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Evaluation of the IceTag leg sensor and its derivative models to predict behaviour, using beef cattle on rangeland

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HIGHLIGHTS

- The IceRobotics IceTag leg sensor was used to predict animal behaviour on rangeland.
- Behaviour was coded from about 300 video observations of 5-min duration.
- IceTag outputs for step counts and upright versus lying positions were reliable.
- The primary problem was misclassification of true grazing as resting or standing.
- Pedometry is not the best means to predict behaviour if primary interest is grazing.

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ABSTRACT

Background: There is interest in using animal-mounted sensors to provide the detailed timeline of domesticated ruminant behaviour on rangelands.
New method: Working with beef cattle, we evaluated the pedometer-like IceTag device (IceRobotics, Edinburgh, Scotland) that records step events, leg movement and body position (upright versus lying). We used partition analysis to compare behaviour as inferred from the device data with true behaviour as coded at high resolution from carefully synchronized video observations of 5-min duration.
Results: Malfunctions reduced the target dataset by 7%. The correspondence between IceTag and video-coded step counts was excellent ($r^2 = 0.97$), and the device's indications of upright or lying corresponded well (error rate = 1.4%) to the video-coded values. However, the proportion of steps that could be matched individually was relatively low (65% at a tolerance of 0.5 s), and the indicated start of a lying bout was often triggered by leg movements of an upright animal. Partition analysis of Grazing versus Not-Grazing yielded an overall error rate of 22%. In both three- and four-way classifications of behaviour (Graze, Rest, Travel; Graze, Stand, Lie, Travel) error rates were low for non-graze behaviours, but only 25% of Graze observations were correctly classified; the overall error rate was 22%.
Comparison with existing method(s): The IceTag device performed well in mapping the diurnal patterns of animal position and step rate, but less well in separating grazing from upright resting.
Conclusions: Our results suggest that pedometry is not the ideal method for classifying behaviour when grazing is of paramount interest.

1. Introduction

Grazing by domesticated herbivores impacts one-quarter of the land surface area of our planet (FAO, 2014; Lund, 2007) but, nevertheless, quantifying herbage consumption by these animals remains notoriously difficult. There is no method of measuring intake of grazing herbivores that is easy, affordable, and accurate. This imposes a cost on society, in terms of unrealized potential in management of both the vegetation and the animals. Technologies that monitor behaviours related to intake rate aim to alleviate

Abbreviations: AVCHD, advanced video coding high definition; CSV, comma-separated values; IT_{LIE}, IceTag device time in lying state, s; IT_{MI}, IceTag device motion index; IT_{SLB}, IceTag device indicator for start of lying bout; IT_{SLB10}, computed indicator for start of lying bout of duration >10 s; IT_{SLB60}, computed indicator for start of lying bout of duration >60 s; IT_{UPR}, IceTag device time in standing state, s; IT_{STEPS}, IceTag device step number; MTS, type of file extension; SD, standard deviation; SE, standard error.

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this problem of measurement. To the extent that grazing behaviour responds to changes in the quantity and quality of herbage on offer (Gregorini et al., 2006), monitoring key aspects of grazing behaviour should make it possible to indirectly track changes in the herbage and to use that information in decision making. Changes in animal behaviour could also indicate changes in their physiological and health status (Kokin et al., 2014; Thomsen et al., 2012), especially in the context of precision livestock farming (Nadimi et al., 2012).

Various studies have examined the relationship between animal behaviour and the information received from various monitoring devices (Moreau et al., 2009; Turner et al., 2000; Umstätter et al., 2008; Ungar et al., 2005, 2011), but the most suitable type of sensor and the level of precision that can be attained remain open to question. The challenge is to reconcile what technology *enables* us to measure with what we would really *like* to measure. A well-trodden path in terms of the technology is the use of accelerometer-based leg sensors that serve as pedometers and that also might quantify other aspects of leg movement. Leg sensors have been used for many years in intensively managed dairy cattle herds, primarily for oestrus detection (Alsaaod et al., 2015; Firk et al., 2002; Silper et al., 2015). These sensors use algorithms to identify specific types of movement from raw accelerometer signals. Our present approach was to build on these foundations and infer behaviour of cattle on rangeland from the output of a leg sensor that is relatively sophisticated in the context of animal-borne devices.

The inferential strength of deriving behaviour from the output variables can be quantified by using synchronized behavioural observations and a classification system. The simplest and most important classification distinguishes between grazing and not grazing. At the next level of detail, behaviour when not grazing can be subdivided into resting and travelling (walking without grazing). Resting itself can be subdivided into resting while upright (standing) and resting while lying down. Standing, too, can be subdivided into standing still, without taking steps, and standing with occasional leg movements (loitering). Grazing can be subdivided into active grazing, characterized by a strong, uninterrupted rhythm of jaw movements, and snacking, characterized by a weak, diffuse rhythm of jaw movements. In this overall scheme, activities such as drinking, grooming and socializing (see Table 2 in Kilgour et al., 2012) would be subsumed into resting.

We worked with the commercially available IceTag leg sensor (IceRobotics, Edinburgh, Scotland, UK), which stores data at a time resolution of 1 s. It was found to be reliable in determination of lying time (McGowan et al., 2007) and in distinguishing between walking and standing (Nielsen et al., 2010). Nielsen et al. (2010) also found the IceTag device reliable in counting steps, but their trial was conducted under controlled conditions in which the cows were led, and in which the animals were induced to raise a leg within an enclosed area. We are not aware of a validation study in which the IceTag device was deployed on animals on rangeland over a significant time period, and in which the synchrony between IceTag data and observed timelines of step actions was evaluated. There was also a need to evaluate the precision of the internal clock of the pedometer, which is important when merging pedometer data with other time-marked data sources.

Our objectives were: (1) to evaluate the quality of the leg sensor output by comparison with synchronized observations; (2) to derive equations for inferring animal behaviour from leg sensor output; and (3) apply the equations to a large database to obtain estimates of daily grazing time.

2. Materials and methods

2.1. Study site

The study was conducted on rangeland of kibbutz Ein HaShofet, in the region of Ramot Menashe, south of Mt. Carmel, Israel. The climate is Mediterranean with hot, dry summers and cool, rainy winters, with mean annual rainfall of 600 mm. The rolling-hill topography has a mean altitude of 300 m above sea level and the rangeland vegetation is primarily herbaceous, with some patches of low shrubs. Two rangeland paddocks were reserved for this study: paddock 1 (8.5 ha centred at 32.595° N, 35.107° E; WGS1984) and paddock 2 (28.0 ha centred at 32.604° N, 35.093° E). Both were of prevailing southerly aspect with moderate slopes of 3–7%, and were equipped with water and supplementary feeding troughs, and with access to separate animal-handling facilities.

2.2. Animals and their management

The experiments were approved by the Animal Experimentation Ethics Committee of the Agricultural Research Organization (ARO) (approval IL 385/12). The experimental animals were mature cows of mixed breeds drawn from a beef cattle herd of 800 cows, representing various crosses of Simmental, Charolais, Limousin, Nelore, Droughtmaster, and Norwegian Red breeds. In general, the herd commences grazing approximately one month after the emergence of vegetation, which is triggered by the first major rains of the hydrological cycle. There is a primary (August to October) and a secondary (January to March) calving season; the calves remain with their mothers on the rangeland until weaning at an age of 6–8 months. Cows to be fitted with leg sensors were randomly selected from the herd, but with the proviso that they should be of similar sizes and should not respond temperamentally when handled. Average (±SD) live weight and age of the selected animals were 517 ± 88 kg and 64 ± 37 months, respectively.

