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IMPORTANCE OF MEASUREMENT AND DATA UNCERTAINTY IN DIGITAL AGRICULTURE SYSTEM

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Abstract

In a digital agriculture system, Internet of Things (IoT) enabled sensors generate farm data including measurements related to environment, soil, plant, and animal status. Farm models (statistical, verbal, visual, deterministic, etc) transform these data to actionable farm knowledge and information. Sensor data is always associated with measurement uncertainty from different sources of measurement error. It is essential to identify, assess, quantify, manage and meaningfully communicate this type of uncertainty around agricultural decision-support systems. The likelihood of undesirable decision outcomes can only be managed when the accuracy of available information is known. In this paper, we review the influence of measurement uncertainty in sensor data as part of a broader research programme around uncertainty in decision making systems in a digitally enabled agriculture system.

Introduction

Agricultural decision-making platforms and environmental regulatory requirements are increasingly dependent on information derived from digitalised data generated by sensors and IoT systems (Smith 2020; Wolfert et al. 2017). In a digitally enabled agriculture system, sensors are our eyes and ears, collecting data by measuring environment, soil, plant, and animal parameters. Internet of Things (IoT) technologies provide real-time connectivity to all digitally enabled components of a farm, linking sensors to farm models, and models to actions. Figure 1 shows some examples of sensor and measurement systems in a digital agriculture environment, collecting digital farm data, from on-farm and on-animal sensors.

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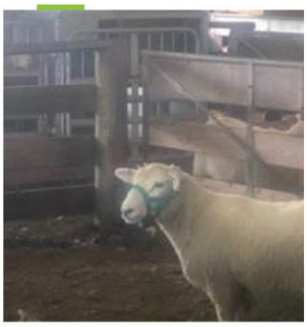

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Figure 1. Examples of sensors used in a digital agriculture system: a) on-farm monitoring systems; b) on-animal urine nitrogen measurement; c) on-animal sheep-behaviour sensing system; d) on-animal cattle-behaviour sensing system; (source: AgResearch NZBIDA programme).

Data generated by on-farm and on-animal sensors are used in different farm simulation models to answer key research challenges. For example, Figure 2 shows a dairy cow equipped with a range of sensors, such as: a Global Navigation Satellite System (GNSS) collar, inertial measurement unit (IMU) motion sensors, urine nitrogen measurement sensors, and sensors measuring and collecting animal movement information. The information collected can be processed to answer key research challenges, such as animal behaviour and welfare, animal and farm production, nitrogen leaching, etc.

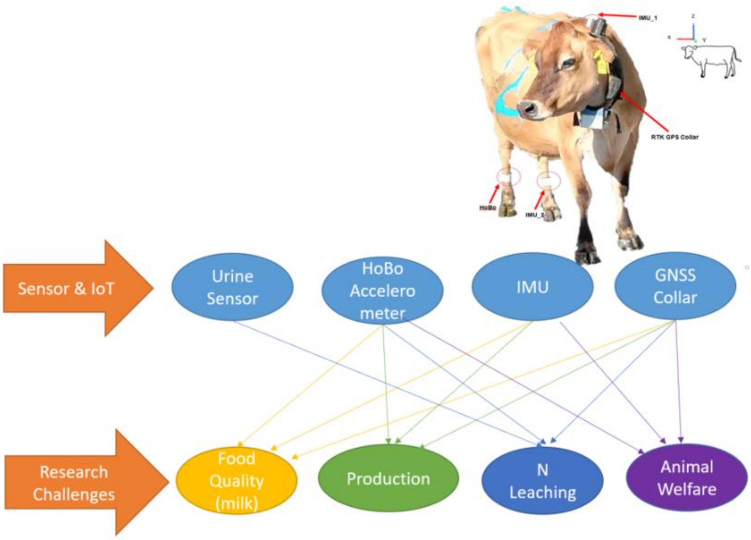

Figure 2. An example on-animal measurement system with the data collected being used to answer different research challenges.

As sensors and big data become more ubiquitous, information derived from these sources are increasingly incorporated into virtual farm (simulation) models. However, regardless of the volume of data available, the models are not perfect representations of real farms, because of various sources of uncertainty associated with the components representing the real farm, such as:

- Uncertainty associated with the sensor data - measurement system,
- Uncertainty associated with the farm models (Meenken, E. D., et al., this volume),
- Social-cultural environment in which decision-making activities occur (Espig, M., et al., this volume).

