an adjusted coefficient of determination (R^2_{adjusted}) and root mean square error of 0.4, 0.3, and 0.42 as well as 0.13, 0.24, and 0.14 were reported for the green, senescent, and total biomass, respectively. The advantages of Sentinel-2 in detecting changes in grass pigments during senescence at a geographical scale adequate for rangelands monitoring are defined by its high spatial resolution

($10\ m^2$) jointly with red-edge section and large swath-width. Despite these promising results, overall observations suggest that the remote sensing of grass senescence remains a challenging undertaking, particularly at a later stage of the senescence period. Consequently, this is the case because of increased spectral mixing between the reflectance of the background soils and those of the senescent grass leaves.

Additionally, Di Bella *et al*. [24] assessed the impact of senescence when estimating the fractional cover of photosynthetically active radiation based on green properties of ryegrass (*Lolium perenne* L. Manhattan) canopy measured with the NDVI. Findings showed that the impact of senescence on NDVI values was significant ($r^2 = 0.78$; $n = 16$ and $p < 0.001$). Likewise, Archibald and Scholes [4] used time-series satellite data to identify environmental factors that influence green-up dates between different rangeland cover features like grass species. Their investigation showed that unlike in the high latitudes where temperature and photoperiod determine phenology, soil moisture is the major driving factor behind plant senescence in the tropical regions [4], [14]. Liu *et al.* (2013) also evaluated the robustness of TIMESAT in monitoring grass phenology in Inner Mongolia, China, using the time-series analysis of the moderate resolution spectroradiometer (MODIS) NDVIs and double logistic function-fitting algorithm. In operation, TIMESAT uses four transition dates, namely, the onset of green-up, maturity, senescence, and dormancy phase of the grass phenology. The derived MODIS NDVIs were fitted in the model (TIMESAT) to construct smoothing time-series curves and to determine each of the transition dates (green-up, maturity, senescence, and dormancy). The NDVI yielded satisfactory explanation in each of the four phenological stages under investigation in the present study. The high temporal resolution of MODIS (daily) along with its global coverage allows for the comprehensive examination of the chronological changes in the distribution and concentration of grass pigments as a result of senescence. However, it could be observed from the evidence presented in this review that the remote sensing of grass senescence has not been keeping up to speed with advancements in remote sensing technology. This is demonstrated by the lack of studies which tested the potential of modern remote sensing techniques like the geostationary sensors (Meteostat of Europe, INSAT of India), unmanned aerial vehicles (UAVs) and phenocameras (PhenoCams) in grass senescence estimation. In this regard, the remote sensing of grass senescence is missing a great opportunity to benefit from high quality data which is acquired at suitable time intervals defined by the user for optimum detection of grass phenology.

VI. Challenges in Remote Sensing of Grass Senescence

One of the major notable drawbacks in remote sensing of vegetation assessment is the difficulty of associating spectra at a given wavelength with individual pigment concentrations [2], [9], [46]. Although it is known that grass spectral signature varies across the spectrum [5], [31], due to phenology and changes in the biochemical components, the confidence of stating categorically that at this specific wavelength the spectra is changing because of a decrease or increase in concentrations of a particular pigment is still very low. For this reason, it has been difficult to highlight explicitly the regions of the electromagnetic spectrum that can characterize grass senescence with optimal accuracies. This is not only common with data from the averaging broadband multispectral remote sensing sensors, as previously reported, but also with hyperspectral remote sensing techniques. Again, the spectral signal of grasses correlate with that of other similar vegetation due to resemblance in either their phenological stages or biochemical components, and this is generally the case despite the sensor resolutions [2] though it is more pronounced in some sensors than others. On the other hand, the spectra of a given species can vary within a particular wavelength because of differences in the age and microclimatic conditions [2]. It is, therefore, logical to question the possibility of having a unique spectral reflectance for a particular grass species, especially at advanced stages of the senescence period. In addition, at advanced senescence stage, a lot of material like the exposed soil background and litter from nongrass plants, whose spectra resembles that of senescent grass leaves [60], is dominant, and this promotes spectral confusion. This problem was also reported by Asrar *et al*. [7].