2.3. IceTag leg sensor

We used the IceTag leg sensor (IceRobotics, Edinburgh, Scotland, UK), which is a pedometer-like device designed for research. Although developed originally for deployment on dairy cattle, the device has since been used on beef cattle (MacKay et al., 2013; Szyszka et al., 2013) and other animals (Askar et al., 2013; Parsons et al., 2015). The device measures 95.0 × 82.3 × 31.5 mm, and weighs 130 g; it contains a tri-axial accelerometer operating at a sampling rate of 16 Hz. The device stores information with a time

Table 1
Confusion matrix for the time spent in the upright and lying states, as indicated by the IceTag device and as coded from video observations. Correct shows the proportion of observations that were correctly classified ("sensitivity").

		Observed animal state					
		Upright		Lying		Total	
		Seconds	%	Seconds	%	seconds	%
IceTag animal state	Upright	56050	68.4	18	0.0	56068	68.5
	Lying	1120	1.4	24706	30.2	25826	31.5
	Total	57170	69.8	24724	30.2	81894	100.0
	Correct (%)	98		99			

resolution of 1 s and has sufficient internal memory to store 60 days of data. The internal battery has an expected operating lifetime of 2 years; it can be neither recharged nor replaced.

Prior to installation on an animal, the IceTag device is activated and configured via a wireless communication device controlled by the IceManager software program. On activation the IceTag synchronizes its internal clock to that of the computer running the program, which in our case had been synchronized manually, and as precisely as possible (within 0.1 s), to an official online clock. The same hardware and software are used to download the stored data after the device has been retrieved from the animal. The IceManager program processes the downloaded raw data and generates an exportable, CSV-format data file at a user-selected time resolution of between 1 s and 1 week. The variables provided are (IceTag-provided name; and our abbreviation): Date, Time, Motion Index (a proprietary metric of the overall leg activity as measured in three dimensions; IT_{MI}), Standing (indicates whether the animal is upright (1) or not (0); IT_{UPR}), Lying (indicates whether the animal is lying down (1) or not (0); IT_{LIE}), Steps (number of steps; almost always 0 or 1; IT_{STEPS}), Lying Bouts (indicates the start of a lying bout; equals 1 when IT_{LIE} changes from 0 to 1, and 0 otherwise; IT_{SLB}).

2.4. Leg sensor deployments

There were four periods of deployment of the leg sensors. Twelve cows in high pregnancy participated in the first deployment, of duration 14 d (27 June through 10 July) in the summer of 2012, conducted in Paddock 1. A different group of 12 cows participated in the subsequent deployments. The latter animals were introduced (without leg sensors) into paddock 2 on 19 Oct. 2012. A bull was introduced 2 days later, at the start of the breeding season. In the winter, spring, and summer of 2013 the animals were fitted with leg sensors for the second (34 d; 4 Jan. through 6 Feb.), third (60 d; 21 Mar. through 20 May), and fourth (23 d; 4 through 26 July) deployments. With some exceptions, each device was allocated to the same cow in these three deployments. The cows were in low, mid and high pregnancy during deployments 2, 3, and 4, respectively; they received *ad libitum* supplementation with poultry litter during the two summer deployments (1 and 4).

The IceTag device was installed on one of the hind limbs, proximal to the fetlock. Because of differences between handling facilities, the device was installed on the animal's right side in the first deployment and on its left side in the other deployments. There is no evidence to suggest that this may have influenced the results (Gibbons et al., 2012).

2.5. Video observations

Video recordings of animal behaviour were collected in order to derive from them a detailed description of behaviour, timed manually as precisely as possible, to serve in validation of leg sensor data and model construction. Approximately 300 recordings were collected in the course of 4, 3, and 2 days of the first, third, and fourth deployments, respectively. Overall, almost every hour of the day was represented in the recordings, with the largest concentration falling between 1600 h and 2000 h, which would include one of the main grazing bouts of the day. The animals acclimated quickly to the presence of the observer. We used an HC-X990 M camcorder (Panasonic, Bracknell, UK) with a 64 GB memory card, recording in AVCHD 1080/50p format (with MTS file extension). Each video segment lasted just over 5 min and focused on one cow. As much as possible observations were spread over the entire group, but the order of cow selection was fairly random. We considered that longer durations of observation raised the risks of operator fatigue in the hot summer months, and of not being able to track the animal during the entire observation. While recording, the observer endeavoured to stand to the side and slightly to the rear of the animal at a distance of 5–10 m, although the distance could increase during sustained travel by the cow. Care was taken to include both the head and the rear legs in the images. Nine video recordings captured a number of resting cows together in the frame.

At the start of each recording, with the aid of a manually synchronized digital watch (within 0.1 s), the observer announced the exact time (hh:mm:ss) at which the core 5-min observation would start, followed by "now" at precisely that moment. The recordings were terminated a few seconds after 5 min had elapsed from that moment.

2.6. Analysis of the video observations

The 5-min video observations were coded in two ways, as described in Sections 2.7 and 2.8, by using a simple, keystroke-operated macro. In both cases a coding session commenced with transcription of the exact starting time, as announced on the soundtrack. The "start" keystroke was pressed on hearing "now", and other keys were then used to record the target actions until the end of the observation. The final output of the macro comprised a list of timestamps and associated actions that occurred during the observation. The analysis of the nine "group" video recordings was repeated for each focal animal.

2.7. Step coding

Step coding served to validate steps recorded by the IceTag sensor, at the resolution of the individual step, and as part of the data used to construct the behavioural timeline. Every gross movement of the leg wearing the IceTag sensor was timestamped and annotated with a code. The keystroke was performed as the hoof touched the ground at the end of the swing phase, giving ample time for the operator reaction and a small, consistent lag. Leg movements were annotated as: (1) full step, in which the backward-extended rear leg was lifted, swung and positioned in the forward-extended position for the support phase of the stride cycle; (2) non-locomotor leg movement, in which the vertical rear leg (in the support phase) was raised close to the abdomen and lowered again without the animal moving forward; (3) rearward movement, in which the vertical rear leg was moved into the backward-extended position; (4) side movement, in which the vertical rear leg was moved sideways, usually to improve balance; (5) full step with raise, in which, during the swing phase of a full step, the leg was raised close to the abdomen; (6) half-step, in which the backward-extended rear leg was lifted, swung and positioned in the vertical position; (7) half-step with raise; and (8) other. All step coding was performed by the same person.

2.8. Animal-state coding

When viewed at a temporal resolution of <1 s, the precise timing of a transition from one behavioural category to another is not always clear-cut, which makes it difficult to code a video in real time in terms of the behavioural categories defined earlier. The timing is also a matter of definition: for how long must a change be sustained in order for it to be registered? To overcome these problems, we used a simple coding system for animal-state transitions that could subsequently be combined with the step coding to define each behavioural category. The following four transitions were coded: to lying; to upright with head up (equated with not grazing); to upright with head down (equated with grazing); to unknown (animal state could not be determined). All animal-state coding was performed by the same person.

Table 2
Analysis of variance of the five IceTag variables for the three classification systems of animal behaviour.

