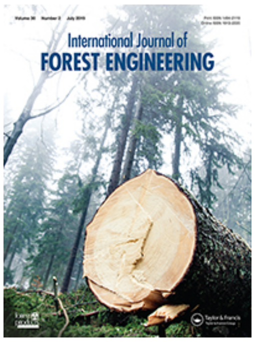

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Use of smartphone sensors to quantify the productive cycle elements of hand fallers on industrial cable logging operations

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ABSTRACT

Analysis of time and motion study data is central to forest operations, but current methods used to study work cycles are limited in the breadth and depth of available predictor variables. The objective of this research was to evaluate whether activity recognition modeling based on smartphone sensor data could be used to quantify work tasks during motor-manual logging activities. Three productive cycle elements (travel, acquire, fell) and delays were manually timed while three hand fallers worked on industrial cable logging operations in North Idaho. Each faller carried a smartphone that recorded sensor data at 10 Hz using the AndroSensor mobile app. The random forests machine learning algorithm was used to classify cycle elements and delay from the device sensor measurements. Four time domain features (mean, standard deviation, interquartile range, and skewness) were extracted for each of four sensor values (acceleration, linear acceleration, gyroscope, and sound) using 10 sliding window sizes ranging from 1 to 10 seconds. For each window size, calculations were performed with and without gaps between subsequent cycle elements. Models with and without sound were compared. Overall model prediction accuracy ranged from 65.9% to 99.6% and accuracy increased as window size increased. The two calculation methods did not result in noticeable differences in prediction error, but the inclusion of sound decreased error in nearly all models. These results have demonstrated the feasibility of developing activity recognition models to quantify work based on mobile device sensors, which is an important step for advancing real-time analysis of productive cycle times.

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Activity recognition; wearable sensors; machine learning; accelerometer; gyroscope; time and motion; location-based services; chainsaw operator

Introduction

In both forest operations research and management applications, time and motion studies (Barnes 1958) are used frequently to quantify work activities (e.g. Olsen and Kellogg 1983; Huyler and LeDoux 1997; Lortz et al. 1997; Bjorheden and Thompson 2000; Wang et al. 2003; Tiernan et al. 2004; Bolding and Lanford 2005; Adebayo et al. 2007; Spinelli and Visser 2008; Magagnotti et al. 2013). Time and motion analysis entails defining, measuring, and analyzing component elements of the productive work cycle for individual pieces of equipment or manual tasks statistically, often in order to help characterize potential opportunities for reducing delay and improving efficiency on logging operations (e.g. Huyler and LeDoux 1997; Spinelli and Hartsough 2001; Adebayo et al. 2007; Spinelli and Visser 2008). Relationships between productive cycle times and stand or site characteristics are developed using regression (e.g. Huyler and LeDoux 1997; Lortz et al. 1997; Wang and Haarlaa 2002; Wang et al. 2004; Adebayo et al. 2007; Spinelli et al. 2009). Predictive regression functions developed from time study data are also pooled with machine rate estimates calculated using methods described in Miyata (1980) and Brinker et al. (2002) to determine system costs per unit wood volume (Matthews 1942) and for broader scale meta-analyses (e.g. Spinelli and Visser 2008; Spinelli et al. 2009; Hiesl and Benjamin 2013; Bell et al. 2017). Production functions developed using this method are also often integrated into simulation models to characterize treatment costs across a range of conditions (e.g. Hartsough et al. 2001; Wang et al. 2003; Bell et al. 2017).

Analysis of cycle times using Global Navigation Satellite System (GNSS) data has been employed to automate sampling of mechanized equipment with reduced need for visual observation (Veal et al. 2001; McDonald and Fulton 2005; Keefe et al. 2014; Strandgard and Mitchell 2015; Olivera et al. 2016; Becker et al. 2017). GNSS-based methods have also been used with ground workers (Zimbelman et al. 2017), ground workers and equipment working together (Wempe and Keefe 2017), and to identify when ground workers or equipment cross virtual boundaries (Grayson et al. 2016; Wempe and Keefe 2017; Zimbelman et al. 2017). However, our ability to infer cycle elements solely from GNSS coordinates is limited, as forest canopy reduces GNSS accuracy (Wempe and Keefe 2017; Zimbelman and Keefe 2018). Multiple GNSS-enabled devices can provide more than one point of reference to characterize movements of individual machines (Becker et al. 2017). However, using additional sensors to quantify manual and motor-manual logging work functions at higher resolution could advance precision forestry.

