

Review

Proximal Sensing in Grasslands and Pastures

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Abstract: Reliable measures of biomass, species composition, nitrogen status, and nutritive value provide important indicators of the status of pastures and rangelands, allowing managers to make informed decisions. Traditional methods of sample collection necessitate significant investments in time and labor. Proximal sensing technologies have the potential to collect more data with a smaller investment in time and labor. However, methods and protocols for conducting pasture assessments with proximal sensors are still in development, equipment and software vary considerably, and the accuracy and utility of these assessments differ between methods and sites. This review summarizes the methods currently being developed to assess pastures and rangelands worldwide and discusses these emerging technologies in the context of diffusion of innovation theory.

Keywords: proximal; sensing; LiDAR; photogrammetry; grasslands; pastures

1. Introduction

Grasslands cover an estimated 40% of the Earth's surface [1], performing vital ecosystem services such as cycling nutrients, carbon, and water, and providing habitat for wildlife and pasture for livestock [2]. However, grasslands are declining globally in extent, due to land-use changes such as development, conversion to cropland, or abandonment [1,3] or degrading due to climate change [4]. Assessing the health of a grassland necessitates the collection of reliable data on its productivity, plant species composition, and potentially its nutritive value [5]. Traditional techniques for collecting these data are time and labor-intensive, requiring field visits, specialized equipment, and teams with expert knowledge of local ecosystems. Advances in sensor technologies may reduce the time or labor required to conduct such measurements. While recent applications of remote sensing technologies in grasslands and pastures have been discussed in detail in prior research [6], proximal sensing technologies such as handheld sensors or sensors mounted on unmanned aerial vehicles (UAVs) flown at low altitude have received less attention.

Innovation diffusion is the study of how novel and potentially useful technologies spread throughout a social system [7]. Innovation diffusion theories emerged out of studies of the dissemination of novel agricultural practices and technologies [8]. As such, they may be superior frameworks by which to evaluate the spread of innovative proximal sensing technologies for measuring or predicting indicators of pasture or rangeland health and function.

To diffuse successfully, an innovation must have five attributes demonstrating its advantage over previous systems: relative advantage, definable as the perceived superiority of the innovation over other methods; compatibility with the technological, cultural, social, and economic systems into which it must be integrated; a complexity not exceeding that of necessity; trialability, which is a term for the ease by which the innovation may be tested without major commitment; and observability of the superior outcomes of the innovation [7].

In this paper, we assess the current state of proximal sensing technologies as they relate to measuring plant height and biomass, species composition, and nutritive value of pastures and rangelands and assess the advantages and obstacles to their adoption within the framework of theories on the diffusion of innovations.



Citation: Ghajar, S.; Tracy, B.

Proximal Sensing in Grasslands and Pastures. *Agriculture* **2021**, *11*, 740.

<https://doi.org/10.3390/agriculture11080740>

Academic Editor: Matt J. Bell

Received: 7 July 2021

Accepted: 31 July 2021

Published: 4 August 2021

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2. Measuring Plant Height and Predicting Aboveground Biomass

Measurements of sward height and biomass can provide data on the structure and health of a grassland. Sward height measurements can indicate the vigor, habitat value, or maturity of a grassland. Similarly, aboveground biomass is an indicator of grassland or rangeland health and, when monitored long-term, can indicate whether a grassland is gaining, losing, or maintaining its capacity to provide valuable ecosystem services such as forage production or preservation of water quality [9]. Data on aboveground biomass allow managers to determine appropriate levels of forage utilization to meet economic goals while maintaining ecosystem services [10].

Traditional methods of measuring aboveground biomass rely on destructive harvest of forage from small areas delineated by a quadrat or frame [11]. The harvested biomass then must be dried in a dedicated oven before dry matter can be determined. This process is labor-intensive, and the ovens needed for drying samples can be a significant investment. On extensive rangelands, an additional limitation of this method is that samples are often collected along a small transect that must represent areas of hundreds or thousands of hectares in size due to limitations on time and labor available to technicians or scientists. As such, improper site selection can mean that the calculated aboveground biomass is not representative of the area, and management decisions based on the results may not have the desired effect [12].