Classes	Model P/Factor	IT_{UPR} (s)	IT_{LIE} (s)	IT_{MI}	IT_{STEPS}	IT_{SLB}
2	Model P	<0.0001	<0.0001	0.0283	0.0022	<0.0001
	Grazing	290 a	10 b	86 a	22 a	1.4 a
	Not grazing	171 b	129 a	50 b	12 b	0.3 b
3	Model P	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
	Graze	290 a	10 b	86 b	22 b	1.4 a
	Rest	168 b	132 a	33 c	9 c	0.3 b
	Travel	299 ab	1 ab	823 a	158 a	1.0 ab
4	Model P	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
	Graze	290 a	10 b	86 b	22 b	1.4 a
	Stand	288 a	12 b	57 c	15 c	0.6 b
	Lie	9 b	291 a	2 d	0.2 d	0.0 c
	Travel	299 a	1 b	823 a	158 a	1.0 abc

2.9. Definition and derivation of behaviours

The coded records of steps and of animal states were merged so that each time segment spent in a particular state was associated with the corresponding number of steps and step rate. The following criteria, containing six thresholds, were then used to define the behaviour for each segment (see Supplementary Material, Table 1). A segment labelled "unknown" or "lying" retained that definition as the behaviour. A segment labelled "upright with head up" that lasted more than T1 s and had a step rate greater than T2 was recorded as Travel. A segment labelled "upright with head up" that lasted more than T3 s and had a step rate no greater than T6 was recorded as Standing Still. A segment labelled "upright with head up" that lasted more than T4 s and had a step rate greater than T6 was recorded as Loitering. A segment labelled "upright with head down" that lasted more than T5 s was recorded as Active Grazing. If a segment labelled "upright with head down" lasted no more than T5 s it was recorded as Snacking. Any remaining segments were designated Undefined.

Sensitivity analysis was performed by comparing seven combinations of the threshold values (see Supplementary material, Table 1). Within this parameter space the proportion of observation time allocated to each behaviour did not change at all for Active Grazing, Snacking, Lying, or Undefined; it changed by a few percentage points, at most, for the other behaviours. The values of combination 2 in Supplementary material Table 1 were selected at the standard values to be used by the algorithm. The frequency distribution of segment-level behaviours is shown in Supplementary material, Table 2.

Having selected and applied a set of threshold values by which to define behaviour, we assigned to each video observation the one behaviour to which the animal allocated the most time. For the two-way classification of behaviour, i.e. Grazing versus Not-Grazing, segments defined as Active Grazing or Snacking were merged under the Grazing classification, and all other segments, other than Undefined and Unknown, were merged into Not Grazing. For the three-way classification of behaviour (Graze-Rest-Travel), Grazing was defined as above; segments defined as Lying, Standing Still and Loitering were merged into Rest; segments defined as Travelling were simply merged. The four-way classification of behaviour (Graze, Stand, Lie, Travel; Graze-Stand-Lie-Travel) was the same as Graze-Rest-Travel except that segments defined as Standing Still and Loitering were merged as Stand, and segments defined as Lying were simply merged. For the six-way classification of behaviour, the initial, detailed classification of behaviour was retained, and the respective segments were simply merged.

2.10. Processing of leg sensor data

Data were downloaded from each IceTag device at the highest time resolution of 1 s, and the identity of the device and the deployment number were added. All variables were screened for inconsistencies and suspect values. We computed two variables on the basis of the start-of-lying-bout indicator (IT_{SLB}) and the lying indicator (IT_{LIE}): start-of-lying-bout indicator for a lying bout longer than 10 s (IT_{SLB10}) or 60 s (IT_{SLB60}). Using a 3-day subsample from each IceTag and deployment, we derived the effects of time (seconds) relative to the registration of a step event on mean IT_{MI} and on the probability of a non-zero IT_{MI}. All processing of original IceTag data files was performed with SAS 9.4 software (SAS Institute Inc., Cary, NC, USA).

2.11. Correction for clock drift of leg sensor

In order to determine the internal clock drift, each device was shaken vigorously for 3 s – once prior to deployment on the animal and again after retrieval from the animal. The exact time of shaking was noted. The shakings showed up clearly and unmistakably in the motion index (IT_{MI}), and the IceTag times corresponding to the start of the 3-s shakes were noted. The correction factor was then defined as the ratio between the true and the IceTag time differences between the initial and terminal shakings. To convert any IceTag time to true time, the IceTag time that had elapsed since the first shaking was multiplied by the correction factor to yield the true time that had elapsed, and this was added to the true time of the first shaking. Since the time resolution of the device was 1 s, the correction expressed itself in the data as occasional repeats of the same time, or occasional 1-s skips. Care was taken to account correctly for transitions between winter and summer times.

2.12. Validation of step number and timing

The IceTag records corresponding precisely (within 1 s) to the 5-min core of each video observation were extracted. The total step number registered by the IceTag device in the course of a 5-min observation was compared with the corresponding true number. For a more rigorous validation, we compared the IceTag timeline of step events with the corresponding timeline that was manually coded from the video observation. An existing program (Ungar and Rutter, 2006) was used to match the two timelines of events. The first phase of the analysis fine-tuned the alignment of the two timelines to account for possible lags, and this was performed for each observation independently. In the second phase of the analysis, following alignment, a pair of events was deemed to match if their time difference was within a defined tolerance, subject to no event being matched more than once. The number of matching events, expressed as a proportion of the number of manually coded steps, was calculated for tolerances of 0.1 through 0.5 s.

2.13. Validation of upright versus lying positions

The two IceTag variables related to being in the upright or the lying position provide animal position directly. The corresponding observed timeline of animal position was derived from manually coded transitions between lying and any other state. We generated the confusion matrix for animal state after merging the timelines at a resolution of 1 s.

2.14. Statistical analysis

Based on an earlier study (Ungar et al., 2011), classification and regression tree (CART) analysis was employed to infer cow behaviour from IceTag data. This approach is well suited to naturally unbalanced data sets such as our present set, in which the proportion of time allocated to different behaviours may vary greatly (Han et al., 2011). The Partition platform of the statistical software JMP, Version 12.0.1 (SAS Institute Inc., Cary, NC, USA), was used to generate a decision tree comprising a series of binary splits, each determined by one of the candidate IceTag (or derived) variables in the model, all defined as 5-min totals: IT_{MI}, IT_{UPR}, IT_{LIE}, IT_{STEPS}, IT_{SLB}, IT_{SLB10}, and IT_{SLB60}. The splitting process was constrained by the stopping rule of *k*-fold cross-validation, but we invariably "pruned" the decision tree to a parsimonious model of relatively few splits without major sacrifice in quality of prediction. At each node on the tree the predicted behaviour was that with the highest computed probability. Decision trees were generated for the 2-, 3-, and 4-way classifications of behaviour. Default parameter settings of the Partition platform were used, except for 2-way classification; here the number of instances of each behaviour enabled us to increase the minimum size split to 15. The model predictions were summarized in a confusion matrix from which we computed the error rates for each behaviour and overall. We defined the bias as the absolute difference between the number of misclassified events above and below the observed = expected diagonal of the confusion matrix, expressed relative to the total number of events.

