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PRODUCTION AND MANAGEMENT: *Technical Note*

Deployment of a LoRa-WAN near-real-time precision ranching system on extensive desert rangelands: What we have learned*

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ABSTRACT

Objective: Precision livestock farming technologies show great promise for the management of extensive, arid rangelands, but more practical knowledge is needed to allow ranchers to determine potential applications and limitations for adoption. We tested a long-range wide area network (LoRa-WAN) precision livestock system over 3 mo (April–June 2020) in a ranch in southwest New Mexico, USA. The system monitors cattle position and movements, precipitation, and water trough water levels at pasture and ranch scales, in real time.

Materials and Methods: Here we describe the components of the system and share what we have learned from our preliminary experiences. This system included a solar-power LoRa-WAN receiving station with the corresponding gateway, radio frequency antenna (824–894 MHz), and Wi-Fi bridge for data transmission into the Internet. The testbed network for testing LoRa-WAN sensors included 43 GPS-trackers deployed on lactating beef cows and 2 environmental sensors used to monitor precipitation regimens and trough water levels, respectively.

Results and Discussion: The system collected data consistently for the trough levels and precipitation, whereas data from the cow GPS-trackers was highly heterogeneous. On average, 46 ± 4% of daily data packets logged by GPS-trackers were successfully transmitted through the LoRa-WAN system, exceeding 80% of successful transmission in several cases. This report documents the necessary infrastructure, performance, and maintenance of system components, which could be of significant information value to ranchers and researchers with a desire to deploy similar monitoring systems.

Implications and Applications: This Technical Note documents the implemetation of a LoRa-WAN monitoring system at the ranch scale for a 3-mo period. The system has allowed the ranch manager and assisting staff to efficiently manage cattle inventories and promptly address animal welfare concerns. However, further research is required to assess the scalability of this system across commercial operating cattle ranches in the Southwest United States, thereby unlocking its potential for broader adoption and effect.

Key words: precision livestock farming, precision grazing management, digital agriculture, beef cattle, GPS tracking, rain gauge sensor, water level sensor

INTRODUCTION

Precision livestock farming (**PLF**) is an emerging animal agriculture system that incorporates sensors and data analytics to inform day-to-day management decisions (Tedeschi et al., 2021). An important element of PLF is real-time monitoring of animal behaviors that enables farmers to proactively address nutrition, health, breeding, or parturition issues of individual animals. Such interven-

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tions are not possible with traditional management alone (Laca, 2009; Neethirajan, 2017). Although this technology has the potential to enhance livestock wellbeing, improve profitability, and increase opportunities for additional ecosystem services, to date, PLF systems for ranching are lacking (Elias et al., 2020; Makinde, 2020). There is a need for user-friendly PLF platforms suited to the management needs of western ranchers who raise livestock in areas with limited Internet or cellular connectivity and deficient power infrastructure (Laca, 2009; Bailey et al., 2018). Most commercial telemetry devices available today are designed for on-board storage of large volumes of animal data and are therefore not well suited for real-time surveillance and monitoring. Conversely, many devices are designed for, and their data communication routes are suited to, farm building complexes with network connections that can use communication media such as Wi-Fi (Neethirajan, 2017). Technological advancements in microprocessors that allow online data processing (Chelotti et al., 2020) and low power data transmission are now widely available (Iwasaki et al., 2019) and could support PLF systems on rangeland. Development and adoption of technology-assisted management platforms could yield a timely response to declining availability of ranch labor and increased consumer demand for traceable animal products that are both environment and livestock friendly (Morgan-Davies et al., 2018).

Long-range wide area networks (**LoRa-WAN**) are wireless low-power communication systems that can collect and transmit small data packets within a radius of up to 10 km (Ayaz et al., 2019; Georgiou et al., 2020). The LoRa-WAN system, commonly used to connect smart sensors in the Internet of Things (**IoT**), could serve as a possible low-cost solution to increasing network coverage across extensive rangeland systems (Holechek et al., 2020; Spiegal et al., 2020; Dos Reis et al., 2021). These networks exhibit far-reaching (presumed to extend to 10 km [~6.2 mi]) and stronger radio signal strength compared with other radio transmission systems (e.g., Wi-Fi and Bluetooth), can penetrate insulated objects such as buildings or dense vegetation, require minimum maintenance, and have a longer lifespan compared with alternative data transmission systems (Ayaz et al., 2019). The IoT typically consists of LoRa-WAN-enabled widgets or sensors or "things" connected to a LoRa-WAN network that collect multiple streams of data in real time, use AI-assisted analytics to process and visualize retrieved data, and can be controlled remotely via cloud-based applications and dashboards (Ayaz et al., 2019; Georgiou et al., 2020). The most common example of IoT applications consists of "smart" networks involving home appliances such as cameras, lighting fixtures, or thermostats that can be adjusted remotely using computer- or smartphone-assisted apps (Laplante et al., 2018; Ayaz et al., 2019).

We deployed a pilot LoRa-WAN network covering a ~5,000-ha (12,355-acre) area at the New Mexico State University Chihuahuan Desert Rangeland Research Center in southern New Mexico, USA. This case study tested the feasibility of installing and using a PLF system designed for extensive rangelands. Our objectives were to describe (a) what it takes to deploy a LoRa-WAN network in a typical western ranching operation and (b) the practical aspects of using the data acquisition network and the maintenance requirements and routines needed. Additionally, we sought to identify future needs for development of PLF system data analytics, software and dashboard visualization, and their practical applications.

MATERIALS AND METHODS

Our PLF system (Figure 1) consisted of a single solar-powered Kerlink LoRa-WAN iStation, V1.5 4G, an outdoor US915 gateway (https://www.kerlink.com/) with an external SCAN 9dB1 Antenna (824–894 MHz, https://scan-antenna.com//), connected via Wi-Fi to a computer with broadband Internet. This base station acted as a bridge between widgets and the network and was able to continuously communicate with a complex of field and animal sensors. All animal handling procedures were approved by the New Mexico State University Animal Care and Use Committee (IACUC) protocol # 2019-008. Animal sensors included 43 LoRa-WAN-enabled Abeeway (https://www.abeeway.com/) Industrial Trackers equipped with GPS and triaxial accelerometer motion sensors mounted on livestock collars and fitted on rangeland-raised mature beef cows (either Rarámuri Criollo or Brangus). Cows were continuously monitored while grazing for approximately 3 mo on 4 extensive desert pastures previously used for a long-term comparison of stocking rate treatments (Thomas et al., 2015). Pastures were assigned a conservative (~35% vegetation use) stocking rate, and biotypes were stratified by pasture based on previous grazing treatments. Brangus cows (521.0 ± 10.5 kg [1,148.7 ± 23.2 lbs]) were assigned to pastures 4 (n = 4; 974 ha [2,406.8 acres]) and 1 (n = 11; 1,267 ha [3,130.8 acres]), whereas Rarámuri Criollo cows (350 ± 9 kg [772.3 ± 19.9 lbs]) were assigned to pastures 3 (n = 3; 1,219 ha [3,012.2 acres]) and 2 (n = 25; 932 ha [2,303.0 acres]). Field sensors tested included 2 LoRa-WAN-enabled DecentLab (https://www.decentlab.com/) sensors, one connected to a tipping bucket rain gauge and the other installed over a water trough in pasture 4. These stationary sensors, mounted approximately 2 km from the base station, monitored rainfall events and drinking water level in close-to-real time. Specifics regarding hardware and installation are detailed below.