2.1. Traditional Alternatives to Destructive Harvest

A number of alternatives to hand-harvesting forage samples have been developed to shorten the time required to assess biomass in a pasture. Plate meters are used for quick, non-destructive estimations of pasture biomass by measuring the height of a sward under compression by a plate on a measuring stick or pole. Plate meters are calibrated by taking measurements in a pasture typical of the area in which they are to be used, harvesting biomass on the site of each measurement, and comparing plate height to biomass with a regression model to develop a predictive equation [13]. Plate meters vary in accuracy depending on site and season, as morphology and stage of growth influence a tiller's resistance to compression [14]. Plate meters cannot be used if pasture species have robust reproductive tillers or stems that hold the plate above the sward canopy, as this will lead to inaccurate biomass predictions when plates are calibrated on vegetative swards [13]. Additionally, while the shortened sampling time compared to hand harvesting may allow for more sites to be sampled, the number of samples and area that can be sampled is still smaller than what can be accomplished with UAVs [15].

Robel poles are another non-destructive method of estimating pasture or rangeland biomass [16]. A Robel pole is a rod marked with contrasting colors at set intervals that is placed vertically in a sward. Personnel then stand at a set distance from the pole and record the height at which the sward obscures its markings. This is performed from four directions (often the cardinal directions) per placement, and the process is repeated until the necessary sample size has been collected. Robel poles avoid many of the issues intrinsic to plate meters by providing an indication of vegetative height and density without the need for compressing tillers. However, they face many of the same logistical limitations: a significant commitment of personnel and time to measure relatively small areas of often large ecosystems.

2.2. Use of Proximal Sensors to Measure Plant Height and Predict Biomass

Methods for assessing pasture height and biomass using proximal sensors vary. However, the principle for most methods is similar to that of plate meters in that pasture height measurements are initially compared to hand-harvested biomass to calibrate a predictive equation [15]. Photographs, LiDAR, and ultrasonic measurements are the most common methods used in proximal sensing pasture assessments [17,18].

Photographic determinations of pasture height may be carried out with a simple red-green-blue (RGB) camera mounted onto a UAV or other vehicle [19] or held on a

pole [20]. Ground control points (GCPs) are high-visibility objects used to provide a frame of reference for determining the position of the UAV in the pasture being photographed and are georeferenced using GPS after they are placed in the pasture [21]. The UAV is flown over the pasture, taking pictures rapidly at low altitude. The pictures are then loaded into a Structure from Motion (SfM) photogrammetry program which uses the GCP to reconstruct the path of the UAV and generate a point cloud, from which a digital surface model (DSM) and digital elevation model (DEM) are derived (Figure 1). By subtracting the height of the DEM from the DSM, canopy height may be calculated for a given point [21]. As with plate meters, these height data are then combined with hand-harvested biomass to derive a regression model to predict pasture biomass as a function of UAV-measured height [22]. Once the model has been developed and tested, the UAV's height data may be used for determining biomass without the need for further hand-harvesting of biomass samples [21].