For leg sensors that provide data at a high temporal resolution, one can envisage two approaches to deriving the behavioural timeline. The first is based on change detection; it seeks to identify the transition point between behaviours. The second is based on a fixed-window approach and defines a single behaviour for each time window. Larger windows increase the likelihood of containing more than one behaviour, whereas narrower windows reduce the quantity of data in each sample. The fixed-window approach is simpler computationally and easier in terms of sampling logistics in the field; it was adopted in the present study. Daily grazing time was computed according to each of the derived classification models. First, the entire IceTag database was summarized into 5-min periods; then the above classification models were applied to these values. The results were summarized as grazing time (h/d) for each combination of deployment, IceTag and day, from which means and SEs were computed.

Calculations of clock drift were based on the entire database of IceTag files, from the initial shake prior to installation of the leg sensor on the animal and until the terminal shake after removal. The overview of IceTag data presented in Results (Section 3.2), as well as the temporal patterns of IceTag variables (Section 3.5), were based on the entire database of IceTag files, trimmed to comprise complete 24-h (midnight-to-midnight) periods. All other analyses were based on files containing data for the 5-min segments of the video observations.

3. Results

3.1. Clock drift of leg sensor

The absolute magnitude of the clock error ranged from 0.98 to 2.18 s/day ($n = 41$). Correction factor values >1, i.e., internal clock running slow, occurred in approximately equal proportion to those <1, i.e., clock running fast. In most instances, a given leg sensor generated similar estimated clock errors in all deployments.

3.2. Overview of leg sensor data

In deployment 1 (27 June through 10 July 2012) we obtained complete sets of data from 10 leg sensors; data from two devices were excluded because those sensors had been attached incorrectly to the cows' legs. In deployment 2 (4 Jan. through 6 Feb. 2013) we obtained complete sets of data from 11 leg sensors, but only 7 days of data from one device before it malfunctioned. In deployment 3 (21 Mar. through 20 May 2013) we obtained complete sets of data from eight leg sensors; one sensor became detached from the animal after yielding data for 1 week; a second yielded erroneous data (no standing or steps, and out-of-range values for IT_{MI}) for the first 60 h of operation, whose data were deleted; a third yielded erroneous data, which were also deleted, for 20 h of operation in April; data from a fourth sensor were discarded because its values for Standing and Lying were clearly erroneous. In deployment 4 (3 through 7 July 2013) we obtained complete sets of data from 10 leg sensors; one sensor malfunctioned for 60 h in July and another was not deployed because of an earlier malfunction. The total number of records after the above exclusions and deletions was 119.6 million, comprising 11.5, 32.6, 52.2, and 23.3 million from deployments 1, 2, 3, and 4, respectively. Overall, malfunctions caused a 7% data loss.

The IceTag data showed basic logical consistency: (i) IT_{UPR} was equal to 1 when IT_{LIE} was equal to 0, and vice versa; (ii) IT_{STEPS} was almost always equal to 0 when IT_{LIE} was equal to 1 (or IT_{UPR} was equal to 0); (iii) IT_{SLB} took a value of 1 at the moment IT_{LIE} transitioned from 0 to 1, and otherwise was 0; (iv) when $IT_{LIE} = 1$, IT_{MI} was almost always 0. The vast majority (94%) of IT_{MI} values were 0; of the non-zero values, 90% were in the range 1–5, followed by a long tail that reached 75. The IceTag variable IT_{STEPS} showing the number of steps registered in 1 s could take values of 0, 1, 2 or 3, which occurred in 96.1, 3.8, <0.1 and «0.1% of records, respectively.

Step registration and IT_{MI} showed weak correspondence at the 1-s resolution: 49% of non-zero IT_{MI} values corresponded to a step registration and 32% of them to zero IT_{MI}. Nevertheless, IT_{MI} was related clearly to the registration of step events; mean IT_{MI} was elevated at the time of step registration and 1 s previously (Fig. 1). The relationship between ΣIT_{MI} and ΣIT_{STEPS} was weak within a narrow time window of several seconds, but strengthened considerably as the time window was extended to several minutes.

A total of 302,394 lying bouts were identified, of which 42% were of 1-s duration and could not be true lying bouts. The frequency distribution of bout duration did not yield a clear threshold by which to separate true from false lying bouts; however, use of a threshold of 1 min eliminated 95% of bouts, which accounted for only 3% of total lying time.

3.3. Validation of number of steps and their timing

At the 5-min time scale, there was broad correspondence between the number of steps (of any type) observed and manually coded, on the one hand, and the number of steps registered by the IceTag device ($n = 280$), on the other hand. When the observed step

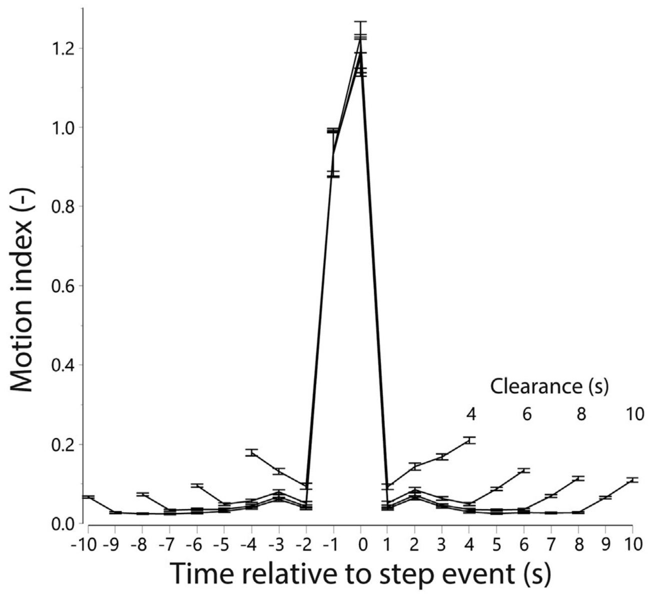

Fig. 1. Mean IceTag Motion Index value (IT_{MI}) at a 1-s time resolution as a function of the time offset relative to the registration of a step. Time offset = 0 at step registration; negative values are prior to step registration; positive values are subsequent to step registration. Based on a 3-day sample from each IceTag device during each deployment. Error bars show ±1 SE of mean of deployment × IceTag device × offset means. Clearance is minimum number of seconds that contain no steps on each side of the step event. Mean motion index increases at the extremities of the curves because of the effect of neighbouring step events.

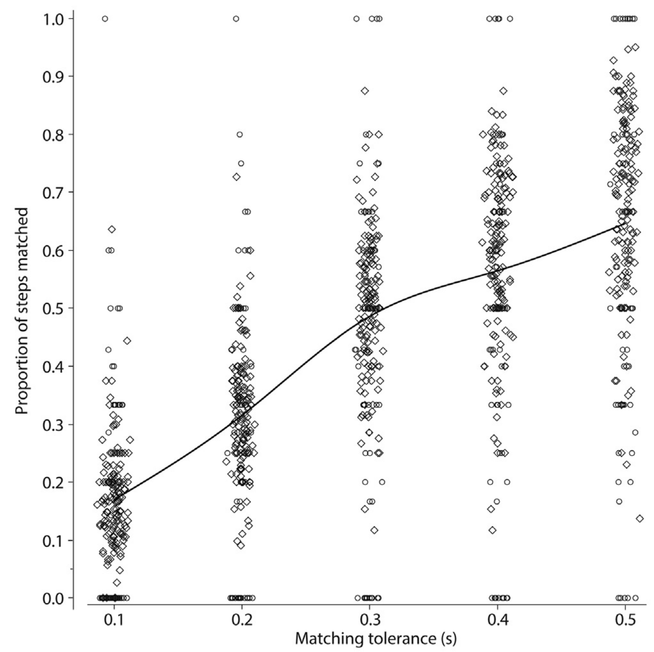

Fig. 3. The proportion of video-coded steps that were deemed to match with IceTag step events within the matching tolerance. The matching tolerance is the maximum permitted time difference between an observed and an IceTag step. Each point represents a 5-min video observation during which there was at least one step. Points are jittered to reduce overlap. Circle: Observations with <8 observed steps; diamond: observations with at least 8 steps. Line passes through means.