Sensor-based activity recognition uses data collected about individuals and their environment to characterize physical

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activities. Activity recognition is a central technique in big data science and underlies the concept of the *quantified self* (Swan 2013). Activity recognition using sensors based on the body or on objects is used in personal fitness applications (Ermes et al. 2008), health care (Anjum and Ilyas 2013; Lau et al. 2010), and the development of smart homes (Gu et al. 2009; Chen et al. 2012). Both smartphones and smartwatches are used widely in activity recognition, as many of these devices are now equipped with a variety of sensors, including accelerometers, gyroscopes, barometers, thermometers, decibel meters (microphones), magnetometers, lux meters, optical heart rate sensors, and GNSS chips (Anjum and Ilyas 2013; Trost et al. 2014; del Rosario et al. 2015; Shoaib et al. 2015, 2016; Weiss et al. 2016). These sensors can identify position, movement (Anjum and Ilyas 2013; Bayat et al. 2014), physiological indicators (Chen et al. 2012), and environmental characteristics (Gu et al. 2009), which in turn can be used as the basis for predictive models.

Activity recognition studies based on smartphone or smartwatch inertial sensors have not previously been conducted in forest operations. The primary difference between conventional time studies and automated activity recognition is in (1) the richness of data available for analysis, and (2) the potential for activity recognition-based models to subsequently be integrated into phone apps for continuous, long-term monitoring and analytics. Data can be collected simply by wearing a phone and enabling software apps to record sensor values. This reduces the need for integration of independent sensors when distinct GNSS devices and accelerometers are used for time study analyses (e.g. McDonald et al. 2008; Gallo et al. 2013; Borz et al. 2018). Thus, this new method for quantifying work could make it possible to conduct real-time analysis and reporting at multiple time scales in ways that could be deployed inexpensively using devices that are already ubiquitous in forestry.

A recent study in Idaho showed that 72.4% of loggers in the inland northwest United States (US) own smartphones and carry them at work (Wempe et al. 2019). Activity recognition using these devices could serve to enhance and supplement traditional time study analyses and those conducted using video surveillance (Mitchell and Gallagher 2007; Contreras et al. 2017). When fitted models are programmed into smartphone apps, predictive models can then provide a continuous record of work cycles over time, much as onboard computers now provide for mechanized logging equipment (Figure 1). Analysis of inertial sensor data can also help improve positional movement accuracy under the canopy where GNSS error is high (Qian et al. 2017).