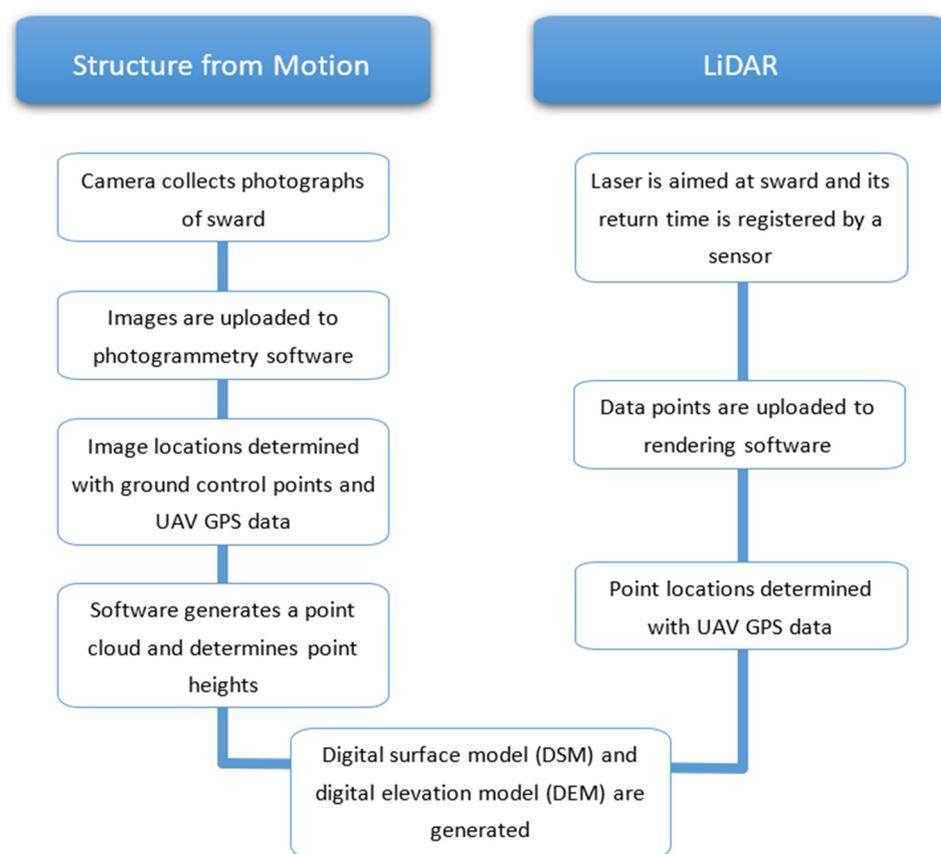


Figure 1. The processes by which pasture height data are generated using Structure for Motion photogrammetry and LiDAR in proximal sensing.

Light detection and ranging (LiDAR) generates point clouds much like SfM techniques but relies on a different mechanism to do so. With LiDAR, a laser aimed at the ground bounces back to a sensor, which records the time it took for the light to return, and from this interval calculates the distance from the LiDAR equipment [20].

When combined with the position of the UAV, LiDAR data can provide thousands of height measurements of a pasture or rangeland with a single flight [23]. Once the point cloud has been generated, a DSM is developed. The calibration of biomass prediction from height data is similar to the process used in SfM, with an initial comparison of LiDAR-generated height data with hand-harvested biomass samples [20].

Ultrasonic sensors operate similarly to LiDAR in that they emit a signal and calculate sward height based on the time it takes the signal to return to the sensor—the primary

difference between the two being that one sensor uses ultrasound, and the other, light [24]. Ultrasonic sensors are mounted to vehicles both to facilitate more speedy measures and because the height of the sensor relative to the ground needs to remain constant for the sensor to correctly calculate sward height [17]. Recent improvements in ultrasonic sensor technology allow the sensor to detect the distance of both the ground and the sward canopy, resulting in more accurate measurements of height, as well as predictions of biomass [25]. However, the improved sensors are not yet commercially available.

Height measurements generated by proximal sensors can also be combined with spectral reflectance measurements to more accurately estimate pasture biomass [26]. Spectral reflectance indices are a measurement of the reflectance of objects at specific wavelengths. In a pasture setting, spectral reflectance is influenced by a number of factors, including chlorophyll concentration in leaves, plant species in the pasture, the presence and proportion of senescent leaves, and the leaf area index (LAI) of the pasture, which is the ratio of leaf area per given unit of ground area [27]. Spectral reflectance indices have been used on their own to estimate biomass in pastures and rangelands, but the many factors influencing reflectance at different wavelengths lead to difficulties in standardizing approaches between sites. Additionally, as the LAI increases, the sensitivity of reflectance indices decreases as less light is reflected back from denser swards [17]. In practical terms, this means that the most productive pastures present the greatest difficulty in accurately estimating biomass using spectral reflectance indices.