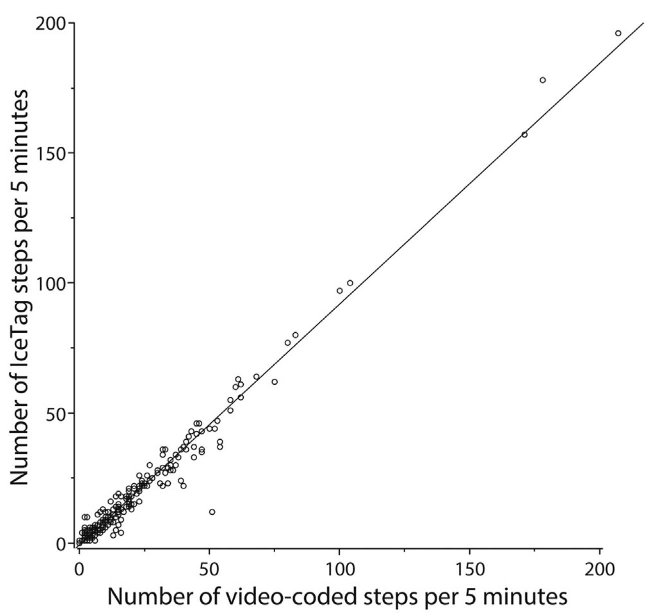

Fig. 2. Relationship between the number of steps coded from video analysis and the number of steps registered by the IceTag pedometer during a 5-min observation. Each point represents one 5-min video observation. Line shows linear fit.

number was zero, the corresponding IceTag value almost always was also zero. Regression of IceTag records against observed step numbers (range 0–207) yielded a strong, positive relationship that accounted for 97% of the variation (Fig. 2). Exclusion of 75 [0,0] data pairs had a negligible effect on the regression line; the average deviation of IceTag step number from the observed value was 1.9; it ranged from −8 through +39, with interquartile range = 3.

The first task in comparing the IceTag and video-coded timelines of step events was to bring the two timelines into general alignment, for each observation separately. The average time offset required to achieve this was 0.52 s; it ranged from −2.2 through 1.6 s (n = 205). Following alignment, the proportion of IceTag and video-coded step events that were deemed to match depended strongly on the maximum permitted time difference between an observation and an IceTag event (Fig. 3); use of a strict threshold of 0.1 s resulted in matching of only 17% of observed step events, on average; this rose steeply to 49% at 0.3 s, and less steeply to 65% at 0.5 s. Use of greater thresholds would be highly unlikely to yield true matches.

A total of 5194 step events were observed and coded, of which about 95% were classified as full steps, as defined in Section 2.7. Non-locomotor leg movements and rearward movements each accounted for less than 2%, and each of the remaining step types for less than 1%. On the whole, the seven irregular types of leg movement defined in Section 2.7 could be matched with IceTag step events. The proportion of leg movements that could not be matched was 19% for non-locomotor leg movements and 33% for rearward movements. About a quarter of the leg movements of other irregular types could not be matched.

3.4. Validation of upright versus lying states

Animal state (upright versus lying) as determined by the IceTag device corresponded well to animal state as determined by video-based observation and coding (Table 1): the overall error rate was 1.4%. This was almost entirely due to true upright being registered as lying by the IceTag; the error rate was zero for 197 of the 280 5-min observations that were analyzed. There were 73 sessions in which the animal was observed to be lying down throughout the observation; the error rate in all these observations was zero. Of the 188 observations in which the animal was observed to be upright throughout, 121 had an error rate of zero, a further 27 had an error rate of no more than 1%, i.e., 3 s out of a 300-s observation. There were 18 observations with error rates of 1–5%, and eight with error rates of 5–10%. The error rates of the remaining 14 observations

