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Editorial

Perspectives on the Special Issue for Applications of Remote Sensing for Livestock and Grazingland Management

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Abstract: The use of geospatial sciences and technologies for the management of grazinglands has fostered a plethora of applications related to ecology, wildlife, vegetation science, forage productivity and quality, and animal husbandry. Some of the earliest use of remote sensing dates to the proliferation of aerial photography in the 1930s. Today, remote sensing using satellite imagery, global navigation satellite systems (GNSS), and internet-connected devices and sensors allow for real- and near real-time modeling and observation of grazingland resources. In this special issue of *Remote Sensing*, we introduce nine original publications focusing on varying aspects of grazingland management, such as animal health and telemetry, climate change, soil moisture, herbaceous biomass, and vegetation phenology. The work in this issue spans a diverse range of scale from satellite to unmanned aerial systems imagery, as well as ground-based measurements from mounted cameras, telemetry devices, and datalogging devices. Remote sensing-based technologies continue to evolve, allowing us to address critical issues facing grazingland management such as climate change, restoration, forage abundance and quality, and animal behavior, production, and welfare.

Keywords: geographic information systems; spatial data science; modeling; drone; unmanned aerial systems; unmanned aerial vehicle; herbivory; rangelands; climate change; ungulates

Citation: Rhodes, E.C.; Perotto-Baldivieso, H.L.; Reeves, M.C.; Gonzalez, L.A. Perspectives on the Special Issue for Applications of Remote Sensing for Livestock and Grazingland Management. *Remote Sens.* **2022**, *14*, 1882. https://doi.org/10.3390/rs14081882

Received: 30 March 2022
Accepted: 7 April 2022
Published: 14 April 2022

1. Introduction

Grazinglands, natural and managed systems used primarily for livestock production, make up approximately 40% of the global ice-free land mass [1–3]. The application of geospatial sciences and technologies to the art and science of grazingland management has progressed immensely since the use of black and white aerial photography in the 1930s [4,5]. Collectively, geospatial sciences and technologies encompass the spatial techniques and principles that used through geographic information systems (GIS), remote sensing, and global navigation satellite positioning systems (GNSS) and their applications (such as spatial data science analytical techniques). In this context, instead of being content with merely knowing where something happens, where and why are equally important [6].

The launch of the Landsat-1 satellite in 1972 marked a new era in the ability and applicability of spatial science applications to increase our understanding of grazingland dynamics through mapping, modeling, managing, and developing decision support tools [4,7–9]. Recent proliferation of publicly and privately owned satellites, the use of unmanned aerial systems (drones), advances in high-resolution imaging sensor technology, and computational abilities of desktop and cloud computing have all contributed enormously in recent years to the rapid growth and expansion of geospatial sciences and technologies. In this vein, capabilities have advanced in recent years to evaluate questions that were unthinkable a decade ago.

In this special issue, we (1) highlight the role of remote sensing in livestock and grazingland management; (2) provide a brief overview of historical applications and challenges over the past 50 years; and (3) introduce the reader to the current work featured in this Special Issue of *Remote Sensing*.

2. Satellite Imagery Applications

With an ever-expanding constellation of remote sensing satellite and communications platforms, many of today's geospatial technologies encompass considerable temporal and spatial depth. In recent years, we have seen temporal resolutions of multi-spectral satellite imagery increase from 18 days to daily (sub-daily near the poles), and spatially from 80 m to the sub-meter level [10,11]. Online publicly-available databases have drastically reduced the costs of remote sensing data. At one time, a single Landsat image would cost the end-user $3600 USD [4], and could take months to receive [9]. Today, the entire Landsat archive is online and freely available, as are many other remote sensing datasets from the United States Government, European Space Agency, and others. In the past 40 years, there has also been a shift in the ownership of satellites from totally government-driven to a growing number of private-sector, for-profit remote sensing platforms such as Planet Labs [10] and DigitalGlobe [12].