However, when spectral reflectance is combined with LiDAR or ultrasonic measurements of pasture height in a linear model, predictions of pasture biomass can be more accurate than by using either technique alone (Table 1). LiDAR combined with the NDVI resulted in a 25% increase in prediction accuracy for green pasture biomass [27]. This is a result of the capacity of spectral reflectance to differentiate between green biomass and senescent material, while LiDAR measurements can detect only standing biomass regardless of stage of growth [26]. Similarly, combining ultrasonic height measurements with spectral measurements such as the normalized spectral vegetation index (NSVI) can result in higher accuracy for predicting biomass than using either technology alone [26].

Table 1. Studies using proximal sensing technologies to estimate pasture height or dry matter (DM) yield.

Author(s)	Year	Technology Used ¹	Variable	R ²	Pasture Type	Location
Frick and Wachendorf [26]	2013	Combination of ultrasonic and spectral sensors	DM	0.83 in mixed swards 0.88–0.90 for species-specific calibrations	Mixed grass and legume swards	Germany
Schaefer and Lamb [27]	2016	Combination of LiDAR and spectral sensors	Green DM	0.61	Tall fescue (<i>Schedonorus arundinacea</i>)	Australia
Cooper et al. [28]	2017	SfM, TLS	DM	SfM: 0.72 TLS: 0.57	Smooth brome (<i>Bromus inermis</i>)	South Dakota, USA
Wang et al. [23]	2017	LiDAR	DM	0.34	Semi-arid steppe	Inner Mongolia, China
Legg and Bradley [25]	2019	Ultrasonic sensor	DM	0.7–0.8	Unspecified	New Zealand
Grüner et al. [21]	2019	SfM	DM Height	0.64–0.75 0.59–0.81	Mixed grass and legume swards	Germany
Obanawa et al. [20]	2020	SfM from pole-mounted and UAV-mounted cameras; LiDAR	Height	0.94 for UAV SfM, 0.91 for handheld SfM, 0.93 for LiDAR	Annual ryegrass (<i>Lolium multiflorum</i>)	Japan

¹ Abbreviations: LiDAR: light detection and ranging; SfM: structure from motion photogrammetry; TLS: terrestrial laser scanning; UAV: unmanned aerial vehicle.

Structure from Motion, LiDAR, and ultrasonic sensor technologies generate useful predictions of forage height and biomass using current techniques. However, each has unique advantages and disadvantages. The primary advantage of LiDAR is its accuracy. Obanawa and colleagues reported a margin of error for measured pasture height of 12 ± 10 mm for LiDAR compared to 24 ± 13 mm for SfM [20]. Additionally, ultrasonic sensors usually assume a fixed distance to the ground due to being mounted on a vehicle, yet terrain and bumpy driving may interfere with the validity of that assumption [17]. However, LiDAR

equipment can be prohibitively expensive compared to the equipment needed for ultrasonic measurements or SfM. Another consideration is weather—SfM may be confounded by days with highly variable light conditions, whereas LiDAR and ultrasonic technologies are more robust to such situations. In summary, SfM and ultrasonic approaches may be more accessible for many people due to the simplicity and cost of equipment, but for height and yield estimations, LiDAR can be more accurate.

3. Grassland Species Composition

Determining the composition of plant communities in pastures and rangelands is critical to assessing the ecological health of a landscape and making informed management decisions. A census of plant species composition can identify species of economic value, conservation concern, or undesirable species which may need suppression. Regular monitoring of plant species composition can provide data on shifts in plant communities resulting from past management, biotic and abiotic stressors, or disturbances such as fire or drought [5]. Most surveys of plant species composition in pastures or rangeland require the same dedication of time and labor as the assessments of biomass discussed above and also face the same limitations in sampling area and representativeness of sites selected for survey. However, measuring plant species composition also requires personnel with proficiency in plant identification and familiarity with species local to sampling sites. The seasonality of plant growth may also limit preferable survey seasons to certain times of the year. Consequently, time and personnel availability remain substantial constraints to the number and scope of surveys that can be conducted on any particular landscape. Developing more efficient survey methods could increase the scope and frequency of monitoring programs.