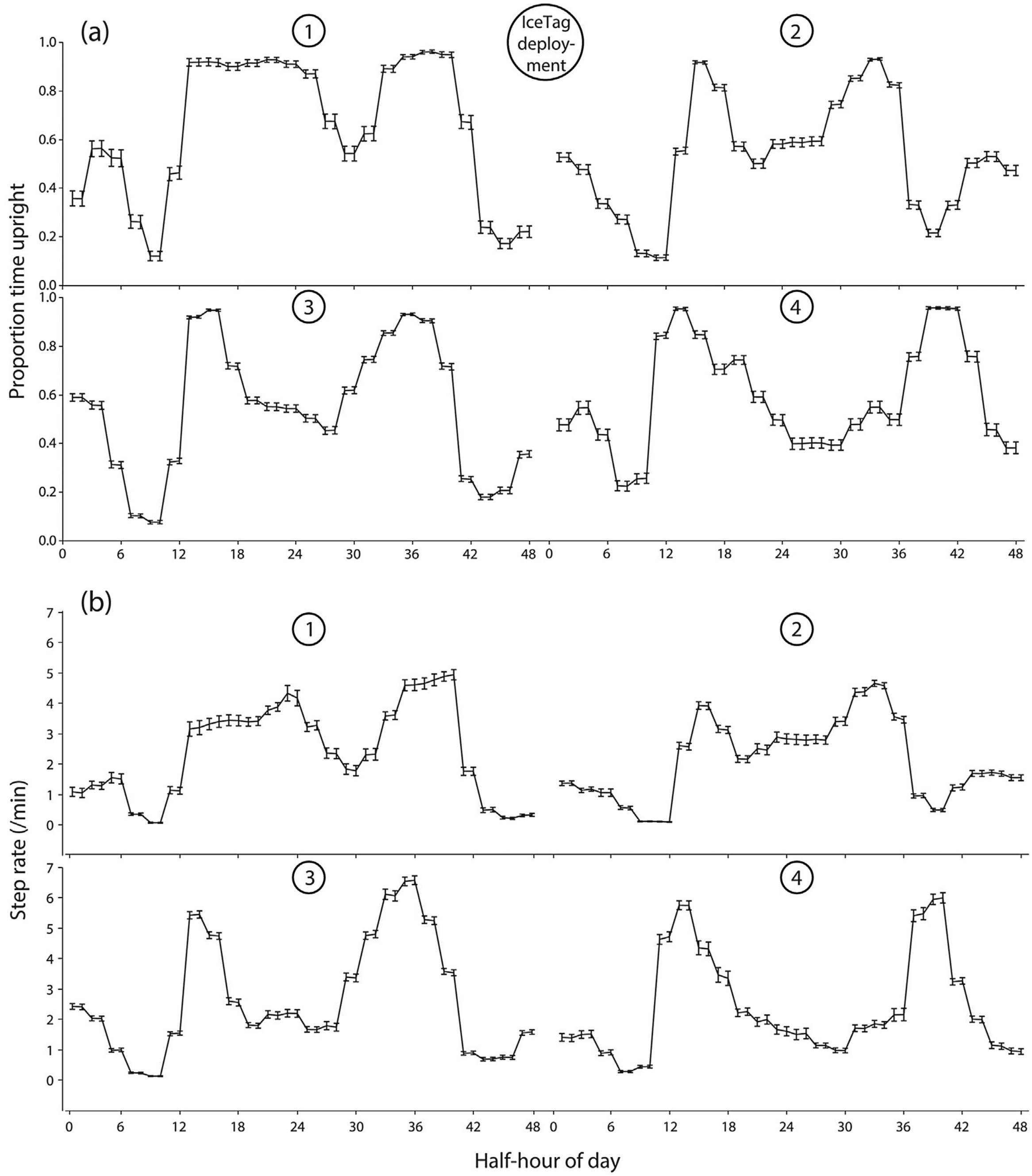

Fig. 4. The diurnal patterns of (a) proportion of time spent upright and (b) step rate, for each IceTag deployment, as determined from IceTag data. Error bars show ±1 SE of mean of animal-day values. The deployments occurred in different seasons of the year: summer, winter, spring and summer for deployments 1, 2, 3 and 4, respectively, and deployment 1 was conducted with a different group of animals from that used in the other deployments.

ranged from 10 to 31%; nine of these 14 observations involved two IceTag devices.

3.5. Temporal patterns of upright versus lying states and stepping

A basic feature of animal behaviour that can be determined reliably by the IceTag device is the division of time between the upright and the lying states. The daily time spent upright ranged from 6.9 through 22.4 h and averaged 15.5, 12.7, 13.0 and 14.1 h in deployments 1 through 4, respectively. The daily step number ranged from 1300 through 6553, and averaged 3444, 3048, 3803, and 3408 in deployments 1 through 4, respectively. The diurnal pattern of time spent upright for each deployment is shown in Fig. 4a. In all deployments there was a trimodal pattern of activity (minutes upright per half-hour), with main peaks in the early morning and late afternoon, and a minor peak in the middle of the night, as adjusted to match sunrise and sunset times. The variability among animals and days was lowest during the two main peaks of activity. The diurnal pattern of the number of steps registered per half-hour (Fig. 4b) was similar to that for being upright. Step rate in the two main peaks was approximately five steps per minute.

For all subsequent reported analyses, 15 observations for which the total observation time was much less than the planned 5 min were excluded, in order to avoid possible bias.

3.6. Summary of behavioural coding

When behaviour at the 5-min observation level was classified as Grazing or Not-Grazing ($n = 265$), 27% of observations was classified as Grazing and 73% was classified as Not-grazing. For the three-way classification, the proportions of Graze, Rest and Travel observations were 27, 72, and 2%, respectively; these do not sum to 100% because of rounding errors. Interestingly, 83% of the observations classified as Rest comprised only resting, whereas only three "Graze" observations comprised only grazing and one only travelling. All other observations ($n = 117$) comprised mixtures of behaviours (Supplementary material, Fig. 1).

Under the four-way classification, the proportions of Graze, Standing, Lying, and Travel observations were 27, 41, 31, and 2%. Of the observations classified as Standing 60% comprised only Standing, and 89% of those classified as Lying comprised only Lying (Supplementary material, Fig. 2).

Under the most detailed classification, the proportions of Active Graze, Loiter, Lying, Stand, and Travel observations were 28, 39, 31, 1, and 2%, respectively; only two observations were classified as Standing and none was classified as Snacking. Of the observations classified as Loitering, 63% comprised only Loitering, whereas 89% of those classified as Lying comprised only lying (Supplementary material, Fig. 3).

There were just two instances of greater subdivision causing a change to the broad classification of an observation: what was previously classified as No-Graze (2-way) or Rest (3-way) or Stand (4-way) became Active Grazing (6-way).

3.7. Analysis of IceTag variables

Analysis of variance of the IceTag variables in terms of the classes used to define behaviour yielded highly significant results, as would be expected (Table 2). The variables IT_{MI} and IT_{STEPS} separated very clearly according to behaviour in both the 3-way and 4-way classifications.

3.8. Results of partition analysis

Although partition analysis using default stopping criteria produced quite highly branched decision trees, most of the predictive ability was obtained after relatively few splits of the data. We report here the most parsimonious models, which are least likely to suffer from over-fitting.

3.8.1. Grazing versus not-Grazing classification

Partition analysis yielded a decision tree with two splits, which created three partitions, which we summarize in Table 3(i). Note

Table 3

Specification of the partition models to classify behaviour at three levels of detail: Grazing versus Not-Grazing; Graze-Rest-Travel; Graze-Stand-Lie-Travel. Multiple conditions in the same partition must all be fulfilled. Variable definitions: IT_{LIE}: IceTag device time in lying state, s; IT_{MI}: IceTag device motion index; IT_{SLB}: IceTag device indicator for start of lying bout; IT_{SLB60}: computed indicator for start of lying bout of duration >60 s; IT_{UPR}: IceTag device time in standing state, s; IT_{STEPS}: IceTag device step number.

Model	Partition	Criterion	Decision	n	P (%)
(i) Grazing versus Not-Grazing	1	$IT_{MI} < 13$	Not Grazing	108	98
	2	$IT_{MI} \geq 13$, $IT_{SLB} < 2$	Not Grazing	117	64
	3	$IT_{MI} \geq 13$, $IT_{SLB} \geq 2$	Grazing	40	68
(ii) Grazing versus Not-Grazing; IT_{SLB} excluded	1	1. $IT_{MI} < 13$	Not Grazing	108	98
	2	2. $IT_{MI} \geq 13$, $IT_{UPR} < 297$, $IT_{UPR} \geq 252$	Grazing	30	70
	3	3. $IT_{MI} \geq 13$, $IT_{UPR} < 297$, $IT_{UPR} < 252$	Not Grazing	15	73
	4	4. $IT_{MI} \geq 13$, $IT_{UPR} \geq 297$, $IT_{STEPS} < 22$	Not Grazing	71	66
	5	$IT_{MI} \geq 13$, $IT_{UPR} \geq 297$, $IT_{STEPS} \geq 22$, $IT_{MI} \geq 175$	Not Grazing	16	69
	6	$IT_{MI} \geq 13$, $IT_{UPR} \geq 297$, $IT_{STEPS} \geq 22$, $IT_{MI} < 175$	Grazing	25	60
(iii) Graze-Rest-Travel	1	$IT_{MI} < 13$	Rest	108	98
	2	$IT_{MI} \geq 13$, $IT_{MI} \geq 384$	Travel	5	80
	3	$IT_{MI} \geq 13$, $IT_{MI} < 384$, $IT_{SLB} \geq 3$	Graze	23	78
	4	$IT_{MI} \geq 13$, $IT_{MI} < 384$, $IT_{SLB} < 3$	Rest	129	61
(iv) Graze-Rest-Travel; IT_{SLB} excluded	1	$IT_{MI} < 13$	Rest	108	98
	2	$IT_{MI} \geq 13$, $IT_{MI} \geq 384$	Travel	5	80
	3	$IT_{MI} \geq 13$, $IT_{MI} < 384$, $IT_{SLB60} \geq 1$	Rest	10	80
	4	$IT_{MI} \geq 13$, $IT_{MI} < 384$, $IT_{SLB60} < 1$, $IT_{LIE} \geq 6$ s	Graze	29	69
	5	$IT_{MI} \geq 13$, $IT_{MI} < 384$, $IT_{SLB60} < 1$, $IT_{LIE} < 6$ s, $IT_{STEPS} \geq 22$	Graze	41	54
	6	$IT_{MI} \geq 13$, $IT_{MI} < 384$, $IT_{SLB60} < 1$, $IT_{LIE} < 6$ s, $IT_{STEPS} < 22$	Rest	72	67
(v) Graze-Stand-Lie-Travel	1	$IT_{UPR} < 174$ s	Lie	82	100
	2	$IT_{UPR} \geq 174$ s, $IT_{MI} \geq 384$	Travel	5	80
	3	$IT_{UPR} \geq 174$ s, $IT_{MI} < 384$, $IT_{MI} < 13$	Stand	29	93
	4	$IT_{UPR} \geq 174$ s, $IT_{MI} < 384$, $IT_{MI} \geq 13$, $IT_{SLB} \geq 3$	Graze	23	78
	5	$IT_{UPR} \geq 174$ s, $IT_{MI} < 384$, $IT_{MI} \geq 13$, $IT_{SLB} < 3$	Stand	126	60
(vi) Graze-Stand-Lie-Travel; IT_{SLB} excluded	1	$IT_{UPR} < 174$ s	Lie	82	100
	2	$IT_{UPR} \geq 174$ s, $IT_{MI} \geq 384$	Travel	5	80
	3	$IT_{UPR} \geq 174$ s, $IT_{MI} < 384$, $IT_{MI} < 13$	Stand	29	93
	4	$IT_{UPR} \geq 174$ s, $IT_{MI} < 384$, $IT_{MI} \geq 13$, $IT_{LIE} < 6$ s	Stand	113	59
	5	$IT_{UPR} \geq 174$ s, $IT_{MI} < 384$, $IT_{MI} \geq 13$, $IT_{LIE} \geq 6$ s, $IT_{SLB60} \geq 1$	Stand	7	71
	6	$IT_{UPR} \geq 174$ s, $IT_{MI} < 384$, $IT_{MI} \geq 13$, $IT_{LIE} \geq 6$ s, $IT_{SLB60} < 1$	Graze	29	69