In this system, small packets of data flow from sensors to the LoRa-WAN gateway and onto the network server via one or more backhaul systems (a wireless data transport bridge between the Internet and subnetworks) that may include Ethernet, Wi-Fi, and 3G or 4G cellular GSM (Global System for Mobile Communications). Given the remote location and limited communication coverage, our system used a Wi-Fi backhaul, although it had GSM backhaul capability as well. Data transmission from the network server

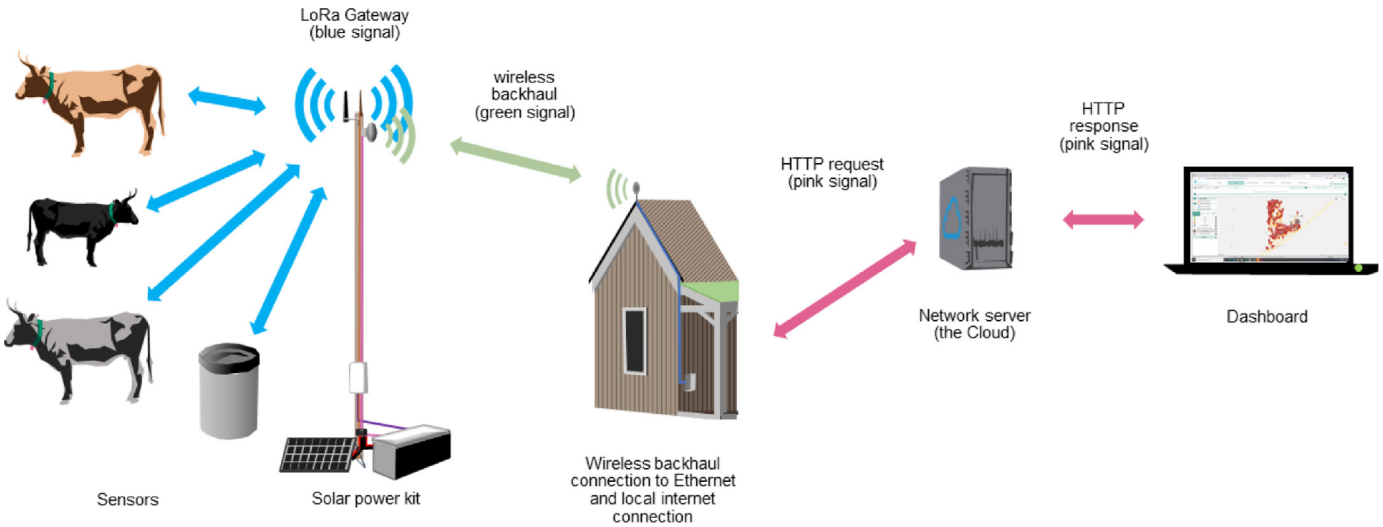

Figure 1. Dataflow between long-range wide area network (LoRa-WAN)-enabled sensors, network gateway and antenna (tower with solar-power kit), local Internet connection, network server, and dashboard. Collars on cows represent LoRa-WAN-enabled industrial tracking sensors used to monitor animal location in close-to-real time. The gray bucket represents a LoRa-WAN-enabled tipping-bucket rain gauge. The wireless backhaul connected to a modem and local Internet connection via Ethernet at the ranch house, where the client-made HTTP request was sent to the cloud, stored, computed, and returned to the near-real-time dashboard server. The solar panel kit powered the gateway and Wi-Fi backhaul at the centralized ranch location. The wireless backhaul transmitted LoRa data packets to and from the hardwired Internet connection at the ranch house. The applications dashboard is shown on a laptop computer with red points illustrating near-real-time cow location. Blue bi-directional arrows represent LoRa-WAN signal, whereas a green bi-directional line represents Wi-Fi backhaul, and a pink bi-directional line represents the transmission control and coupled Internet protocol (TCP/IP) secure sockets layer (SSL) secure transmission of sensor payloads.

to the cloud or application endpoint was achieved via a secure payload transmission control and coupled Internet protocol or secure sockets layer (Figure 1). Flow of data was bi-directional such that sensor configuration could be modified using the application server and transmitted via the cloud and network server back to the sensors to configure data acquisition frequency and precision.

The Nuts and Bolts of the PLF System

Power (Solar Panel). Due to the remote location of the gateway and lack of access to the power grid, a basic solar panel kit was used to power the gateway and antenna and Wi-Fi systems. A Renogy 100-W 12-V monocrystalline solar panel was ground mounted for easy seasonal sun-angle adjustment (Figure 2a). The solar panel was connected to a Renogy Voyager (20A negative-ground pulse width modulation waterproof solar charge controller with liquid crystal display [LCD] and light-emitting diode [LED] bar) via a Renogy 10 American wire gauge adapter and cable with female and male connectors (Figure 2a). The charge controller was mounted at the base of a ~6-m (20-foot) telephone pole. The charge controller was connected to a 12-V and 100 A hours Renogy Deep Cycle absorbent glass mat battery (usually implemented in RV, solar marine, and off-grid applications), using an adequate Renogy 10 American wire gauge copper wire cable (Figure 2a). Both the battery and power inverter were housed inside a locked weatherproof insulated storage box to protect against elements, rodents, and passersby.

Gateway, Antenna, and Backhaul. The Kerlink LoRa-WAN Wirenet Station—923 MHz outdoor gateway—and companion SCAN 9dB1 Antenna (824–894 MHz) were used as the sole method for collecting and transmitting data from several widgets. The presumed coverage for data collection is between 5 and 10 km (3–6 miles); therefore, the station was mounted in a central location with regard to the experimental site. The gateway and antenna were connected via a coaxial cable fixed to the same telephone pole used for the solar panel charging system and controller. The gateway was powered over Ethernet (**PoE**) using a surge protector that was connected to the solar inverter via a 110-V AC 3-prong type B plug (American standard NEMA 5–15; Figure 2b). The surge protector was housed inside the weatherproof box, alongside the solar battery and power inverter.

To transmit data from the LoRa-WAN gateway to the network server, a backhaul transmission system via Wi-Fi was used. Two antennas were installed that transmitted data via Wi-Fi from the LoRa-WAN gateway to the ranch headquarters. Once at the ranch headquarters, data were transmitted via local hardwired Internet connection. The transmission of data from the gateway to the ranch headquarters was achieved using a pair of Ubiquiti Wi-Fi backhaul extenders (model: Ubiquiti NanoBeam M2 High-Performance airMAX Bridge; https://dl.ubnt.com/qsg/NBE-M2-13/NBE-M2-13_EN.html). The Kerlink gateway used has the capability for data transmission using a cellular transfer system with suitable subscriber identification module (SIM card) for a 3G communication