A lack of clarity about uncertainty can escalate risk in farm decision-making systems. If we acknowledge that every sensor measurement is prone to error, it follows that understanding, assessing, quantifying, managing, and communicating uncertainty is an essential component of agricultural decision-support systems, and continues to be important for decision-making activities based on information derived from disparate data sources and big data sets (M. Shah, et al. this volume). For example, Figure 2 shows an on-animal GNSS collar with integrated IMU that can be used to determine timing and duration of animal grazing (to potentially diagnose illness, quantify intake and feed conversion efficiency) by monitoring the distance travelled and spatio-temporal measurements of the animal movement. Uncertainties associated with the GNSS data lead to uncertainty in the calculated distance travelled, and subsequently to uncertainty in the estimate of animal grazing, which will affect confidence in the farm-decision making system around illness, intake and feed conversion efficiency based on the measurement data derived from the sensors.
In this paper, we briefly review the concept and definition of measurement error, uncertainty, and traceability, followed by a case study discussing the importance of measurement uncertainty analysis. In the final section, final remarks and conclusion are presented.

Measurement Error and Uncertainty

The measurement uncertainty associated with data from a sensor represents doubt about how close the measurement result is to the truth. All measurements are subject to error and hence to uncertainty, i.e. a measurement is never going to produce the exact 'true' value of the quantity of interest (the *measurand*) (B. D. Hall, and D. R. White, 2018). Measurement uncertainty is due to *measurement errors,* which can be classified as either random (aleatory) or systematic. Random errors, or 'noise', can arise from unpredictable spatial or temporal changes that influence the data being generated. Random errors change from one observation to the next. Systematic error, sometimes called 'bias', is an enduring error that is predictable from one observation to the next (Figure 3C). Often, a systematic error is a residual offset, or a scale factor, that remains after the calibration of a measurement system. In general, many measurement influences can lead to errors:

"sensor devices have hardware restrictions and perform data collection in hostile environments turning data more imprecise and uncertain. Moreover, the quality of sensor data is often decreased by sensor failures or malfunctions. Thus, deficiencies on sensor data cannot be ignored, but [must be] tackled in order to reduce information misunderstanding and assist experts in the decision-making process." (Rodriquez & Sevigne, 2013)

In the metrology vernacular (De Bièvre, P. , 2012), error and uncertainty are different things:

- Measurement error is the difference between the measurand and a measured value; an error is never known, but we may know the range of error values that can occur,

- Measurement uncertainty expresses doubt in taking a measurement result as an approximation for the measurand; it may be thought of as expressing the quality of the measurement procedure.

Precision and accuracy are also different:

- Measurement accuracy is how close a measurement is to an accepted value,
- Measurement precision is how close a group of values are to each other; in other words, how repeatable the data is.

Precision of measured data is influenced by random errors. **Random errors** cause data to fluctuate around some mean value and this fluctuation contributes to the uncertainty. The accuracy of a measurement is affected by systematic error. **Systematic error** (Figure 3C) causes measured values to shift to one side; they may be consistently too high or too low, which is why this type of error may be called bias. Systematic errors may be introduced by both measuring instruments and measuring procedures.

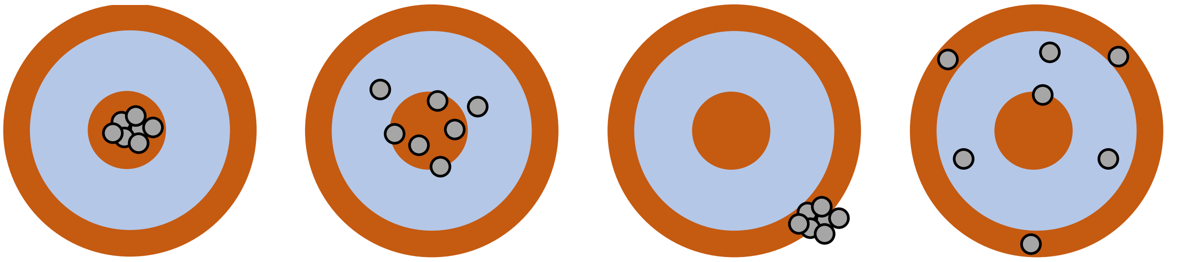

Figure 3. Precision vs. accuracy.

In summary, measurement uncertainty represents information about the lack of exact knowledge of the measurand. Importantly, even after correcting for known systematic errors via calibration, a measurement result is only an estimate of the actual quantity of interest. For decision makers to access as much information as possible, it is clear that a measurement is not complete without providing a statement of uncertainty. In order to provide a complete measurement uncertainty analysis, identifying the sources of uncertainty and contributing factors are very important. A list of key contributors including repeatability, resolution and drift are discussed by (A2LA, R205, 2015).