Table 4
Confusion matrices generated by partition analysis of animal behaviour. Values for activities are numbers of observations. Top, middle, and lower sections of Table, respectively are for two-way (Graze, No Graze), three-way (Graze-Rest-Travel), and four-way (Graze-Stand-Lie-Travel) classifications of behaviour. N is total observations; Correct shows the proportion of observations that were correctly classified ("sensitivity").

Classes	With IT_{SLB}	Observed activity	Predicted activity					Correct (%)
			Graze	No Graze			N	
2	Yes	Graze	27	44			71	38
		No Graze	13	181			194	93
		Overall					265	78
	No	Graze	36	35			71	51
		No Graze	19	175			194	90
		Overall					265	80
			Graze	Rest	Travel			
3	Yes	Graze	18	52	1		71	25
		Rest	5	185	0		190	97
		Travel	0	0	4		4	100
		Overall					265	78
	No	Graze	42	28	1		71	59
		Rest	28	162	0		190	85
		Travel	0	0	4		4	100
		Overall					265	78
			Graze	Stand	Lie	Travel		
4	Yes	Graze	18	52	0	1	71	25
		Stand	5	103	0	0	108	95
		Lie	0	0	82	0	82	100
		Travel	0	0	0	4	4	100
		Overall					265	78
	No	Graze	20	50	0	1	71	28
		Stand	9	99	0	0	108	92
		Lie	0	0	82	0	82	100
		Travel	0	0	0	4	4	100
		Overall					265	77

that in this notation, multiple conditions in the same partition must all be fulfilled. At the first split the analysis subdivided the data according to an IT_{MI} value of 13. The 108 observations that fell below this threshold were classified by the algorithm as Not Grazing, and 98% of them indeed were classified correctly. The remaining 157 observations had been manually classified as Graze or Not Grazing; subdividing them at the second split according to an IT_{SLB} value of 2 yielded some further degree of separation, with 117 observations that fell below this threshold being classified by the algorithm as Not Grazing (with 64% probability), and the remaining 40 observations as Graze (with 68% probability). Further subdivisions (not shown) did not reduce the error rate or bias. The confusion matrices for this and the following analyses are given in Table 4. The overall error rate, i.e., the proportion of misclassified observations, was 22% – due primarily to misclassification of 62% of Graze observations as Not Grazing. The bias (relative imbalance between over- and under-estimation) was 12%. A different decision tree was obtained when IT_{SLB} was excluded from the analysis but IT_{SLB10} and IT_{SLB60} were retained; after five splits this yielded an error rate of 20% and low bias, of 6% (Table 3(ii)).

3.8.2. Graze-Rest-Travel classification

Partition analysis yielded a decision tree with three splits, which created four partitions (Table 3(iii)). All four Travel observations were correctly classified, as also were 97% of Rest observations. However, only 25% of Graze observations were correctly classified, which contributed to an overall error rate of 22% and bias of 18%. When IT_{SLB} was excluded from the analysis, the bias fell to almost zero in a decision tree with five splits, which created six partitions (Table 3(iv)).

3.8.3. Graze-Stand-Lie-Travel classification

Partition analysis yielded a decision tree with four splits, which created five partitions (Table 3(v)). Travel observations were correctly classified, as above; all Lie observations were correctly classified and 95% of Stand observations were correctly classified. However, again, only 25% of Graze observations were correctly classified; the overall error rate was 22%, and bias was 18%.

When IT_{SLB} was excluded from the analysis, the overall error rate was 23% and bias was 16% in a decision tree with five splits, which created six partitions (Table 3(vi)).

3.8.4. Six-way classification

The partition analysis for the six-way classification of behaviour was essentially the same as that for the Graze-Stand-Lie-Travel classification, with Loiter and Active Grazing substituted for Stand and Graze, respectively. There was no improvement in the overall error rate.

3.9. Estimates of daily grazing time

Estimated daily grazing time was strongly affected by the set of equations used, as determined by the classification method, and the inclusion or not of IT_{SLB} in the model. There were also wide variations among animals within the chosen equation set. The 24 estimates of daily grazing time (four deployments × six sets of equations) ranged from 1.4 through 5.9 h. In general, exclusion of IT_{SLB} increased estimated daily grazing time. In all deployments, use of the Graze-Rest-Travel classification and exclusion of IT_{SLB} yielded the highest grazing times, of 5 through 6 h/d.

