Performance of LoRa-WAN Sensors for Precision Livestock Tracking and Biosensing Applications

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Abstract
This study investigated the integration of Long Range Wide Area Network (LoRa WAN) communication technology and sensors for use as Internet of Things (IoT) platform for Precision Livestock-Farming (PLF) applications. The research was conducted at New Mexico State University's Clayton Livestock Research Centre. The functionality of LoRA WAN communication technology and performance of LoRa WAN motion and GPS sensors were tested using static sensors that were placed either, a) outdoors and at incremental distances from the LoRa WAN gateway antenna (Field, n=6), or b) housed indoors and close to the same LoRa WAN gateway antenna (Indoor, n=5). Accelerometer data, reported as motion intensity index, and GPS location were acquired, transmitted and logged at 1 and 15 minute intervals, respectively. We evaluated the tracker's GPS accuracy (GPSBias as the euclidean distance between the actual and projected tracker location) and variables associated with the tracker's data transmission capabilities. The results indicate that field trackers had a greater accuracy for remote sensing of GPS locations compared to indoor trackers facing increasing communication interference to acquire satellite signals (GPSBias; 5.20 vs. 17.76 m; $P<0.01$). Overall, the trackers and deployments appeared to have a comparable GPS accuracy to other tracking devices and systems available in the market. The total data packets that were successfully transmitted were similar between the indoor and field trackers, but the number of data packets that were processed varied between the two deployments ($P=0.02$). Due to the static deployment of indoor and field trackers, activity data was almost non-existent for most devices. However, same trackers embedded on collars that were mounted on mature cattle showed clear diurnal patterns consistent with time budgets exerted by grazing cattle. The pilot testing of GPS and accelerometer sensors using LoRa WAN technology revealed reasonable sensor sensitivity and reliability for integration in PLF platforms.

Introduction
The continued advancement of Internet of Things (IoT) ecosystems (Madakam et al. 2015) has facilitated the development of various animal biosensors (Halachmi et al. 2019), new data transmission capabilities (Navarro et al. 2020; Sanchez-Iborra et al. 2018), and improved online data processing and storage through advanced analytics (Laca 2009). As a result, the IoT is emerging as one of the preferred ecosystems for use in Precision Livestock Farming (PLF) and Ranching (PLR) applications (Bailey et al. 2021). The hypothetical paradigm shift for PLR is the transition of traditional livestock production to aspirational management systems capable of optimizing production efficiency with increasing standards for animal welfare and sustainability (Tedeschi et al. 2021; Greenwood et al. 2016). Among the potential benefits of PLF is the individualized monitoring of animals in large herd settings, less need for physical labour, improvements of ranching lifestyle, flexibility to schedule ranch and livestock management tasks, and minimization of undesirable environmental and financial impacts facilitated by more timely, adaptive, and accurate decision-making. In this study, we conducted a pilot test to investigate the performance of LoRa WAN technology for use as a real-time animal monitoring system. The research tested the behaviour and functionality of tracking devices while using two deployments (Field and Indoor). We tested the accuracy of GPS trackers under the hypothesis that lower satellite signal interferences associated with field trackers will result in a better acquisition and accuracy of GPS data than trackers deployed indoors. We also expected the tested trackers to have a comparable accuracy to GPS devices and applications currently available on the market or described in the literature. Finally, we evaluated the LoRa WAN data transmission capabilities of the tested platform hypothesizing a similar and satisfactory data acquisition and transmission rate for the two tested deployments.

Methods and Study Site

The study was conducted at New Mexico State University's Clayton Livestock Research Centre (CLRC), located 7miles east of Clayton, New Mexico, USA, after approval by the Institutional Animal Care and Use Committee. The research site consisted of 1.39km^2 (320acres) of open flat terrain. The LoRa WAN communication technology was chosen as the system to transmit data between LoRa WAN-trackers (widgets) and the LoRa WAN-gateway station (Navarro et al. 2020; Sanchez-Iborra et al. 2018). The theoretical coverage of the network was approximately 5-8 km, based on the modelling of a deployment for flat and open topography and the use of a high gain LoRa WAN antenna placed at the top of a 27.4 m feed mill elevator (Navarro et al. 2020).