This abundance of remote sensing data allows grazingland managers to address a series of probing research questions related to past, present, and future landscape conditions [13,14]. The advanced very high-resolution radiometer (AVHRR) has been used in the past to estimate net primary production on grazinglands at a 1 km^2 resolution [15]. However, more recent advances in cloud computing availability has allowed for Landsat and MODIS (moderate resolution imaging spectroradiometer) data from 1984 to present to be used in the United States (US) to model grazingland primary productivity at a much finer scale [14,16–18]. The Rangeland Analysis Platform (https://rangelands.app/ accessed on 5 January 2022) is a new tool utilizing satellite imagery and big data to help private and public land managers in the US to observe current and past rangeland conditions to aid in research and decision-making processes [19,20]. Potential applications of these datasets include: determination of appropriate stocking rates [21], identifying indicators of rangeland health, locating areas impacted by overgrazing, identifying state and transition phases [22–24], training new land managers on the history of management areas and allotments, and developing new management schemes by learning from past management practices [14,17,18,25].

Advancements in privately-owned satellite services, such as RapidEye (5 m) and Planetscope (3 m) have provided grazingland scientists with exciting new opportunities to observe and study grazinglands [10,26,27]. Using high-resolution, multi-spectral imagery, normalized difference vegetation index (NDVI) data can be obtained with much more detail than with the Landsat platform. With daily global datasets available, grazingland production, woody plant cover, land use, and even species identification in some cases may be possible at high spatial and temporal resolutions [26,27]. When combined with other geospatial data, management and restoration measures could be prioritized to areas where the potential of success is most prevalent [26]. However, this technology is currently subscription-based and may be out of reach for many producers and grazingland managers. Many academic institutions and federal research labs have limited free access for research purposes. As additional geospatial service providers emerge and contend for market share, pricing may become more competitive in the future.

Another emerging use of satellite imagery is the mapping of forage quality for grazing animal diets [28,29]. Coupled with GNSS tracking of livestock movements, we can begin to see how dispersion of forage quality and topography across the landscape may affect forage access, as well as movement and foraging behaviors of livestock [30–34]. This is especially useful as forage quality can be tracked and/or modeled in near-real time to allow for timely management interventions that improve animal productivity. Laboratory based analyses of diet quality, either through processing of vegetation or fecal matter, provide data days after the fact, whereas remote sensing estimates can provide near-real time information on current conditions [29] that is non-invasive and nondestructive and is easily scalable. When paired with biomass estimates, this technology has a lot of potential for affecting management decisions in remote pastoral regions. This is especially true in areas where virtual fencing is used to automatically and remotely control herd dispersion and location [35–37].

Historical vegetation and long-term weather data with remotely sensed data processed with machine learning algorithms can be used to visualize past patterns and anomalies and produce short and long-range forecasts for biomass production and drought modeling [29,38,39]. Similar technologies are currently in use for US crop and rangeland insurance programs [38]. However, the spatial resolution of many remotely-sensed weather products are still quite coarse [38]. While this may be appropriate for analyzing conditions over a broader region, it is not always applicable to localized areas such as ecological sites or pasture paddocks. Fortunately, accurate and modestly priced consumer grade weather stations are becoming more common among private users, providing a new source of georeferenced climate data. Always-on data collection and processing technologies, known as the Internet of Things (IoT) [40], is a growing wellspring of spatially dispersed data. Recently, new modeling packages for the R programming language, such as NicheMapR and Microclima have allowed researchers to model microclimates at hourly intervals at less than 30 m resolution [41,42] As private weather and climate data collection grows in popularity, modeling and ground truthing capabilities will benefit from the additional data as well.