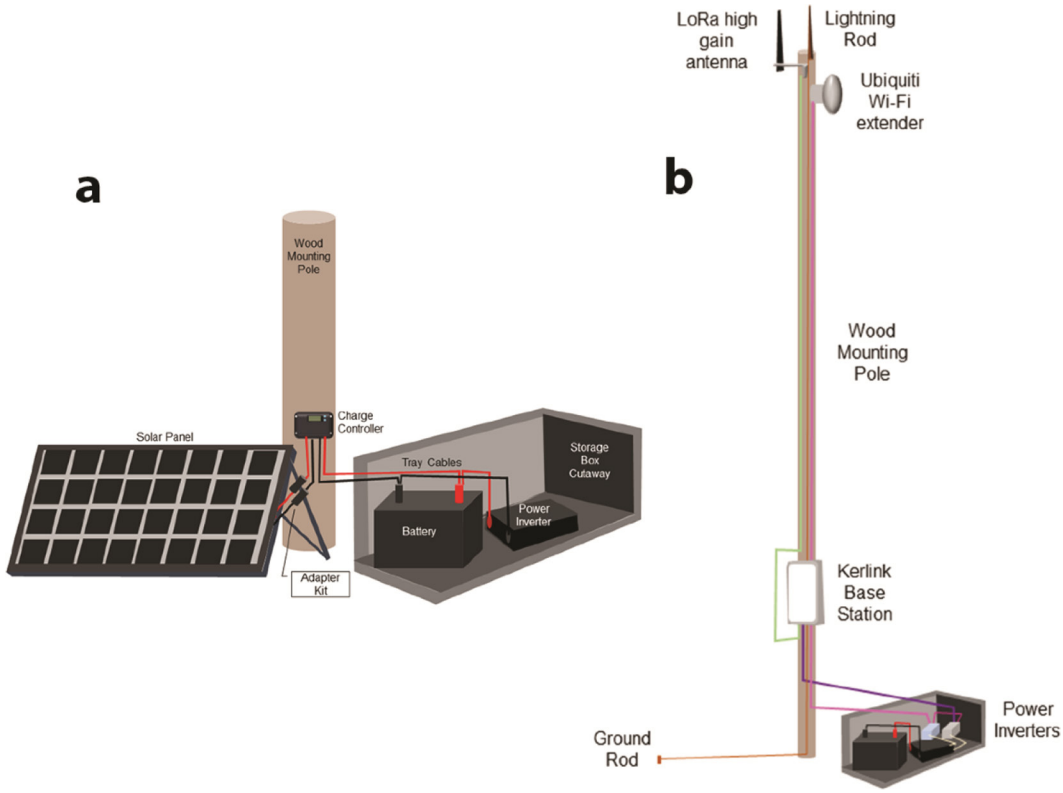

Figure 2. (a) Solar panel setup including cable connections between the solar panel and charge controller, and charge controller, battery, and power inverter. The solar panel was ground mounted, and the charge controller was pole mounted. The battery and power inverter were housed in a weather-tight storage box. Red lines indicate positive (+) leads, whereas black lines indicate negative (−) leads. (b) Installation of the long-range wide area network (LoRa-WAN) base station, antenna, wireless fidelity (Wi-Fi) backhaul, and grounding rod. The LoRa-WAN gateway (Kerlink) is connected to a high-gain antenna via lime-green coaxial cable. The Kerlink gateway is connected to its own power inverter (white box) via pink power-over-Ethernet (PoE) wire; yellow wire attaches an AC adapter to a solar-powered inverter. The Wi-Fi backhaul (Ubiquiti) is mounted atop a pole and connected to its own power inverter (light blue box) via purple PoE wire. The backhaul inverter is attached to an AC inverter via a yellow AC adapter to provide power supply. A copper lightning rod is denoted in orange and is mounted at the highest point on pole; copper wire runs to the grounding rod driven ~2.5 m (8 feet) into ground.

network, though newer models are equipped for 4G communication. However, Wi-Fi extender antennas were used in this application due to a limited availability of cellular communication in this remote area and to lower operation cost by avoiding cellular data plan subscription charges. At the gateway site, the Wi-Fi extender was mounted at the top of the telephone pole (described previously) used for mounting all other gateway and power supply components and pointing toward the ranch headquarters. The extender was also powered via PoE, using a power surge protector that was connected to the solar-power inverter via a 110-V AC 3-prong type B plug (American standard NEMA 5–15). The second Wi-Fi backhaul extender was mounted on the roof of the ranch headquarters house, pointing toward the gateway location. This Wi-Fi extender was powered via PoE, using the modem and router that supplied Wi-Fi to the house. Upon connection to the Wi-Fi backhaul network, the LoRa-WAN gateway was online and began logging data within ~24 h.

A copper rod was mounted approximately 0.3 m (1 foot) above the level of the antenna as a lightning rod to prevent it from being short-circuited by lightning strike during frequent summer thunderstorms.

Animal Wearable Sensors. Abeeway Industrial Trackers were used to track cow GPS locations (Figure 3e). These widgets are LoRa-WAN enabled and powered via a single 19 A hours/3.6-V lithium-thionyl chloride type D battery. The GPS sensors were housed within Pelican R20 Ruck cases that were affixed to a Weaver nylon cow collar via a Weaver nylon dog collar strap attached via a box stitch on either side of the case (Figure 3f). Foam was placed around the GPS-Industrial Tracker to prevent it from moving within the Ruck case.

The Abeeway Device Analyzer (**ADA**) is a proprietary device controller that allows for widget configuration, data management and download, and near-real-time map visualization but lacks data analytics capabilities. Industrial trackers were configured using the ADA to collect data at 15-min intervals using only the GPS setting. Other possible geolocation settings included Low Power GPS (**LP-GPS**), and Wi-Fi Sniffer, or a combination of 2 settings at a time. Low Power GPS is a proprietary Actility setting