4. Discussion

The IceTag device is designed and calibrated to be attached to the rear leg of the animal. In the light of our experience with beef cows in the present study, caution is advised: installation can result in operator injury when working with animals unaccustomed to regular handling. We started out with 12 new IceTag devices, of which 10 were correctly installed during the first deployment and performed without malfunction. Reliability was lower in the second,

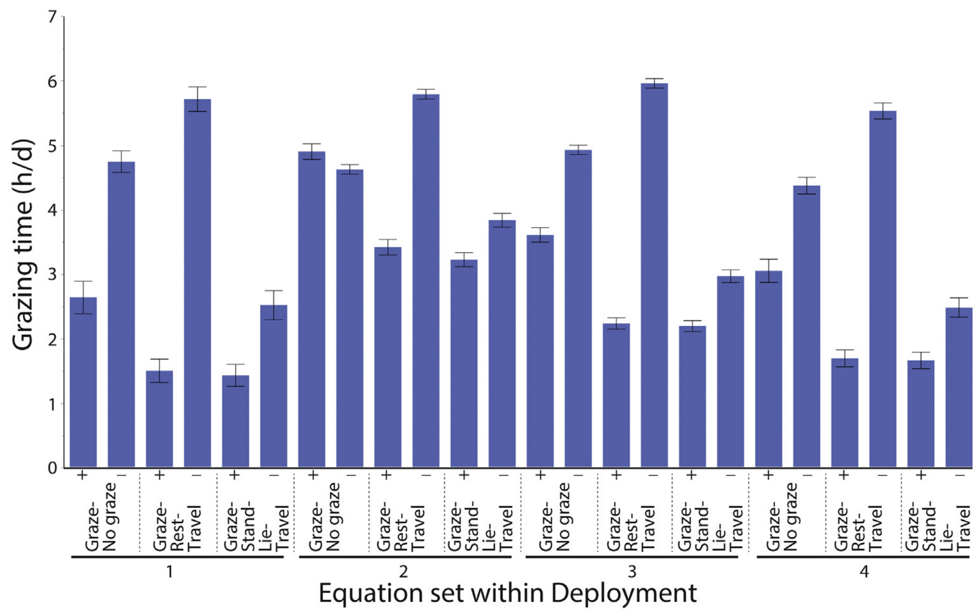

Fig. 5. Daily grazing time predicted by the application of six equation sets to the entire IceTag database for each deployment. The equation sets represent 2-way (Graze-No graze), 3-way (Graze-Rest-Travel) and 4-way (Graze-Stand-Lie-Travel) classifications of behaviour, with (+) and without (−) IT_{SLB} as a candidate variable in the model. Error bars show ±1 SE of mean of animal-day values.

third, and fourth deployments, with 11, 8, and 10 devices, respectively, performing without malfunction. Some malfunctions were transitory, which highlights the need for careful screening of the device data prior to analysis. In a research context we would recommend that users determine the clock drift for each device (which can be done very simply), especially if the intended deployment is long and device data are to be synchronized with other sources of information. In terms of the robustness of our results, we note that our sample size of 24 animals was greater than that used in most of the studies – broadly similar to ours – of cattle behaviour reviewed by Kilgour (2012). Furthermore, our operating conditions encompassed differing paddocks and seasons.

After the IceTag data had been corrected for clock drift and synchronized with video-based coding of step events, the correspondence between IceTag and observed 5-min step counts was excellent ($r^2 = 0.97$) over the entire range encountered (Fig. 2). This stood in contrast to the rather poor quality of match between the two timelines when examined at the resolution of the individual step event (Fig. 3). However, the scope for timing errors in the video-coded data is too small to account for this poor match: one possible reason is that precise timing of the registration of a step by the IceTag device is somewhat variable relative to the time the hoof touches the ground, which was the indication used in video coding. This issue would need to be examined further if the precise timing of step events were important.

The synchronized IceTag and video-based data showed that the IceTag variables that indicated whether the animal was upright or lying were subject to a small error of about 1%. The error was caused by the IceTag device occasionally getting stuck in lying mode when an upright cow raised the rear leg close to the abdomen and lowered it again. Given the apparently low rates of error in the variables related to upright versus lying positions, and step count, interest in these variables at the within- and between-day levels is well served by the IceTag device. However, the above leg movement often triggered the variable indicating the start of a lying bout (IT_{SLB}), and this greatly inflated the apparent frequency of lying bouts. This problem can be at least partially resolved by using a variable that ignores lying bouts shorter than some threshold; in our present analysis a threshold of 60 s proved more useful than one of 10 s. This makes intuitive sense given that cows are unlikely to lie down for periods of less than one minute.

Many of the 5-min video observations contained a mixture of behaviours, but a much greater proportion of the observations defined as Rest (in the Graze-Rest-Travel classification) indeed comprised only rest than the proportion of observations defined as Graze that really comprised only graze; in fact, there were very few occurrences of pure grazing. This introduces a bias when the partition equations are applied to large datasets. Cows spent little time walking without grazing, therefore there were few observations defined as Travel. However, because the motion index (IT_{MI}) and step count (IT_{STEPS}) are so much increased during travelling, this behaviour can readily be separated out by partition analysis, despite the low number of cases. It was rare for a cow to stand without leg movements for minutes at a time, therefore most of the observations classified as Stand under the Graze-Stand-Lie-Travel classification became Loiter under the six-way classification. Although step rate differed significantly among Rest, Graze, and Travel, a partition model based only on IT_{STEPS} resulted in 52% of Graze observations being misclassified as Rest, even in a highly branched decision tree. Likewise, applying the step rate criteria of Aharoni et al. (2013) for the separation of Stand, Graze, and Travel to our dataset resulted in considerable confusion between Graze and Stand, and an overall error rate of 28%.

Our basic partition analysis model offered all IceTag variables for selection. The fact that IT_{SLB} was always selected as a split criterion, even though the number of lying bouts was inflated indicates that the tendency to raise the rear leg to the abdomen, which can trigger IT_{SLB}, is indirectly linked to behaviour at the time. That could be caused by local conditions, e.g., insect irritation, and therefore could lack generality. Because of this doubt we examined models that excluded IT_{SLB} as a candidate variable, and obtained results comparable with those of the basic model, but at the cost of a more branched decision tree. Either way, the overall error rate across all models was about 22%. More serious was the relatively high proportion of true Graze observations that were misclassified as Not Grazing, Rest, or Stand. This problem was reported in an earlier study, which used an older IceTag model that generated different output variables (Ungar et al., 2011). The high-resolution methodology adopted in the present study suggests strongly that the problem lies not with the IceTag device but with the frequency of step movements when the animal rested in the upright position, coupled with a quite low step rate when the animal grazed actively, itself a consequence of long residence times at feeding stations. Visual comparison between the timelines of step events during loitering and active grazing, respectively, did not suggest any obvious difference that could be used as a criterion to separate the overall patterns of step events. It is conceivable that much longer observations might enable emergence of some difference between the temporal patterns of steps, e.g., regarding regularity, during loitering and active grazing, respectively; on the 5-min time scale, there was a highly variable pattern of stepping within observations classified as grazing.

Even though the overall error rates were similar across the six examined models, large differences between the models emerged when they were applied to the entire IceTag database, and summarized in terms of daily grazing time (Fig. 5). Even the highest values, close to 6 h, were lower than almost every value that was found in a literature survey covering comparable systems (Nevo, 2015). The variation in daily grazing time among individual animals was clearly erroneous in all models that included IT_{SLB} as a candidate variable; the only results that were plausible were generated under Graze-Rest-Travel classification without IT_{SLB}, but here too the underestimation of grazing time may be large.

5. Conclusions

The IceTag device performed well in mapping the diurnal patterns of animal position and step rate, but less well in separating grazing from upright resting. Reliability issues were encountered. Error rate for classification between Grazing and Not-Grazing was 22%. In both three- and four-way classifications of behaviour, error rates were low for non-graze behaviours, but only 25% of Graze observations were correctly classified. Our results suggest that pedometry is not the ideal method for classifying behaviour when grazing is of paramount interest.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jneumeth.2017.06.001.

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