3. Aerial Remote Sensing

Long before the launch of Landsat 1, high-resolution aerial photography was the only form of remotely sensed data that was publicly available. After World War I (WWI), many public and private collections of aerial imagery began to be collected and made available [43]. In 1928, former WWI fighter pilot Edgar Tobin formed Tobin Aerial Surveys (later named Tobin International) and began capturing stereographic aerial imagery of much of the US Gulf Coast states to aid in oil and gas exploration, creating one of the oldest and largest aerial datasets in the world [44–46]. Tobin went on to aid in the allied reconnaissance effort in World War II (WWII), and later created the first computerized database of oil well locations in Texas [44]. In the 1930s, the US government began using fixed wing aerial photography to assist in the implementation of conservation programs under the Agricultural Adjustment Act of the New Deal [47]. After WWII, aerial photography was used extensively to monitor compliance with agricultural incentive programs [47]. Today, much of this imagery is publicly available, and can provide much needed historical perspective to past grazingland and agricultural management decisions [5,48,49] that may not be captured in historical ground-based datasets [50]. Though historical images are mostly single-band, they do allow us to perform geospatial and geostatistical analyses through nearly 90 years of imagery [5,48].

The invention of laser technology in the late 1950s to the early 1960s eventually led to the development of the modern Light Detection and Ranging (LiDAR) platform [51,52]. Early LiDAR was used in bathymetric and topographic measurements [53], but soon was used in forestry [52,54,55], and later in the identification and management of grazinglands [56–59]. The ability to add LiDAR sensors to unmanned aerial systems (UAS), has greatly expanded its applicability [60–62] by lowering the barrier to acquire high resolution data over smaller parcels.

The use of UAS have increased substantially in recent years across many industries, including research, construction, law enforcement/rescue, real estate, cinematography, and personal use to name a few [63]. Subsequently, UASs have become a commonly used tool for solving geospatial problems in grazingland science and management [64].

Tasks tackled with UAS range from basic such as animal inventory, checking of fences and water troughs [65], to complex measures such as aboveground biomass, NDVI and other spectral indices, land cover classification, plant identification, and digital surface models [26,27,65–67].

Spatial data collected from UASs have high spatial resolution [66]. Digital surface models and orthomosaics with 1 cm resolution can be obtained with a consumer-grade UAS when combined with state of the art 3-D processing software that discerns structure from motion [66–68]. UAS applications can be used to supplement field-based measurements to reduce overall time spent in the field, allowing grazingland managers and scientists to gather information more efficiently and with less subjectivity [60,68,69]. Once considered impossible [4], plant heights and biomass may now be attainted through remote sensing with the use of UASs when combined with on-the-ground measurements [66,70]. UAS data are advantageous for determining stocking rates and grazing utilization in hard-to-reach locations [71], defining areas of woody plant encroachment [69], managing wildlife habitat [72], and documenting anthropogenic effects on natural areas [73].

UAS systems are not without their limitations. In the US, several agencies stipulate when and where one can operate UASs. Federal and state agencies have regulations aimed at creating a safe environment for both manned and unmanned aircraft. Flight paths are restricted to line of sight of the operator and visual observers, and payload cannot exceed 25 kg (55 lbs.) for the total weight [65]. Deployment times are usually less than one hour due to the power supply needed to maintain flight [74]. Furthermore, the most capable and diverse devices are cost prohibitive to purchase and maintain, putting them out of reach for most managers [65]. A final limitation of UASs is a relatively small spatial footprint, sacrificing large spatial extent for high spatial resolution. However, as technology expands, flight times will increase, airspace monitoring will improve, and a safer flying environment will allow for increased data collection in the field. The cost of sensor technology is also decreasing, making them more affordable for research and operational purposes on grazinglands.

4. Field Data Integration

These technologies provide the opportunity of automation and almost real-time remote access to data and information. However, most still require field-based ground truthing and local knowledge (sourced from those that live and work the land) to complete the puzzle [18,38,75,76]. For example, the Quick Carbon project builds interpolated datasets of soil carbon at the property level by using 3-D printed spectrometers, remotely sensed satellite data, and spatially referenced soils data [75,77,78]. Likewise, models of plant aboveground biomass are based upon field collected data which are calibrated to remote sensing methods [14,18,66,79–81]. UAS use necessitates ground control points and ground truth data. Ground-based LiDAR has been field-validated to estimate woody plant biomass on grazinglands [82,83], and may even be useful for estimating browse important in stocking rate estimates [84].