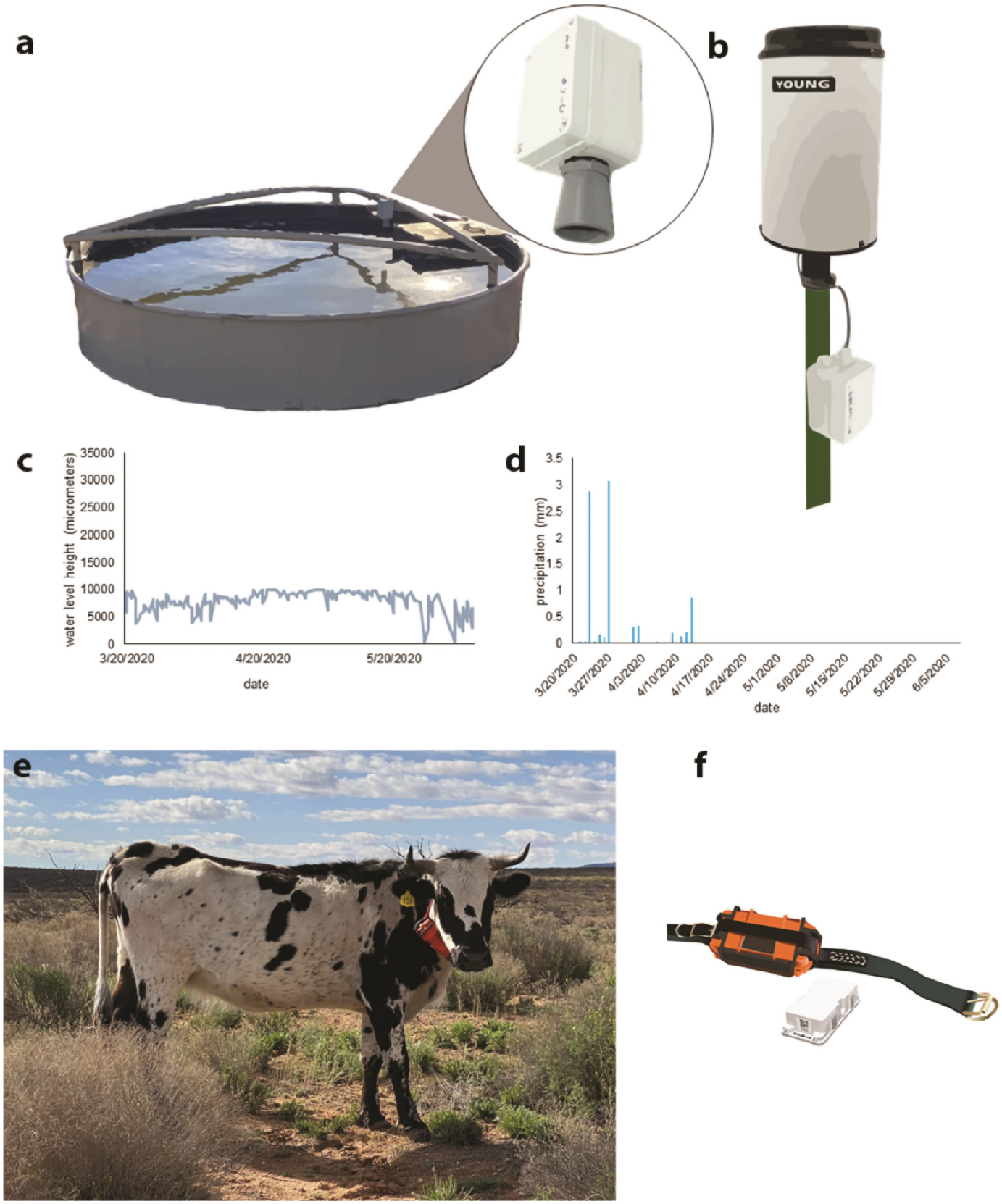

Figure 3. (a) Water level sensor and attachment point on a livestock tank; (b) long-range wide area network (LoRa-WAN)-enabled rain gauge (DecentLab); (c) daily water level (distance from sensor to top of water recorded by sensor; date = mo/d/yr); (d) daily precipitation records from rain gauge collected across the study period; (e) global positioning system (GPS) collar design featuring a Ruck case (Pelican) affixed to a cow collar via a box-stitched dog collar (black), alongside an industrial tracker (Abeeway; white box).

that conserves power by reducing GPS fixes when trackers are stationary. The Wi-Fi Sniffer option also conserves power by using localized Wi-Fi networks to geolocate trackers rather than GPS. Industrial Trackers were also equipped with temperature sensors, located within their housing, which relayed thermal information synchronously with GPS data transmission at 15-min intervals. Triaxial accelerometers within the Industrial Trackers were also programmed to compute and transmit an animal movement counter within LoRa-WAN data packets at 15-min intervals. The movement counter and algorithms were proprietary and revealed either a "0," indicating no movement, or a "1," indicating movement. Newer generations of the animal trackers allow for more frequent data collection and access to the raw data for algorithm applications.

Although trackers could be remotely adjusted through the ADA, there was a time lag between when dashboard changes were made and when the new configuration settings went into effect. Per Abeeway, the position accuracy was reportedly greatest for GPS, followed by LP-GPS and then Wi-Fi, with approximate ranges of 10 to 18 m (33–59 feet), 15 to 30 m (49–98 feet), and 20 to 50 m (65–164 feet), respectively (Abeeway, n.d.). A more detailed evaluation of Abeeway sensor reliability, currently underway, will allow our team to determine the best use of GPS and movement sensor data to inform management decisions via a precision ranching dashboard, also currently under development.

Rain Gauge and Water Level Sensor. A DecentLab LoRa-WAN-enabled tipping bucket rain gauge was installed on a ~1.5-m-tall (~5 feet) T-post approximately 2.5 km (~1.5 mi) south of the gateway (Figure 3b). The rain gauge was programmed to record precipitation events at 10-min intervals and to deliver those data packets to the gateway once daily (Figure 3d). The tipping bucket rain gauge is powered by 2 C alkaline batteries and works by generating a pulse each time 0.1 mm (0.004 in) or more of precipitation is sensed within its trap (DL-TBRG Datasheet: https://cdn.decentlab.com/download/datasheets/Decentlab-DL-TBRG-datasheet.pdf). Precipitation event readings are transmitted through the LoRa-WAN network to a DecentLab server and are available through an online dashboard via a subscription described in the following section. Battery life may last ~2 yr or more depending on prevailing weather conditions.

A near-real-time DecentLab (DL-MBX) ultrasonic distance/water level sensor was also deployed as part of the ranch monitoring system (Figure 3a). This sensor computed and transmitted the distance to the trough water level throughout the day at 10-min intervals (Figure 3c). The water level monitor is also powered by 2 C alkaline batteries and works by transmitting ultrasonic waves toward the water, which are reflected back and recorded as a measure of distance (DL-MBX Datasheet: https://cdn.decentlab.com/download/datasheets/Decentlab-DL-MBX-datasheet.pdf). As with the rain gauge data, distance measurements from the sensor to the top of the water surface were also transmitted through the LoRa-WAN network to a DecentLab server and were available through an online dashboard via a subscription described in the following section. Battery life may last ~2 yr or more depending on prevailing weather conditions.

Network Management and Cloud-Based Dashboards

The LoRa-WAN network management and device controller and dashboards require an annual subscription to a cloud-based software platform. We used a LoRa-WAN network platform operated by Actility (https://www.actility.com/). The platform is available via annual subscription and allows detailed monitoring of data traffic, functionality of gateways, decoding of sensor data, and downlink communication to allow modification of sensor configurations. The costs of annual subscriptions are detailed in the following. New users interested in open-source LoRa-WAN network services may consider using free services provided by The Thing Network, a collaborative LoRa-WAN ecosystem available at https://www.thethingsnetwork.org.

Data from the Abeeway animal tracking sensors were displayed on the ADA or "Device Manager" that mapped geographic coordinates of GPS fixes on a Google Maps layer over a 7-d window (Figure 4a). The dashboard has capability to monitor up to 10 devices at any time and also allows access to other individual sensor data such as motion sensor indices, sensor temperature, radio signal strength, theoretical battery level, data acquisition intervals, and data packets lost. An interactive menu on the ADA dashboard allowed user configuration of sensors by adjusting location data type (LP-GPS, GPS, Wi-Fi sniffing, or any combination of the 3) as well as the frequency of data acquisition. The rain gauge and water level sensor data were displayed in a separate device manager and dashboard interface available from DecentLab, which allowed us to monitor data collection and battery life of the deployed widgets. Visualization of sensor data through selectable timeframes as well as configuration of data acquisition frequency were possible. In the Actility platform, all transmitted LoRa-WAN data packets have a preamble, header, payload, and cyclic redundancy check, and the actual payload size varies with the message type (https://www.actility.com/). The preamble is used to synchronize the transmitter with the receiver and allows the receiving base station to adjust its gain and timing. The length of the preamble ranges between 8 and 16 bytes. The header provides information of the data packet length and type and is usually 4 bytes in length. The payload is the sensor data being transmitted and is a message 11 bytes in length for Abeeway GPS position fixes. This payload includes information of the GPS fix age (in seconds), latitude, longitude, estimated horizontal error, and previous GPS fix position and age. The cyclic redundancy check is 16 bytes in length and is used to check the integrity of transmission and errors of GPS data.