Surveys of species composition using UAVs rely on the collection of high-resolution imagery for plant identification, followed by data processing and analysis. High-resolution imagery can be collected with a variety of cameras mounted to UAVs, including unmodified commercially available RGB cameras, or cameras specifically designed or modified to capture light outside the visible range, such as NIR [29]. After images have been collected, they may be evaluated to determine if blurring, overexposure, or other issues that preclude reliable analysis are present. Remaining images are then processed with software, which uses the timestamp and GPS data associated with each photo to create an orthomosaic—a single image stitched together from the many collected by the drone [30]. The orthomosaic may require additional processing prior to final analyses depending on the site, equipment, software, and species being surveyed. Methods of analysis can then include visual tagging of species by human operators or using mapping or image processing software to identify objects or areas based on patterns of pixels in the orthomosaic [31].

Past research using UAVs to identify plants at the species level have largely focused on a single highly visible species, such as tree species [32,33], weeds in monocropped farming systems [34], woody invasive species [35], species with conspicuous blooms [36], or species in arid landscapes with unique morphology [37]. These studies consistently found that analyses of UAV-derived high-resolution imagery compared favorably with traditional sampling methods when assessing the abundance and distribution of a target species.

We found only one study using UAV-derived high-resolution imagery to classify multiple species simultaneously in a grassland setting. Lu and He used blue, green, and NIR spectrum imagery processed with machine learning software to assess the abundance and distribution of six species in a temperate grassland, including forbs and grasses [29]. The simultaneous assessment necessitated training the image analysis program to recognize the species. This was achieved by identifying species in the field and photographing them with the equipment to be used in the UAV surveys in order to generate differentiable reflectance values for spectral analysis. This approach averaged 85% accuracy when compared with on-ground assessments; however, the authors noted that the method failed to detect plants below the sward canopy, whether from lodging or early growth stage. Additionally, due to differences in spectral reflectance species had at different stages of

their life cycles, it was necessary for the authors to sample some species multiple times during the growing season to retrain the software.

Though comprehensive species inventories remain beyond the capabilities of proximal sensing technology at present, UAV-derived high-resolution imagery has been used to map cover classes in a variety of environments: desert ecosystems in West Asia [38], Western rangelands of North America [30,39–41], and grasslands in the Tibetan plateau [42]. The processes are similar to those outlined above for species identification but with lower-resolution imagery and training personnel or programs to recognize vegetation types rather than species based on pixel patterns [30].

Thus far, plant identification and mapping using proximal sensing technology is incapable of replacing field work for comprehensive inventories of species on most landscapes. Even when multiple species may be identified using sensor imagery, species lower in the sward canopy may go undetected, and a field crew proficient in plant identification is necessary for helping train image processing software to recognize species of interest. Nevertheless, proximal sensing technologies have demonstrated their utility in expanding the scope and frequency of monitoring programs in many contexts, as well as their usefulness in collecting data about large shifts across landscapes. As such, they can readily augment, rather than replace, traditional methods of conducting plant surveys for scientists and land managers.

4. Nutritional Status and Nutritive Value

The process for estimating the nutritional status of plants—e.g., what concentrations of nitrogen or phosphorus they may have—is functionally identical to the process for estimating nutritive value of the sward for grazing animals. For both, a proximal sensor collects images of the site across a range of spectra, while a field crew collects samples of pasture from geotagged sites in the field. The samples are chemically analyzed for the variables of interest, and then these values are compared to spectral data by means of linear regression and/or machine learning to find the spectrum and equation that best explain variance in the variable of interest [43].

Results using this technique vary, with high reported coefficients of determination for some monospecific stands of forage [40] and more variable predictive capability in heterogeneous swards [44] (Table 2). Approaches combining spectral data with other environmental variables reported higher prediction accuracy than those relying on spectral data alone, both in homogenous and heterogenous swards. A study of nutritive value of alfalfa (*Medicago sativa*) in the United States reported 9–17% higher prediction accuracy when combining spectral data and growing degree units than when models were based on spectral data alone [45]. Another study on mixed temperate grasslands in Germany reported a 21% increase in prediction accuracy for crude protein (CP) and 91% increase for prediction accuracy of acid detergent fiber (ADF) when ultrasonic sward height measurements were included in calibration models than with spectral data alone [46]. Similarly, a study on perennial ryegrass (*Lolium perenne*) and white clover (*Trifolium repens*) swards in New Zealand reported 21% greater prediction accuracy for CP and 28% greater prediction accuracy for metabolizable energy (ME) when spectral data were combined with selected topographic and edaphic variables in models [47].