A pool of 40 LoRa-WAN-enabled Abeeway® (https://www.abeeway.com/) Industrial Trackers US915 were configured to communicate with a Kerlink (https://www.kerlink.com) Wirnet gateway station. The trackers were set to an "Activity Tracking" configuration, making the reporting of activity the "main operation" and the periodic reporting of position the "side operation". Data collection interval was 1 minute for the detection of motion intensity using the three-axis accelerometer sensor and 15 minutes for the positions acquired using the GPS-only technology option.

From October 24 to November 17, 2020, a subset of 6 trackers (Field) were randomly selected from the pool of 40 trackers and were positioned in the field at different distances from the LoRa WAN gateway and high gain antenna. Field trackers were secured on a fence post at ~1 m above ground. Five of the remaining trackers were housed indoors and kept inside the feed mill office located few meters away from the feed mill elevator and LoRa WAN gateway and antenna.

Data collection from Field (6) and Indoor (5) trackers lasted 7 days. Prior to analyses, date and time stamps were converted from the default Greenwich time zone (+00:00) to the Mountain time zone (-06:00). The position data, including geographic coordinates for latitude and longitude (in decimal degree units), were converted and projected into the UTM coordinate system (Zone 13 N) using ArcGIS software (ESRI 2018, ArcMap Desktop v. 10.6). The shapefiles containing recorded positions from trackers (Field and Indoor) were overlaid onto an ortho-imagery that was used as ground truth reference to manually enter the actual location of trackers. In most cases the truth location of trackers was concurrent with the centroid point from the tracker's GPS data.

For each tracker GPS point, a measurement of position bias (GPSBias) was calculated as the euclidean distance between the tracker actual location and the projected GPS point according to the Pythagorean Theorem:

$$\text{GPSBias} = \left(\sqrt{(x - x_k)^2 + (y - y_k)^2}\right)$$

where x and y are the easting and northing projected data points of the tracker, and x_k and y_k are the actual easting and northing location points of that tracker. The total daily Activity, Energy, HeartBeat, and GPS data payloads transmitted and received (#Activity, #Energy, #Heartbeat, and #GPSData, respectively) were calculated by counting the number of messages retrieved per unit tracker. The daily data packets sent were calculated as the sum of individual messages received per tracker (#TotalData). The "sequenceNumber" was the unique cumulative ID stamp given to each data packet computed by a tracker, either successfully transmitted and received or not. The number of daily data packets processed (#ProcessedData) by a tracker was the difference between the maximum "sequenceNumber" value for that day and the maximum "sequenceNumber" value for the previous day.

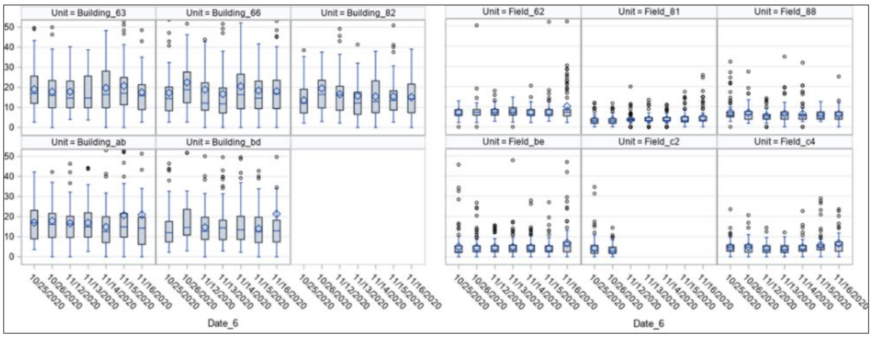

Figure 1: Box plot of the GPS bias for static trackers, either positioned outdoors (right panel) in the field (n=6), or indoors (left panel) inside a building (n=5) with an obstructed line of sight to satellite signals and/or the gateway antenna. The panels represent visualization of GPS bias measures up to 50 m.