In spite of that, not all ground truth data are created equal. Special provisions for calibrating remotely sensed data products to biophysical landscape parameters can ensure research efforts are more successful. Thus, it would be wise to consider how the scale and resolution of field-based and/or satellite measurements might correlate to the scale and resolution of UAS imagery, considering the latter may be sub-centimeter [60,70]. For example, GNSS-enabled collars have been used to track and monitor livestock behavior in grazinglands for some time [30,31,33,85–88]. Distinguishing resting and foraging behaviors [30,89–92], distance traveled to/from water [33,93], seeking out high quality forage [31,90], terrain/topographical preferences/avoidance [32,93], response to disturbance and environmental stressors [94–96], birth detection [97], and circadian rhythms [98] have all been studied through GNSS tracking collars and accelerometers.

5. New Management Applications

In this Special Issue of *Remote Sensing*, we spotlight researchers who are applying remote sensing geospatial technologies and/or spatial data science in novel ways in the management of livestock and grazinglands. The first article by Barwick et al. [91] examines the application of a moving window behavior state classification method using time segments of varying length on accelerometers mounted to collars, ears, and legs on Merino ewes. These authors differentiate between grazing, standing, walking, and lying with up to 10-s moving window durations. Pearson et al. [97] outfitted cattle with GNSS collars and intravaginal devices to test the ability to detect birthing events, and potential behavioral changes due to birthing. They found that birth detection in these systems were lacking, most likely due to the length of time the devices must remain implanted. Alerts that were successful demonstrated that cattle are quite active leading up to and after birthing, indicating a need for better real-time alert systems than communication using the Iridium satellites followed by GSM and email alerts.

DiMaggio et al. [66] conducted a pilot study to assess forage biomass using UAVs on a south Texas semi-arid rangeland. By combining field collected data with UAV-derived surface models, they estimate forage biomass at varying altitudes. Kimura and Moriyama [99] developed a satellite-based aridity index (SbAI) using MODIS imagery and weather data to estimate water use and growth/expansion of grassland areas in China and Mongolia, providing a potential new tool to monitor the effects of climate change and desertification.

Giralt-Rueda and Santamaria [100] observed grazing effects related to ecosystem resilience from wild and domesticated ungulates using NDVI-based phenology and rainfall accumulation in a Mediterranean ecosystem. They report that current pressure by herbivores lowers ecosystem resilience in the face of potential climatic changes. Likewise, Richardson et al. [101] matched field observations with ground-based, time-lapse phenological cameras (phenocams) and Landsat NDVI data to determine the phenological timing of vegetation in dry, mesic, and wet riparian meadows in the Central Great Basin. They reported strong correlations between NDVI, field measurements, and green chromatic coordinates from ground based phenocams based upon yearly precipitation and vegetation type.

Poděbradská et al. [102] developed the expected ecosystem performance (EEP) model which is based upon climate, growth potential and variability, and greenness. By combining MODIS NDVI data and the USDA soil survey geographic (SSURGO) database, they were able to correlate the model to ground-truthed biomass data. Pearson et al. [103] coupled remotely sensed vegetation indices with electronic identification of cattle via automatic weighing stations at watering points to show that cattle live weights, and live weight change can be modeled from a combination of vegetation indices, Julian day, and rainfall data. Finally, Irisarri et al. [104] present a novel way to estimate crude protein content of forages using the MODIS platform. What distinguishes this work from previous attempts is that they focus mostly on the red and green portions of the electromagnetic spectrum, rather than relying solely upon NDVI. This information could be useful in determining feeding ration needs or prompt producers to sell cattle earlier to avoid additional feed costs.

6. Future Directions

Remote sensing technologies have been a crucial tool in understanding and further developing grassland management systems. However, there is still ground left to cover. Approximately one-third of the earth's land mass is covered in grasslands, making up 70% of all agricultural areas [105–107], with grazing animals producing as much as one-third of the global human protein supply [108,109]. Much of the published literature regarding grasslands and remote sensing come from North America, China, and Australia. Comparatively, literature for much of Africa and South America, two continents with large grassland regions [107], is limited. Also, current research tends to focus on climate change and production, compared to research conducted on management [107], when they may not be mutually exclusive.