More so, the application scale of remote sensing techniques does not allow the assessment of grass senescence at the plant of leaf level, and this results in studies of this nature being conducted at the canopy level. Blackburn [9] noted that the problems associated with the characterization of plant senescence at the canopy scale are not unusual in remote sensing of vegetation. They mainly stem from the uncertainty of whether the entire canopy is senescing or parts of it are going through senescence [59]. Also, the adoption of the "big-leaf-hypothesis" which was proposed by Stylinski *et al*. [63] would not always yield the intended outcomes when estimating grass senescence through remote sensing methods due to the possibility of having crucial information obscured. The "big-leaf-hypothesis" proposes that the entire canopy of the plant, including grasses, be treated as a single big leaf when analyzing its spectral reflectance [63]. However, this approach assumes uniformity in the spectra of the canopy and overlooks the possibility of spectral variation because of differences in factors such as the age or health status of each individual grass plant or among different grass leaves. As a result of these challenges, remote sensing detection of plant senescence has predominantly focused on crops [15], [32], [46] than on other vegetation types such as grasses. This is the case because crop fields are reasonable plots that can be sampled in totality, at the leaf or plant level, if needs be, for the estimation of senescence, unlike rangelands which are largely extensive [65]. Also, senescence is relatively uniform in crops because they are often grown as mono-species and at the same time.

VII. Possible Directions for Future Research Endeavors

Despite these shortcomings, there is no doubt that remote sensing has a vital role to play in characterizing grass senescence by identifying spatial and spectral resolutions, wavelengths, and image processing techniques, suitable for estimation at this phenological stage. During senescence, grass canopy cover decreases because of reduction in chlorophyll content and biomass [2], and this partly addresses the known problem of saturation which is common with remote sensing of green and dense covers [49]. Cole *et al*. [18] also confirmed that the dry season offers a perfect time for discriminating between vegetation types. Using Sentinel-2 data, Mutanga and Shoko [48] observed that the winter season, when vegetation was dry, was the best for discriminating between C_3 and C_4 grasses. Previous studies have also confirmed that the assessment of plant senescent through remote sensing techniques is an achievable task [15], [18], [59]. For these reasons, it is evident that remote sensing of grass senescence estimation is an achievable task. However, for objective quantification of grass senescence through remote sensing techniques, this study suggests that in addition to the adoption of the "big-leaf-hypothesis," the time/period in which the analysis is conducted should be considered. It, therefore, proposes the use of the "big-leaf-hypothesis" jointly with autumn senescence. During autumn, grass senescence is driven by natural processes such as seasonality and the age of the plant, and this helps to promote uniformity in the spectral reflectance at the canopy level.

Previous studies [18] indicated that at the beginning of senescence, the spectra in the red edge portion shift toward the shorter wavelengths due to alterations in the distribution and concentration of plant pigments. Likewise, Peñuelas and Filella [53] state that the increasing concentration of carotenoid with respect to chlorophyll in senescing canopies serves as an indicator of the onset of senescence in the vegetation. With improved spatial and spectral properties and the availability of specially located bands, current remote sensing sensors like Sentinel-2 are robust enough to detect these phenological changes in grass canopies. In another study, the concentrations of plant pigments (i.e., chlorophyll and carotenoid), based on an ASD field spectrometer data, were used successfully as a presymptomatic indicator to determine senescence [18]. This was possible because chlorophyll generally degrades faster than carotenes during senescence while leaving the carotenoids dominant at the canopy. Again, research has discovered that most compounds such as starch, glucose, and nitrogen are reversed by the vegetation during senescence, thereby leaving the lignin and cellulose dominant [18]. It is, therefore, fulfilling to assume that the estimation of proportions between these pigments can serve as proxies for plant senescence from a remote sensing perspective.