Case Study - Animal activity and behavioural sensor system

On-animal sensors (such as: **GNSS collars**, motion sensors, 9-axis inertial measurement units (**IMUs**) and **HOBO** accelerometers) have been used to collect animal location and activity data (Pletnyakov et al., 2019). The GNSS receiver and IMU sensor are integrated into an animal collar. The GNSS receiver provides animal location information and the IMU provides animal head movements.

GNSS receivers are typically uncalibrated but, in good conditions (open sky from 15 degrees and above), they can achieve sub-metre precision. GNSS error (noise) is due to satellite cancelations and the triangulation error when estimating the target location in latitude, longitude, and altitude. The noise might increase for a moving object. Besides random error (noise) due to satellite constellation, GNSS receivers also suffer from random noise due to satellite signal multipath errors, through buildings, trees and other objects in the environment. This noise typically produces outlier data, which can be filtered in the data processing stage.

Figure 4: Comparison of noisy (left) and filtered (right) animal location data (Pletnyakov et al., 2019).

In GNSS measurements of spatio-temporal data to estimate animal movement, GNSS random errors, or ‘noise’, is the main contributor to the system uncertainty. Figure 5 shows the GNSS measurement noise when a dairy cow is lying down. Dealing with GNSS noise (and overall measurement uncertainty) is context dependent (M. Espig., et al., see this volume), i.e. it is more critical in defining some behaviours such as animal state in the mob, rather than defining states such as the location of animal in an expected paddock. However, other factors such as operational constraints (sampling intervals, battery power, memory size, unit failure, etc.) can also contribute to the measurement system uncertainty.

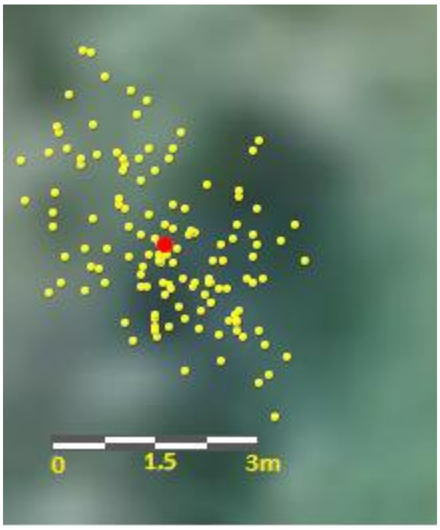

Figure 5. GPS noise while lying down while ruminating (yellow) at a fixed location. The mean estimated position is shown in red (Pletnyakov, et al., 2019).

On the other hand, each **IMU requires calibration** of a 3-axis magnetometer/angle (soft and hard iron bias) and a 3-axis acceleration bias. GNSS receivers are the less certain (precise) sensors in comparison to IMU, due to the dynamic environment. Multi-sensor data integration is used to mitigate uncertainty contributions from the GNSS receivers with more certain data from IMUs by filtering the noisy data.

Potential sources of measurement uncertainty in these sensors are:

- uncertainty from random errors in GNSS receiver and IMU measurement,
- uncertainty from random errors caused by environment such as signal multipathing,
- uncertainty from IMU calibration process,
- uncertainty from performance/stability of the sensors and their failure rate,
- uncertainty from the ways data is collected and integrated from disparate sources,
- uncertainty from the IoT aspect of the sensors, e.g. wireless communication, data transfer, battery life, etc.

An uncertainty assessment of animal activity and the behavioural sensor system would provide a quality assessment of the information generated for farm decision making processes such as more accurately identification of animals that are sick, immobile or in another paddock (animal welfare). Therefore, it is important to identify, evaluate, and communicate the overall system measurement uncertainty caused by the influencing factors as mentioned above.

Measurement Traceability

According to the GUM, metrological traceability is:

> *"The property of a measurement result whereby the result can be related to a reference through a documented unbroken chain of calibrations, each contributing to the measurement uncertainty"*.

Through measurement traceability, the accuracy of a measurement can be determined by properly accounting for contributing errors. Traceability implies a framework to identify, evaluate, and propagate uncertainties associated with a measurement system. The following steps summarizing the framework by GUM as explored (Sajid, Muhammad Jawad, et al. 2020):

1. Definition of the measurand and input quantities,
2. Modeling the measurement process, sensitivity analysis, developing an uncertainty budget,
3. Evaluating estimates of the input quantities and propagating the uncertainties in those estimates through the measurement model,
4. Reporting the measurement result and the associated measurement uncertainty.