As climate change and desertification continues to be an ever-pressing concern, geospatial analyses focusing on their extent and effects upon grassland management will become increasingly important [13,110,111]. Research from the US has shown the potential for increased grazingland production in the northern Great Plains from increasing temperatures due to climate change, while the southwestern US will most likely face severe reductions in biomass production [112,113]. Research from west Asia and north Africa indicate potential reductions of desirable species and an increase in less palatable species [114]. Moreover, a global analysis of desertification shows that it is being magnified in central North America, eastern Asia, the Pacific Rim, and central Australia [115]. As global food demands continue to rise over the next 50–100 years [116–118], remote sensing-based models will be critical to managing grazinglands, and to define, identify, and prioritize areas for rehabilitation to provide the critical ecosystem services of food and fiber production. An additional benefit of remote sensing technologies is that private and restricted-access lands can be included in regional and global surveys without need for physical access. Having accurate and timely data and models to inform land management decisions is vital to proper grazingland management [13].

As geospatial sciences and technologies continue to evolve, there has been much progress over the past 10 years in the development of free and open-source software for viewing and analyzing geospatial data. The market for geographical information systems (GIS) and remote sensing software was once completely dominated by a few expensive proprietary packages, but has given way to numerous freely available products and services such as QGIS (https://qgis.org/ accessed on 5 January 2022), GRASS (https://grass.osgeo.org/ accessed on 5 January 2022), the R (https://www.r-project.org/ accessed on 5 January 2022) and Python (https://www.python.org/ accessed on 5 January 2022) programming languages, Google Earth (https://www.google.com/earth/ accessed on 5 January 2022), and Google Earth Engine (https://earthengine.google.com/ accessed on 5 January 2022) [119,120] just to name a few. Many of these alternatives have steep learning curves, but by making geospatial sciences and technologies available to a wider audience, scientists and managers now have access to affordable tools to conduct research, process data, perform decision support analyses, and collaborate globally in ways that were once unimaginable.

Advances in cloud storage and computing will be a major asset as geospatial data continues to grow in both resolution and file size. Geospatial and big data integration will be critical to the development of state-of-the-art decision support tools [24,121]. Development of crowd-sourced apps, such as LandPKS [22,23,122] and iNaturalist [123], provides citizen scientists a way to collaborate and provide geotagged field data to inform soil, water, grazing, and wildlife management research and objectives.

7. Conclusions

Geospatial technologies have become indispensable tools in the science and art of grazingland management. Many of these same technologies even permeate everyday life (e.g., in smartphones, public utilities, construction/infrastructure, precision farming, and automobiles). Spatially searchable databases of the research literature may provide in the future a readily available way to locate site- or ecosystem-specific studies and management implications [124]. Partnerships between scientists and grazingland managers will be paramount in the future due to the costs associated with implementation and determining the applicability of the newest cutting-edge technology, as well as the accompanying cloud storage necessary to store and process large datasets. As the technology gets more and more complex, multidisciplinary collaborations with engineering and computer science disciplines may become more common place. The questions we ask, and the solutions we find, will only be limited by our ability to embrace new and exciting ways to tackle research and management problems.

Author Contributions: Conceptualization, M.C.R., H.L.P.-B., L.A.G. and E.C.R.; writing—original draft preparation, E.C.R., H.L.P.-B.; writing—review and editing, E.C.R., H.L.P.-B., M.C.R. and L.A.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: The authors wish to thank *Remote Sensing* for hosting this special issue on *Applications of Remote Sensing for Livestock and Grazing Land Management*, for those that submitted papers to this issue, and to all the anonymous reviewers for their thoughtful insights and comments. We thank Daniel G. Scognamillo and Evan P. Tanner for their comments and suggestions and the editors and anonymous reviewers who helped improve this manuscript. This is manuscript number 22-112 from the Caesar Kleberg Wildlife Research Institute at Texas A&M University-Kingsville.

Conflicts of Interest: The authors declare no conflict of interest.

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