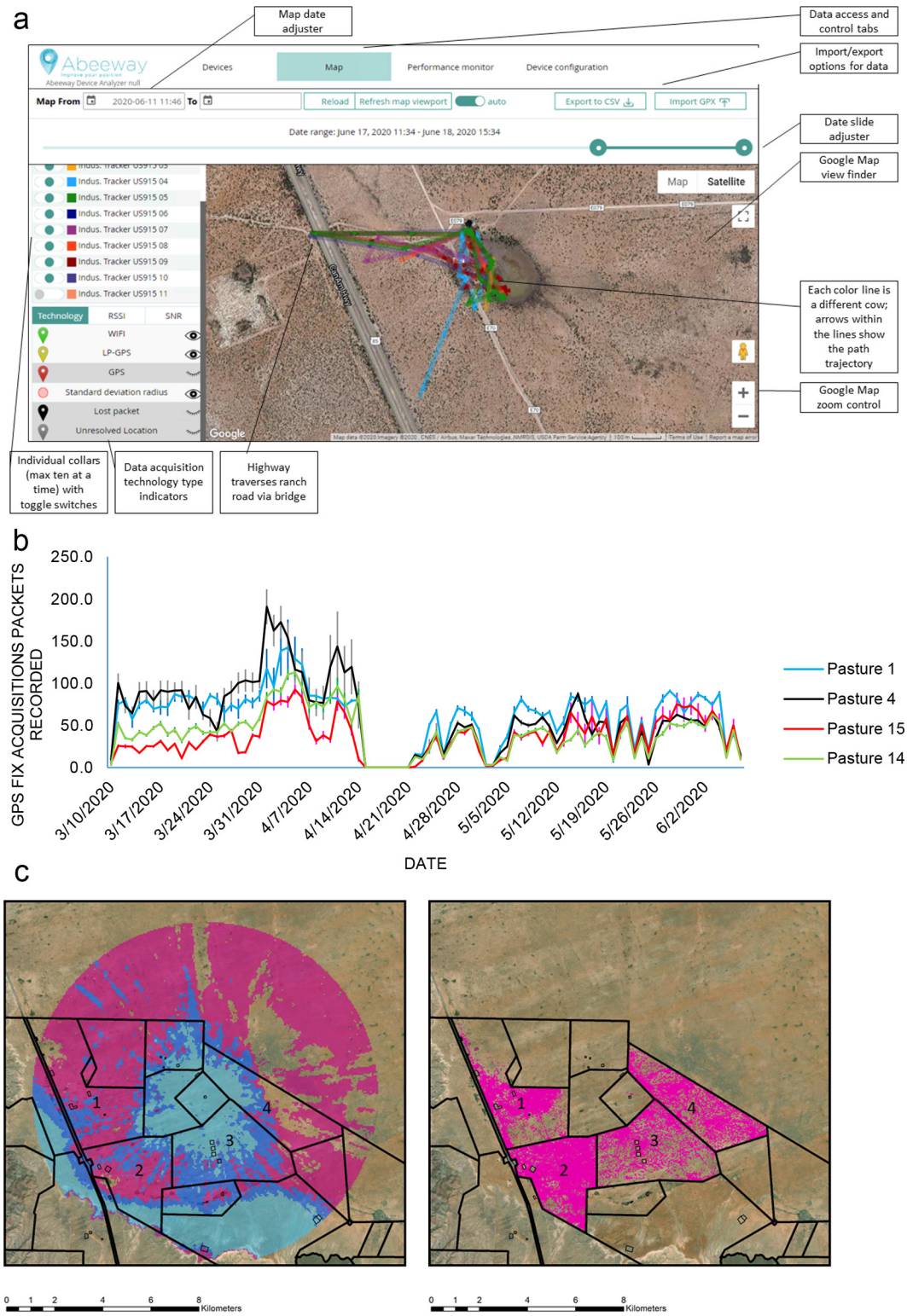

Figure 4. (a) Example of device manager dashboard (Abeeway) and map viewfinder tab. (b) global positioning system (GPS) data packets received via the gateway per pasture and day across the entire study period (date = mo/d/yr). (c) Left: Presumed line-of-sight long-range wide area network (LoRa-WAN) coverage of our research site. The circular buffer is approximately 7 km in diameter; light blue = best coverage, dark blue = moderate coverage, pink = poor coverage, and clear = poor to no line-of-sight coverage. Right: All GPS fix locations for 43 cows tracked between March 9 and June 9, 2020. Note that GPS fixes were still recorded in areas with poor to no line-of-sight coverage.

RESULTS AND DISCUSSION

Sensor Battery Life, Data Acquisition Rate, and System Reliability

The solar panel and associated components appeared to initially provide ample power to the gateway base station and Wi-Fi backhaul, but subsequent system intermittency (described in the following) may have been related to power supply failures due to instrumentation or connectivity issues. The water level and rain gauge sensors used minimal battery over the course of the trial per the manufacturer's stipulation. Battery life of the GPS devices was less than expected (1 yr); it dropped to between 30 and 40% of estimated full charge over a 4-mo period, which was a reduction of approximately 0.5% per day. Battery consumption may have increased when attempting to acquire GPS signal (as opposed to alternate location data types such as LP-GPS) because of repeated transmission attempts to bypass competing signal transmission and collision issues (interferences of LoRa-WAN radio signals).

No GPS tracking collars were lost from cows during the study. Loss of GPS data packets occurred intermittently throughout the trial, with geolocation gaps ranging from 0 to 1.3 h (Table 1). The industrial trackers were configured to record GPS fixes at 15-min intervals for the majority of the study period (except for 1 wk from April 1 to April 7 when fix interval was reduced to 5 min); therefore, 96 GPS fixes were expected per collar per day. On average, 46 ± 4% of expected GPS fixes were collected per day across all pastures during the study time period. These values are very similar to those reported by Dos Reis et al. (2021), who also found that only 40 to 60% of data packets were transmitted in their LoRa-WAN system that covered a much smaller area (1.78 ha; 4.40 acres) with fewer animals (2) and for less time (3 d). Depending on the week or pasture, data acquisition in our study reached up to 80% of expected fixes, which is consistent with Ojo et al. (2021), who evaluated a similar system on 0.7-ha (1.7-acre) Italian pastures and recorded GPS acquisitions at 15-min intervals for a week's time. Data loss was greatest in pastures located further from the gateway (Figure 4b, Table 1) and consistent with variations in LoRa-WAN signal strength for the testing site (Figure 4c). As Dos Reis et al. (2021) suggested, GPS-location packets were likely lost due to system overload, especially because all of the GPS receivers were set to upload at the same frequency and among only 2 of 6 available channels.

LoRa technicians later suggested that staging groups of GPS-trackers to transmit packets through different transmission frequencies (channels and spread factor) and with repeated attempts could greatly enhance the rates of successful data packet upload. In the animal sensor web interface, a "base station" network manager is available to check the status of the gateway. We learned that gateway warnings regarding "repeated FCnt" (repeated frame count error) are good indications of competition between devices to upload data packets; hence, future studies will address this issue at the onset to reduce GPS data packet loss. The FCnt is 1 of 2 frame counters (Up or Down) that the gateway and network server track to validate time-stamped data; however, LoRa-WAN data frame acknowledgment is optional, as opposed to alternate systems such as TCP, hence packet loss is more likely to occur with this system (Brocaar, 2021).