The projected GPS positions (Field and Indoor) were inspected for erroneous GPS locations based on analyses of the GPSBias. Upon visual detection and assessment of erroneous GPS positions, an outlier detection algorithm was then used to filter GPS data. All of daily projected coordinate values for an individual tracker were converted into a normalized z-score, highlighting extreme score values with low probability under assumptions for a normal distribution of data points ($z > |4.5|$). This analysis was done separately for easting and northing data points using the formulae: (z = ($\frac{(i-\mu)}{\sigma}$), where i is the easting or northing value for a particular GPS point, μ is the average easting or northing of GPS data points collected on a given day, and σ is the standard deviation (either for the easting or northing values) of the GPS points collected in that same day.

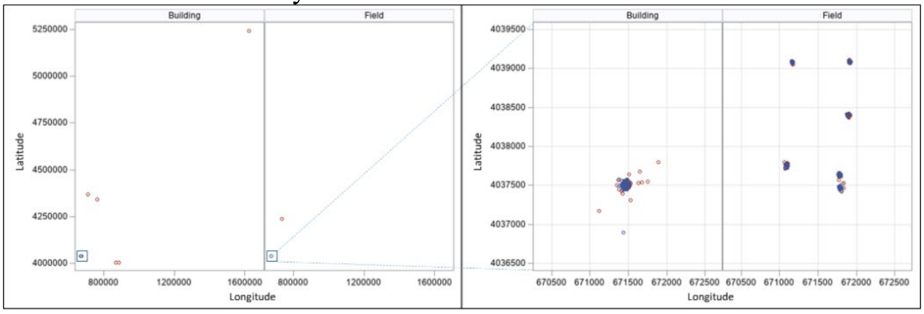

Figure 2; Projected GPS data of static trackers, either positioned outdoors (Field; n=6) or indoors (Building; n=5) with an obstructed line of sight to satellite signals and/or the gateway antenna. All GPS data locations (circles), normally behaving locations (enclosed by blue circles) and erroneous GPS locations (enclosed by open red symbols) computed by a GPS outlier detection algorithm. The left panel shows the spread of all GPS data from both deployments (Building and Field), while the right panel highlights the research site area.

The GPSBias, either for raw data or data previously filtered for erroneous GPS points, and the daily message payload (#Activity, #Energy, #Heartbeat, #GPSData, #TotalData, and #ProcessedData) were analyzed using SAS 9.3 (SAS Institute, Cary, NC). The MIXED procedure with a 'covtest' statement was used to model the fixed effects of deployment (indoor and field), day (n=7), and their interaction. Means were computed and compared by LSMEANS and pdiff tests, and differences were declared statistically detectable at P≤0.05. The effect of trackers (indoor n=5 and field n=6) was modelled as a random effect.

Results

The GPSBias was not affected (P=0.25) by the deployment by day interaction or the main effects of deployment (875.82 vs. 67.10 m for building vs. field respectively) and day when raw data was tested (Figure 1). However, when the GPS outliers were removed, the effect of the deployment type was significant (P<0.01), with indoor trackers having higher GPSBias than field trackers (17.76 vs. 5.20 m). A total of 52 out of the 6369 GPS locations were flagged as outliers (Figure 2).

The daily message payload between deployments (Indoor vs. Field) was not significant for #Activity (P=0.15), #Energy (P=0.96), #Heartbeat (P=0.17), #GPSData (P=0.49) or #TotalData (P=0.15). However, the daily #ProcessedData differed between deployments (P=0.02), with field trackers having more processed data than indoor trackers kept inside the building.

Discussion

Visual assessments and GPSBias measurements highlighted the presence of a low frequency of erroneous GPS data, especially in situations where the trackers had an obstructed line of sight to satellite signals. Similarly, the analysis of GPSBias for trackers placed outdoors, both with direct line of sight to satellites and incremental distances from the receiving antenna (Field), showed that 95% of the GPS data points fell inside a 15 m radius of the actual tracker locations. Conversely, the radius for 95% of GPS points increased to 40 m for nearby indoor trackers with an obstructed line of sight to satellites and the receiving antenna. This lower GPS accuracy of obstructed trackers is consistent with previous reports by Agouridis et al. (2004) that documented a 2.5 increase of GPS error for trackers manipulated under a dense canopy cover obstructing acquisition of satellite signals.