Figure 6 represents the measurement uncertainty framework to conduct measurement traceability.

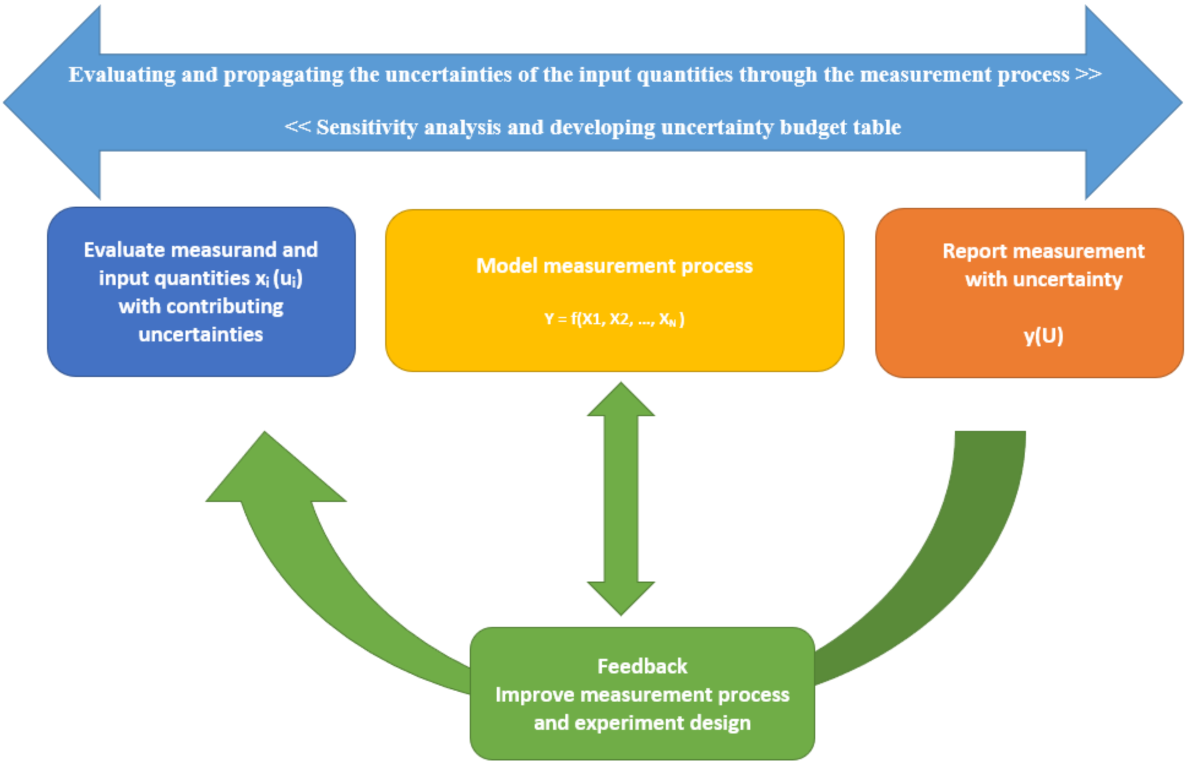

Figure 6. GUM measurement uncertainty framework.

There are software tools that can facilitate the implementation of such a traceability framework. The GUM Tree Calculator (GTC), developed by the Measurement Standards Laboratory of New Zealand, is a data processing tool with full support for processing measurement data and associated uncertainties for real-valued and complex-valued quantities. GTC is provided as a Python package (https://github.com/MSLNZ/GTC).

Conclusion

In a digitally enabled agriculture system, a potential farmer actions are made possible by simulation models relying on sensor measurement data. No matter how carefully these measurements are performed, there will always be some uncertainty in the results due to several sources of error. No statement of measurement results is complete without an assessment of the measurement quality/uncertainty to express the confidence in the generated measurement data. Carrying out an evaluation of the measurement uncertainty is essential to a) enable risk assessment in farm decision making; b) standardised and improved practices in experiment design, sensor calibration, test and validation processes; c) identifying factors and drivers in decision making systems.

Developing a measurement uncertainty framework enables identification of uncertainty sources, evaluation and propagation of uncertainties, and visualisation of uncertainties. Thus, such a framework improves study design (a fit for purpose experimental design) by:

- Determining and communicating measurement uncertainty,
- Enabling comparisons of the contribution to uncertainty of each sensor,
- Prioritising improvements for experimental design,
- Allowing an assessment of the suitability of sensor data to a study's objectives.

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