A third and likely cause for LoRa-WAN GPS data loss, in addition to intermittent power shortage and gateway configuration, was apparent deficient Wi-Fi backhaul connectivity (Figure 4b). We suspect that the Wi-Fi extender antennas may have failed to work as intended, particularly when strong springtime winds began in April or were affected by the limited capabilities of the on-ranch broadband Internet service. GPS fix loss was negligible in previous pilot tests conducted at the New Mexico State University campus farm where the gateway was connected directly to the power grid and local Ethernet via a hardwired connection (McIntosh et al., 2020). Rates of GPS data acquisition dropped dramatically during a weeklong Wi-Fi malfunction from April 15 to 21, when no LoRa-WAN data were collected (Figure 4b). We speculate this failure was the result of a moisture buildup in coaxial cables and conduit systems that suddenly caused the failure of the Wi-Fi backhaul bridge. The issue was confirmed months later, and a replacement of cables and the Wi-Fi bridge system was completed. We also speculated that a few trees lining the ranch headquarters "leafed out" during this period, and we suspect that, in addition to the strong winds and monsoon storms, the Ubiquity Wi-Fi bridge may have failed to transmit data packets as intended. More recent applications at the ranch successfully implemented GSM communication options, in locations where 4G network is available.

Data Modeling

Some preexisting freeware and modeling algorithms were tested to evaluate the robustness of both the network coverage and the GPS-tracker acquisition rates. The Ubiquity software provides a freeware called airView, which allows users to model Wi-Fi coverage according to geolocation and antenna height (per the Fresnel zone). This program was useful for modeling the line of sight between study pastures and the gateway antenna (Figure 4c), as well as for modeling the line of sight needed to bridge the gap of the Wi-Fi backhaul system. Data acquisition from limited line-of-sight areas of the LoRa-WAN gateway surpassed model expectations (Figure 4c), likely due to the robustness of the LoRa-WAN signal transmission.

Andrew's Monotone Convex Hull Algorithm was used to calculate 24-h area explored by individual cows (Andrew, 1979; McIntosh et al., 2022). Data gaps in GPS acquisition rendered some tracker data noncalculable and also restricted calculations of finer-grained behavior metrics, such as distance traveled or sinuosity. We calculated a

Table 1. Means ± SE of long-range wide area network (LoRa-WAN) sensor performance between March and June 2020

Item	Date range (2020)	Week	Pasture 3	Pasture 4	Pasture 2	Pasture 1
Centroid distance (m)			2,567	2,661	4,447	4,979
No. of GPS packets transmitted[1]	Mar 11–Mar 17	1	72.67 ± 2.90	84.29 ± 4.70	42.88 ± 3.00	24.97 ± 1.50
	Mar 18–Mar 24	2	80.38 ± 2.70	78.21 ± 5.40	41.79 ± 2.10	25.87 ± 3.40
	Mar 25–Mar 31	3	76.10 ± 2.70	89.18 ± 8.20	49.75 ± 2.30	32.67 ± 4.00
	Apr 1–Apr 7	4	118.67 ± 8.00	141.32 ± 14.80	93.79 ± 5.50	76.50 ± 4.90
	Apr 8–Apr 14	5	80.48 ± 1.50	103.39 ± 10.30	78.06 ± 5.10	42.88 ± 8.60
	Apr 15–Apr 21	6	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
	Apr 22–Apr 28	7	40.62 ± 9.40	28.14 ± 5.90	23.82 ± 5.30	21.74 ± 5.80
	Apr 29–May 5	8	34.10 ± 9.80	24.92 ± 7.30	21.00 ± 7.30	19.14 ± 7.10
	May 6–May 12	9	64.67 ± 4.50	50.64 ± 4.00	38.17 ± 7.30	35.96 ± 7.10
	May 13–May 19	10	73.33 ± 4.40	58.18 ± 6.10	35.29 ± 2.40	49.60 ± 4.80
	May 20–May 26	11	45.14 ± 10.20	32.04 ± 8.10	27.78 ± 6.70	37.35 ± 7.40
	May 27–Jun 2	12	80.90 ± 3.10	56.07 ± 1.70	49.58 ± 1.80	65.35 ± 3.30
	Jun 3–Jun 7	13	53.22 ± 13.30	39.79 ± 8.10	38.49 ± 9.30	42.79 ± 8.80
Percentage of expected GPS packets transmitted	Mar 11–Mar 17	1	76 ± 3	88 ± 5	45 ± 3	26 ± 2
	Mar 18–Mar 24	2	84 ± 3	81 ± 6	44 ± 2	27 ± 4
	Mar 25–Mar 31	3	79 ± 3	93 ± 9	52 ± 2	34 ± 4
	Apr 1–Apr 7	4	41 ± 8	49 ± 15	33 ± 6	27 ± 5
	Apr 8–Apr 14	5	84 ± 2	108 ± 11	81 ± 5	45 ± 9
	Apr 15–Apr 21	6	0 ± 0	0 ± 0	0 ± 0	0 ± 0
	Apr 22–Apr 28	7	42 ± 10	29 ± 6	25 ± 6	23 ± 6
	Apr 29–May 5	8	36 ± 10	26 ± 8	22 ± 8	20 ± 7
	May 6–May 12	9	67 ± 5	53 ± 4	40 ± 8	37 ± 7
	May 13–May 19	10	76 ± 5	61 ± 6	37 ± 3	52 ± 5
	May 20–May 26	11	47 ± 11	33 ± 8	29 ± 7	39 ± 8
	May 27–Jun 2	12	84 ± 3	58 ± 2	52 ± 2	68 ± 3
	Jun 3–Jun 7	13	55 ± 14	41 ± 8	40 ± 10	45 ± 9
Mean time interval between GPS packets transmitted (h:min:s)	Mar 11–Mar 17	1	0:20:20 ± 0:01:09	0:18:12 ± 0:01:24	0:36:38 ± 0:02:33	1:01:53 ± 0:06:16
	Mar 18–Mar 24	2	0:18:22 ± 0:00:48	0:20:04 ± 0:01:32	0:40:04 ± 0:02:40	1:14:02 ± 0:20:31
	Mar 25–Mar 31	3	0:19:23 ± 0:00:50	0:19:39 ± 0:03:56	0:31:18 ± 0:01:26	0:52:27 ± 0:08:43
	Apr 1–Apr 7	4	0:13:37 ± 0:00:58	0:12:32 ± 0:02:18	0:17:36 ± 0:01:22	0:20:53 ± 0:02:04
	Apr 8–Apr 14	5	0:17:48 ± 0:00:24	0:19:08 ± 0:02:31	0:46:55 ± 0:20:28	1:14:27 ± 0:37:01
	Apr 15–Apr 21	6	0:00:00 ± 0:00:00	0:00:00 ± 0:00:00	0:00:00 ± 0:00:00	0:00:00 ± 0:00:00
	Apr 22–Apr 28	7	2:13:33 ± 1:30:52	2:58:06 ± 1:37:34	4:38:30 ± 1:50:09	7:10:09 ± 1:16:48
	Apr 29–May 5	8	3:05:01 ± 1:52:25	3:59:33 ± 2:11:07	5:40:46 ± 1:51:11	7:37:02 ± 2:54:12
	May 6–May 12	9	0:21:05 ± 0:01:02	0:26:52 ± 0:01:20	1:07:01 ± 0:16:08	0:42:04 ± 0:03:26
	May 13–May 19	10	0:19:10 ± 0:00:40	0:25:03 ± 0:02:14	0:51:15 ± 0:07:55	1:09:10 ± 0:23:50
	May 20–May 26	11	0:22:57 ± 0:05:07	0:29:00 ± 0:04:45	0:29:34 ± 0:00:40	0:30:30 ± 0:02:58
	May 27–Jun 2	12	0:18:03 ± 0:00:45	0:25:53 ± 0:00:45	0:30:17 ± 0:01:36	0:36:10 ± 0:04:48
	Jun 3–Jun 7	13	0:20:01 ± 0:01:52	0:22:22 ± 0:02:31	0:28:28 ± 0:03:07	0:32:14 ± 0:05:19