Given that grass senescence is a process and not a phenomenon, its effective characterization cannot be achieved through a single-date image acquisition but requires multidate images to detect the chronological changes in the phenology and pigments of the grasses. The success of this undertaking relies on the availability of sensors with high revisit time. However, the current excessive acquisition cost associated with the high-spatial and hyperspectral data suggest that this technology is not suitable for multitemporal and time-series analysis of grass senescence at the landscape scale. The provision of free quality data from optical remote sensing sensor like the Landsat 8 and Sentienel-2, therefore, presents new opportunities for objective estimation of grass senescence in a spatial scale complementary to the spatial extents rangelands. Besides the adequate resolutions and being readily available, the Sentinel-2 instrument also captures the red edge region of the electromagnetic spectrum [61], and this can benefit characterization of rangeland resources even at the senescence stage. It is believed that the presence of the red edge portion in Sentinel-2 has contributed to its superior performance (96.18%) when compared with Worldview-2 (94.44%) and Landsat-8 (91.67%) instruments in separating *Festuca costata* from *Themeda Triandra* grasses during the winter season [60]. Certainly, this will improve the monitoring of rangeland resources even by resource limited countries that can barely live up to the price of the high-spatial and hyperspectral sensors.

Furthermore, the recently launched Sentinel-3 satellite instrument by the European Space Agency is a great step toward achieving subcontinental monitoring of grass senescence. Despite the averaged spatial properties, Sentinel-3 data, with high temporal resolution, will promote time-series analysis which is required to detect grass senescence. Again, the utility of sophisticated and robust time-series modeling techniques such as TIMESAT (Liu *et al.* 2013) with quality satellite data (e.g., Sentinel-2 and Landsat 8) can improve the accuracy of grass senescence estimation at the landscape scale. However, for the sustainability of forage resource management efforts based on remote sensing, the current study expands on the proposal made by Dube *et al*. [25], [26] which seeks to accelerate the discussion on the issue of tradeoffs among sensor type, resolution, data cost, and the application scale. Such a discussion will improve our understanding of the potential role that can be played by imaging instruments like the geostationary sensors, UAVs, and PhenoCams which have received limited attention in grass senescence assessments thus far. Broadly, the comprehensive knowledge on all possible sensing instruments and the benefits of merging data from some instruments will not only help in developing novel and cutting-edge methods but also in identifying cost effective techniques that yield accurate estimates of grass senescence at landscape scale. Future studies should try to close this scientific knowledge gap by testing the utility of time-series analysis techniques in modeling grass senescence based on spatial scales that are reasonable to the spatial extents of the rangelands in question. Other studies could also investigate the magnitude of decline in rangeland foraging resource productivity consequent to senescence. Again, the role of environmental variables in influencing the autumn senescence in grasslands is largely unknown. The findings of such studies will help contribute toward developing sound-based decision support systems for monitoring rangelands grazing resources in the face of global change and anthropogenic impacts.

VIII. Conclusion

The present study has provided an overview of remote sensing techniques for characterizing grass senescence with associated challenges and opportunities. Senescence is an important phenological stage in vegetation that determines not only the availability and quality of forage but also its distribution and allocation. Unlike the use of conventional methods, remote sensing provides nondestructive and cost-effective ways of estimating grass senescence at the landscape scale. Remote sensing efforts of grass senescence depend on the use of changes in biochemical and physiological components of the grass at this phenological stage as proxies. Remote sensing derivatives such as the NDVI have proved ineffective for grass characterization at the senescence stage. More so, this review has revealed that grass senescence estimation efforts based on remote sensing approaches has not been up to speed with advancements in remote sensing sensor technology. On the other hand, the adoption of sophisticated and robust time-series analysis techniques like TIMESAT with improved quality data from the Sentinel-2 and Landsat 8 sensing instruments can improve the estimation of grass senescence at the rangeland scale. The results presented in this study are particularly important to the forage production and remote sensing community as they add value to efforts of foraging resource monitoring and management through remote sensing methods.

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