Table 2. Studies using proximal sensing technologies to assess forage nutrient concentrations in pastures or rangelands.

Author(s)	Year	Technology Used	Variables ¹	R ²	Pasture Type	Location
Safari et al. [46]	2016	Handheld spectroradiometer and ultrasonic sensor	CP	0.64–0.85	Mixed temperate grasslands	Germany
			ADF	0.63–0.75		
Noland et al. [45]	2018	Near-infrared sensor	CP	0.87	Alfalfa (<i>Medicago sativa</i>) pasture	Minnesota, USA
			NDF	0.76		
Serrano et al. [48]	2018	Near-infrared sensor and optical sensor	CP	0.69	Dryland Mediterranean pastures	Portugal
			NDF	0.78		
Pullanagari et al. [47]	2018	Hyperspectral sensors and topographic data	CP	0.83	Perennial ryegrass (<i>Lolium perenne</i>) and white clover (<i>Trifolium repens</i>) sward	New Zealand
			NDF	0.76		
Wijesingha et al. [44]	2020	Hyperspectral sensors	CP	0.42	Mixed temperate grasslands	Germany
			ADF	0.34		
Michez et al. [43]	2020	Optical and multispectral sensors	CP	0.54	Timothy (<i>Phleum pratense</i>) pasture	Belgium
			ADF	0.82		
			NDF	0.84		
Duranovich et al. [49]	2020	Hyperspectral sensors	CP	0.78	Perennial ryegrass and white clover sward	New Zealand
			ADF	0.55		
			NDF	0.54		
			ME	0.67		

¹ Abbreviations: CP: crude protein. ADF: acid detergent fiber. NDF: neutral detergent fiber. ME: metabolizable energy.

5. Innovation Diffusion and Proximal Sensing Technologies

Returning to innovation diffusion theory, an innovation must have five characteristics if it is to be widely adopted throughout a system: relative advantage over past methods; compatibility with needs and values of potential adopters, as well as extant social, technological, and economic systems; complexity not exceeding that of necessity; trialability, or capacity to be tested before committing to the innovation; and observability of the superior outcomes of the innovation [7].

5.1. Relative Advantage

Proximal sensing technologies have the capacity to generate vastly more data than traditional methods of pasture and rangeland assessment. Additionally, proximal sensors mounted on UAVs can travel farther, faster than most fieldwork teams. For certain aspects of assessing pasture or rangeland health, such as measuring height and productivity, proximal sensing technology has a high degree of accuracy and clear relative advantage over repeatedly hand-harvesting pasture. In other areas, however, such as comprehensive assessments of pasture species, or measuring the nutritive value or nutrient status of a sward, proximal sensing technology can augment but not replace traditional methods of data collection at present.

5.2. Compatibility

Compatibility refers to the extent to which an innovation aligns with the needs, values, and past experiences of potential adopters, as well as the extent to which it can be integrated into extant social, economic, and technological systems [7]. Scientists and natural resources professionals both need and value enhanced capacity for data collection [50]. Similarly, farmers and ranchers face a trend of increasing intensification in agricultural production, with an increased focus on data collection and precision agriculture [51]; however, in some countries, the median age of agricultural producers is over 60 years [52], and age has been shown to have an inverse relationship with willingness to adopt technological innovations in some agricultural communities [53,54].

While proximal sensing technologies are in the process of emerging from and being further integrated into extant economic and technological systems, prior research on analogous precision agriculture innovations demonstrates that a threshold of adoption may need to be reached before industry-scale informational and technological support for potential adopters is available [55]. At present, there are few studies on the rates of adoption of proximal sensing technologies or related technologies such as UAVs by agricultural producers, and extant studies focus primarily on row crop production rather than pasture [56]. As such, it seems unlikely that the threshold of adoption of proximal sensing technologies is high enough for farmers and ranchers to expect consistent commercial support for proximal sensing technologies they may wish to integrate into their farms.