[1]GPS = global positioning system.

coarse-grained variable, minimum convex polygon, to determine approximate 24-h area explored in spite of missing data, because this commonly used metric only considers the fewest possible x,y locations necessary to determine a bounded area with internal angles <180°. The cow in this example exhibited marked decreases in area exploration during the days surrounding parturition, with the least area explored on the estimated calving day (calving data were also confirmed by visual observation, Figure 5). This anecdotic observation suggests that there might be a possibility to identify significant life-cycle events of grazing cattle in extensive rangeland systems (see Williams et al., 2022, for more discussion).

Cost

Depending on the operation size, both in terms of number of hectares and number of widgets deployed, the cost of mounting a LoRa-WAN PLF system varies, depending on the number of gateway base stations and solar-power kits, and the number of data subscriptions that would be required for all needed cloud and network services. In this

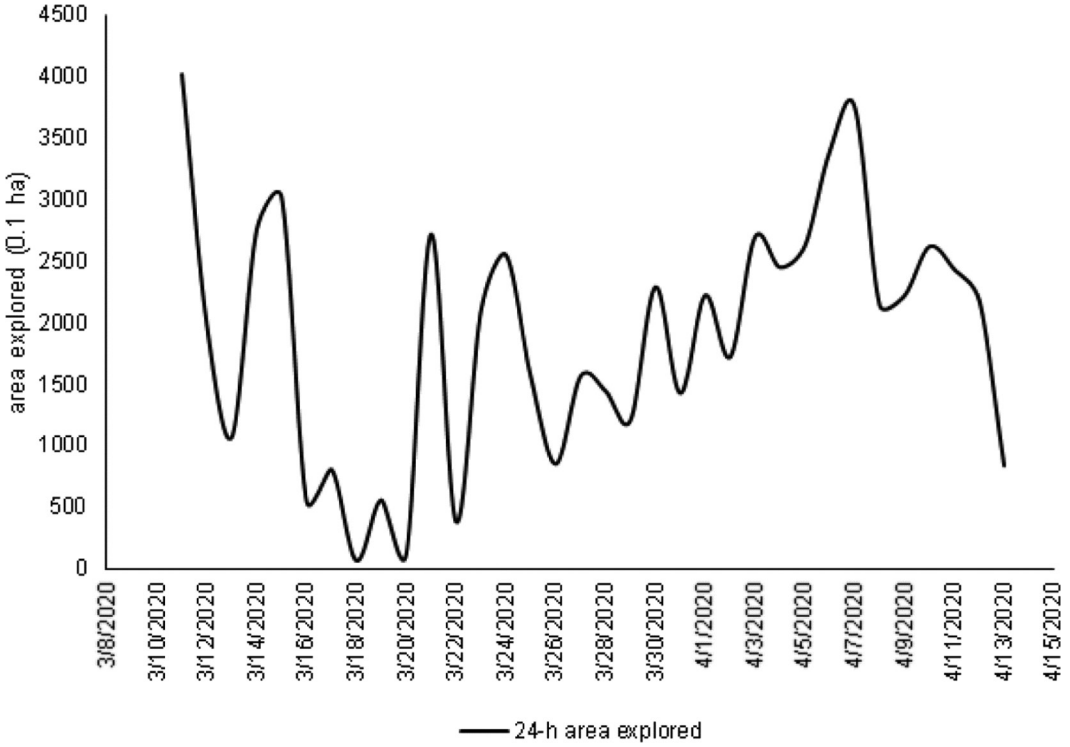

Figure 5. Example of global positioning system (GPS)-derived behavioral metrics and their relationship to parturition date (date = mo/d/yr). In this example, the cow gave birth on March 20, 2020, which coincided with nadir exploration.

instance, large ranches with larger herds could spread the same or similar overhead costs over more animals and land. At the same time, large ranches that would require more significant labor investments and fuel costs could benefit from reductions in travel time and vehicle expense (Spiegal et al., 2020) to monitor cows, drinking tanks, and rain gauges. In addition to the $99.00 for the LoRa-WAN animal tracker (Table 2), the cost per cow for mounting a basic LoRa-WAN ranch infrastructure is expected to range from $35.00 to $90.00 depending on (a) operation size, (b) number of water level and rain gauge sensors deployed, (c) required infrastructure for gateways, and number of gateways, (d) software and network services to manage data from sensors, and (e) configuration of sensors (e.g., IT support; Table 2). A detailed cost analysis of this PLF system has not been completed to date due to its novelty. However, PLF costs will likely become more affordable as sensing and communication technologies evolve and become more common. Future studies should aim to evaluate the lifespan of LoRa-WAN hardware in hot, arid outdoor systems for better estimates of infrastructure lifespan and socio-financial benefits.

Recent reports evaluating producer interests in PLF technology indicated that ranchers consider infrastructure monitoring more feasible to install and more cost rewarding than animal biosensors. However, it is important to note that most survey participants were unfamiliar with the features, scope, and operation of real-time animal monitoring systems. A survey of 36 western ranchers (Elias et al., 2020) revealed that 50% would consider using water sensors even though most travel fewer than 48.3 km (30 miles) from their headquarters to watering tanks. In more extensive systems (e.g., >8,094 ha [>20,000 acres]), preliminary cost-savings analyses suggest that wireless water level monitoring could save up to 3,534 L (934 gallons) of fuel or $10,000 annually (Elias et al., 2020; Spiegal et al., 2020). This conservative analysis does not consider the implications of reducing cow mortality or animal performance due to dehydration (Walker, 2021). Walker (2021) reported a $133 to $690 savings associated with implementation of remote water level sensors on stock tanks using non-LoRa-WAN data transmission systems could be achieved. In that assessment, the author suggested that fewer than 5 round trips to the water tank would elicit a break-even cost for some systems and also suggested that implementing LoRa-WAN-enabled data transmission networks could lower the price for wireless data access (Sadowski and Spachos, 2020; Walker, 2021).