The mean estimation of GPSBias for raw data failed to detect GPS positioning differences between indoor vs. field placed trackers due to a violation of statistical model assumptions associated with the presence of GPS outliers. These results further justify the critical need for internal algorithms to detect and filter for extreme GPS outliers. Furthermore, when erroneous GPS points were detected and filtered, trackers kept indoors and manipulated for impaired line of sight with satellites and receiving antenna showed higher GPSBias than outdoor trackers with a clear line of sight to satellites. The overall results supported the hypothesis that the tested sensors would acquire GPS data with reasonable accuracy and would be comparable to other commercially available trackers on the market (Buerkert and Schlecht 2008).

During the data analysis, the trackers internal variable of GPS accuracy, HA (Horizontal Accuracy) did not show a consistent correlation with GPSBias measurements. The unreliability of internal GPS variables for predicting accuracy of the data was also reported by Buerkert and Schlecht (2008), who concluded that metrics for dilution of precision (DOP) values of three different trackers analyzed had a limited value for use as indicators of GPS data acquisition quality.

Data transmission rates were stable between deployments, supporting the hypothesis that comparable data transmission rates would occur regardless of the location or physical deployment of trackers and the gateway antenna. The percentage of successful data transmission (#TotalData/ #ProcessedData * 100) for the stationary trackers placed either outdoors at distant locations from the antenna or indoors with obstructed line of sight to the nearby receiving antenna was 77.24 and 92.99 %, respectively. This finding is consistent with previous work by dos Reis et al. (2021) that reported up to a 40 to 60% data transmitting loss for LoRa-WAN trackers collecting GPS and activity data from remote locations.

Erroneous transmission of activity data packets was detected for one of the static trackers kept indoors (building_66), and two of the static trackers kept outdoors (Field_62 and Field_88). The remaining trackers transmitted no activity messages as was expected during the stationary testing phase. While no reasonable explanations were found for this unexpected motion sensing, a follow-up deployment of same trackers embedded inside collars and mounted on grazing animals showed satisfactory behaviour of motion data. These motion recordings revealed a clear diurnal activity pattern consistent with published diurnal time budgets (Gregorini 2012) exerted by grazing cattle (Figure 3).

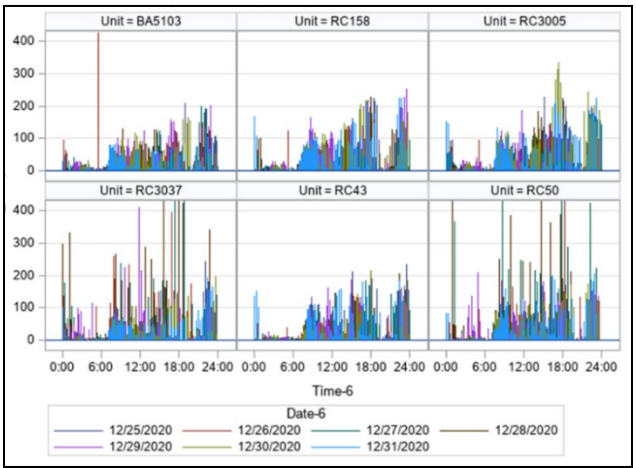

Figure 3: The panel represents the needle plot of activity data as a motion intensity (y-axis) using IoT sensor devices worn by mature cows (n= 6) grazed on pasture fields at the Clayton Livestock Research Center.

The preliminary results of this study support the application of LoRa WAN communication as a useful IoT platform for PLF and PLR applications. The envisioned research that is proposed under the Sustainable Southwest Beef project being led by NMSU is to develop a precision ranching platform able to monitor livestock, drinking water, forage, and rainfall in real-time with the integration of a rancher-friendly visualization dashboard for use as a decision-support tool.

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