5.3. Complexity

The complexity of various proximal sensing technologies is likely to be a barrier to adoption for many land managers such as farmers or conservation professionals. Traditional methods of assessing sward height and biomass, species composition, or nutritive value are labor-intensive, yet straightforward. Individuals can be trained in height and biomass data collection and nutritive sample harvesting in short order, and many manuals, tutorials, and courses on taking these measurements are available [57]. However, assessing plant species composition requires knowledge of plant identification or the use of botanical keys despite the simplicity of the processes often used. In contrast, proximal sensing technologies are novel as well as diverse in their equipment, methods, and results. Consequently, potential adopters must first familiarize themselves with the array of options available, learn to use the sensor technology they deem most suitable for their purposes, and then process the data generated by sensors. Alternately, potential adopters may be able to outsource the data processing stage if the service is offered by organizations or

companies to which they have access; just such an approach is being tested for remote pasture sensing technology in an American dairy cooperative [58].

5.4. Trialability

In general, the barriers to adoption resulting from the complexity of proximal sensing technologies present similar issues in terms of trialability. For example, if opting to use UAV-mounted proximal sensors, operators must learn to pilot a drone and, depending on local laws, may need certification or licensing to do so [59]. Data processing requires computers with robust processors, as well as software capable of processing raw sensor data [11]. However, some proximal sensing technologies are becoming more accessible and require less expertise to use. Some smartphone apps have emerged for the use of SfM for making 3D maps of objects and scenes. Similarly, a smartphone and tablet were recently released with built-in LiDAR capable of generating point clouds from handheld scanning [60].

Cost is another potential obstacle to the trialability of proximal sensing technologies. Many proximal sensors represent a significant financial investment for land managers such as farmers or conservation professionals, beyond what may constitute an acceptable loss if the technology fails to meet their needs. Again, the emerging LiDAR-equipped tablets and cell phones mentioned above may mitigate cost as an obstacle to adoption, to some extent; the smartphone and tablet are a fraction of the cost of most other proximal sensors and may be used simply by walking through a field or pasture. However, the point clouds generated still require postprocessing for accurate determinations of pasture height. While this may be done with open-source software, it still requires an investment of time to learn the program and process the point cloud.

5.5. Observability

Observability, in Rogers' theory, relates both to the visibility of positive outcomes of an innovation as well as to the visibility of the innovation itself when used by adopters [3]. In terms of observable outcomes, for scientists or natural resources professionals, the volume of data generated by proximal sensing technologies is an observable advantage [46]. For land managers such as farmers, observable advantages of proximal sensing technologies may be more in the spheres of economic or ecological outcomes resulting from the data generated. Prior research demonstrates that innovations that augment the capacity of agricultural producers to make decisions benefiting their economic and ecological goals are more likely to be adopted [56].

6. Conclusions

Proximal sensing technologies are becoming more accessible and useful over time, and their increasing adoption for augmenting data collection programs for pasture and rangeland research appears assured. However, many barriers to the widespread adoption of these technologies by farmers remain: they are often complex to deploy in the field and require postprocessing of data; many proximal sensing systems are expensive, reducing their trialability by producers; and the technologies may require more widespread adoption before sufficient informational and technological support is available. At present, proximal sensors cannot replace traditional fieldwork and on-site monitoring programs, but they can greatly enhance the amount of data collected as well as the scope of data collection possible [11]. We conclude that their adoption will increase as the technology matures and barriers to adoption such as cost and complexity decrease. Additional research quantifying the use of these technologies by agricultural producers is needed, as is qualitative research on perceptions of proximal sensing technologies and barriers to their adoption.

Author Contributions: Conceptualization, B.T.; literature review and writing—original draft preparation, S.G. Both authors have read and agreed to the published version of the manuscript.

Funding: This work is supported by the Cyber-Physical Systems (CPS) (Joint NSF) Competitive Grants Program grant no. 2018-67007-28380 from the USDA National Institute of Food and Agriculture.

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

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