In the Elias et al. (2020) study, 75% of respondents already used rain gauges to monitor precipitation and predict forage growth on their ranches. Fifty percent of producers surveyed in that study also mentioned interest in obtaining increased rainfall data but considered installation, maintenance, travel time to monitor, and cost to be deterrents to adoption (Elias et al., 2020). The LoRa-WAN-enabled rain gauge deployed in this study yielded a robust and low-maintenance data set that was easily accessible; despite the cost of the rain gauge, it was not markedly different from the price of other commercially available rain gauges. We predict that deployment of a

Table 2. Initial cost of the precision-livestock-system components tested in this study[1]

Item	$
LoRa-WAN ranch infrastructure (price per unit)	
100-W, 24-V solar-power and battery system	651.70
LoRa-WAN gateway and Wi-Fi backhaul (price per unit)	1,009.22
Sensors (price per unit)	
LoRa-WAN animal tracker (GPS + accelerometer + temperature sensor)	99.00
LoRa-WAN rain gauge	1,257.30
LoRa-WAN water level	656.00
Network and cloud server services (per year)	
LoRa-WAN network connectivity (1 gateway + 200 sensors)	285.00
LoRa-WAN data management and support services	230.00
Sensor license fees	54.00
Total fees for network and cloud server services	569.00

[1]Testing of the present LoRa-WAN digital ranching system included the following infrastructure: 1 gateway, 1 water sensor, 1 tipping bucket, 1 rain-gauge sensor, and 43 cows grazed seasonally over ~4,000 ha of desert rangeland pasture. LoRa-WAN = long-range wide area network; GPS = global positioning system.

LoRa-WAN network could allow greater financial and labor flexibility compared with deploying individual widgets such as rain gauges, because the system as a whole would offset excessive costs of deploying individual widgets and would yield data that are more accessible alongside decreased labor inputs.

Practical Uses of the System

The near-real-time acquisition of GPS location of cows proved to be useful for day-to-day management of the ranch herd. For instance, on several occasions, the platform showed when cows had crossed a fence and revealed their actual locations, which helped the rancher find and move the animals back to the correct pasture. Similarly, the ranch manager became accustomed to checking animals in the morning via the online Abeeway Device Analyzer before heading out to inspect the herd, which resulted in significant time savings. The daily monitoring of cattle via the dashboard also revealed animal campsites or time-frame tendencies for herds to come to water (dashboard depicted in Figure 4a). During our study, 2 cows were struck and killed by a hit-and-run vehicle crossing the ranch at night; in this instance, the ranch manager quickly noticed the lack of movement by those animals on the dashboard, before being notified by local authorities of the incident. The water level sensor was checked at least once daily and provided assurance that animals in that pasture had access to fresh water.

When this project was launched in 2019, there were no commercially available precision systems for western ranching on the market. Over the past 2.5 yr, several startups have entered the precision ranching commercial space. Several of the systems available on the market today are still in the testing phase. Although the tools we are developing have some advantages over similar ones available on the market, our goal is not to duplicate products being developed commercially nor to compete in the marketplace. Our project seeks to provide independent testing of the technologies used in emerging commercial precision systems and offer an unbiased assessment of (a) the feasibility of deploying such systems on western rangelands and (b) the tradeoffs associated with adopting this tool. By building a nonbranded system, we were able to circumvent limitations associated with commercial proprietary data. This strategy is allowing us to fully explore the capabilities of the system and has enabled us to be completely transparent about its capabilities.

APPLICATIONS

This Technical Note suggests several advantages of the proposed PLF system along with areas for potential improvement of existing sensors, network infrastructure, and software engineering and computing, which may enhance future applications of the system on commercial ranches. The functionality of the present base station and PLF system could be improved through enhanced infrastructure and instrumentation. For example, since completing this pilot test, we eliminated AC inverters, which significantly reduced power drainage in the system. In addition, the incorporation of a solar point unit recently helped to reduce the instrumentation and facilitate the operation of various functions such as the solar/battery charger, DC power and PoE by over 30 W. The centralized unit we added can be remotely monitored to forecast any unexpected abrupt change in charge, load, and battery capacity. This is a significant improvement to address power and gateway communication issues in a timely manner. Since implementing these improvements in instrumentation, our remotely

deployed gateway station (5 km away from headquarters) worked consistently in terms of solar and battery charge, supply, and equipment load, which ranged between 9.5 and 10.2 W for the solar point controller, Wi-Fi backhaul, and gateway. On average, the power consumption of the test gateways varied between 5 to 8 W depending on the size of data traffic through the LoRa-WAN system.

Data communication could also be improved through enhanced infrastructure and equipment configuration. For example, typically observed loss of data due to terrain features, such as presence of greening trees, buildings, deep canyons, or long distances to a gateway, suggest that an approach to improve LoRa-WAN communication may come from greater number of gateways, taller antennas, and gateway configurations that include multiple communication channels, repeated communication attempts, and mixing of spreading factors (**SF**; the rate of data transmission). Whereas our SF was set to only 7, typically, LoRa-WAN uses SF between 7 and 12, with the tradeoff that larger SF increase the time on air (e.g., fewer data chirps are sent at greater time intervals), which increases energy consumption and reduces the data acquisition rate.

Methodologically, a reliable PLF approach for western ranches must also fuse traditional statistics and smart analytics with novel dashboard tools to rapidly provide management indicators computed from different streams of real-time data, which are concurrently collected, logged, and transmitted through a network of high throughput sensors, gateways, routers, and cloud computing services. The platform must be adaptive, flexible, and scalable and capable of operating in diverse deployment settings, ranging from sites where grid power is available to sites that require solar energy infrastructure and sites that can be managed with Wi-Fi backhaul bridge, GSM communication, or Ethernet data transfer. Software engineering and IT must be centered on developing a unified web-based server-dashboard application that facilitates the aggregation, visualization, and retrieval of computed data and configurations of multiple sensors. New analytics will need to enhance the harmonization (i.e., common feature representation) and curation of extremely heterogeneous GPS and accelerometer data using preprocessing, cleansing, and normalization steps before implementing machine-learning variants for classification and prediction purposes. This is a fundamental challenge across several machine-learning pipelines where success is usually driven by how well the data collection and curation activities are carried out. A good machine-learning classification pipeline will perform more effectively with well-curated data as opposed to attempting to address data curation issues through more complex machine-learning algorithms. This is especially true for our remotely collected data derived from multiple sensor sources such as ground-based sensors, satellite GPS, and mobile accelerometers worn by animals, which are exposed to varying positions and placement on the animal and to a disparate spectral, spatial, and temporal sampling frequency. In this way, identifying relevant bio sensing analytics will require extensive calibration of sensor measurements through direct observations of cattle in the field.

Dealing adequately with heterogeneous data sources also affords opportunities for the use of fusion analytics and scale-dependent data collection schemes. Issues of heterogeneous GPS data collection (up to 40–80% of potential fixes were collected) could be minimized and information of animal behavior improved by a fusion approach. For example, large-scale habitat selection assessment using less-frequent, uncorrelated GPS information along with high-resolution (frequently acquired) accelerometer data could be combined to classify and assess foraging behavior and welfare with greater degree of cover and resolution. The greatest value of a PLF system for western ranches will be realized when combinations of data streams collected across the ranch are leveraged to inform decision making and drive planning tasks with less effort and reduced risk.

Our team is currently engaged in engineering and computing research to fuse real-time data streams into a unified web-based server-dashboard tool. Most existing efforts (such as the one described here) and PLF applications focus on a single data source or sensor over a short period of time. There is currently a lack of open-source computing and machine-learning libraries or computerized infrastructure standards for compiling and processing general agriculture data at ranch scales. Software engineering research will need to focus on creating these tools and standards in cooperation with rangeland and animal scientists, computer and software engineers, and land managers and ranchers across different cooperating sites and ranches. The goal of our team is to facilitate a web-based, open-source library that can be used by ranchers and expanded upon by other research groups working on PLF applications for western ranches. Such a library will need to be designed with strong machine-learning design and curation principles in mind.

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