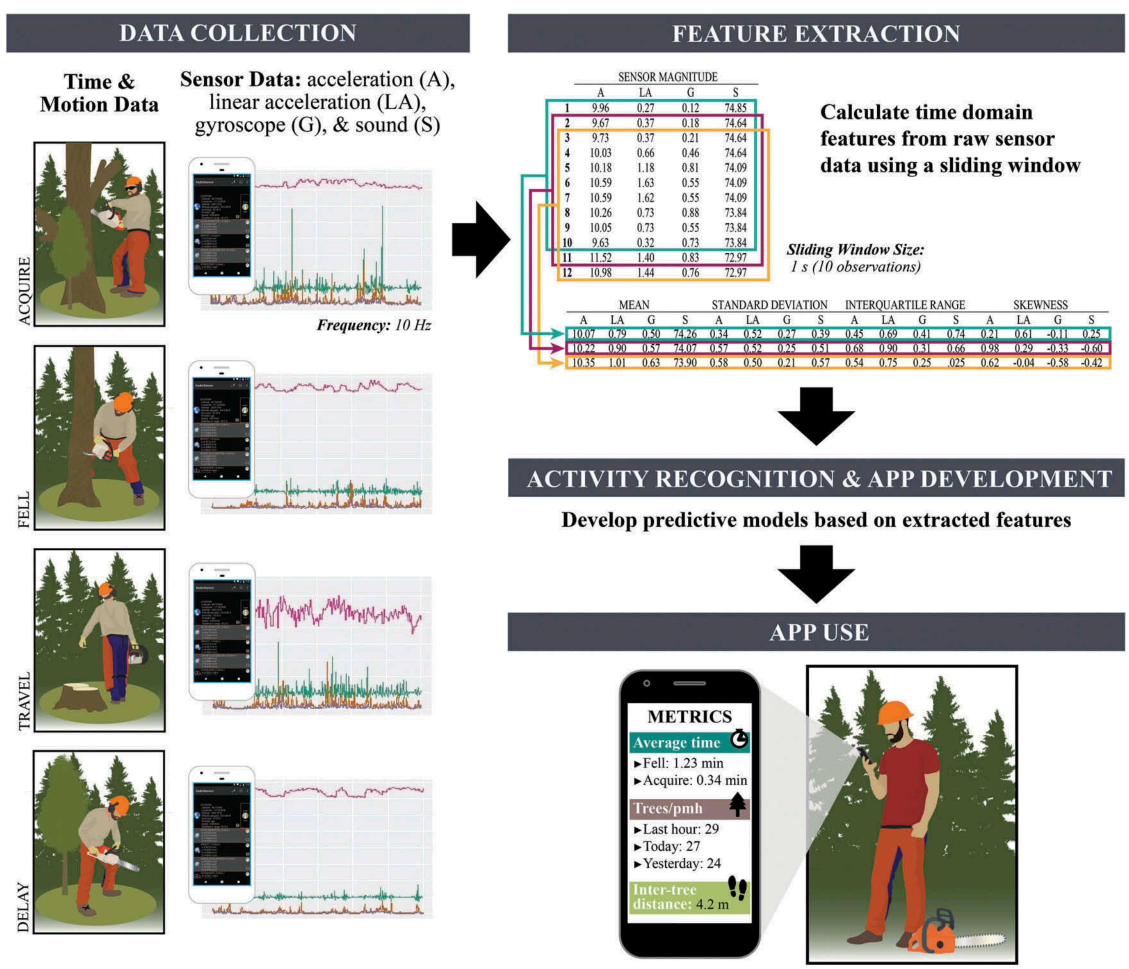

Figure 1. Steps involved in developing and using activity recognition models include (1) collecting time study data to pair with phone-based sensor measurements, (2) extracting time domain features, (3) developing a general activity recognition model using machine learning, (4) encoding the model into a phone app, and (5) using the app to summarize work activities. Analysis described in this paper involves steps 1– 3.

Several machine learning methods that are used in spatial analysis of lidar and other remote sensing data (Lawrence et al. 2006; Zhong et al. 2014; Belgiu and Drăguţ 2016; Becker et al. 2018) are also used to develop activity recognition models (Khan et al. 2013; Attal et al. 2015; Shoaib et al. 2015; Mehrang et al. 2018). The prediction accuracy of activity recognition models depends on a variety of factors, such as the type and quality of sensors in the devices and the machine learning algorithms (such as Decision Trees, Support Vector Machines, K Nearest Neighbor analysis, and Naïve Bayes) used for classification (Khan et al. 2013; Shoaib et al. 2015). Time or frequency domain features extracted for activity classification also affect model quality. Common time domain features used in human activity recognition include mean, median, standard deviation, variance, skewness, kurtosis, and range; frequency domain features include Fast Fourier Transform and Discrete Cosine Transform coefficients (Khan et al. 2013; Attal et al. 2015; Shoaib et al. 2015). Similarly, the size of the *sliding* or *moving window* used to extract these features, sensor sampling rate, and device location on the body may also affect model quality (Khan et al. 2013; Shoaib et al. 2015). Because these analytical methods have not been used previously to study the movements of logging workers, little is known about how these factors influence activity recognition in this field.

Our specific research objectives in this study were to (1) evaluate the use of activity recognition modeling as a new method to characterize three productive work cycle elements (travel, acquire, fell) and delay time for hand fallers on industrial logging operations in North Idaho using only the sensors in a Google Pixel smartphone, (2) evaluate the accuracy of predictive activity recognition models developed using four time domain features extracted with 10 sliding window sizes ranging from 1 to 10 seconds, (3) evaluate the relative importance of different sensor variables with and without microphone sound (decibel) level included, and (4) evaluate the effect of gaps between cycle elements when extracting time domain features to develop models. Our emphasis was on evaluation of a new methodological approach for quantifying operational forestry tasks rather than presentation of a final predictive model intended for widespread use.

Materials and methods

Data collection and processing

Phone sensor data was collected in a time and motion study of three hand fallers working in North Idaho during the summer of 2017. The first faller was observed on 27 July 2017 near 46.74291° N, 115.83660° W for approximately 4 hours. The second faller was observed on 28 July 2017 near 46.74343° N, 115.83366° W for approximately 2.5 hours. The third faller was observed on 8 August 2017 near 46.16627° N, 115.73837° W for approximately 3.3 hours. Three cycle elements (travel, acquire, and fell) plus delay were observed visually and timed using the clock on a Google Pixel smartphone (Google, Mountain View, CA) to record the true start and stop times for each activity cycle. *Travel* began when a faller left one tree to walk to the next. *Acquire* began when the faller arrived at a tree and began to clear brush and lower branches in preparation for felling. *Felling* began when the faller first started making felling cuts. *Delay* was defined as any time the faller was not performing any of these three productive cycle elements and included operational, mechanical and personal delays. Each faller wore a Google Pixel smartphone in a radio pouch attached to a belt and their movements were recorded using the AndroSensor application. AndroSensor records smartphone sensor data at a user-defined sampling frequency. Data was collected at a 10-Hz frequency and exported as a *.*csv* file.

The Google Pixel is equipped with a combined accelerometer and gyroscope called the inertial measurement unit. The triaxial accelerometer measures directional movement in meters per second squared (m/s^2) in the x-, y-, and z-directions while the gyroscope detects orientation or tilt in radians per second (rad/s) in three directions during movement. The Pixel also has a triaxial electronic compass to detect magnetism in the x-, y-, and z-axes in microteslas (μT). A software sensor on the phone combines the accelerometer, gyroscope, and magnetic field values to calculate orientation (in degrees) in the x-, y-, and z-directions, where z is relative to magnetic North, x is relative to the ground, and y is roll or rotation. Other sensors include a barometer that records data in hectopascals (hPa), proximity sensor that records in inches (in) from the device, and sound sensor that records in decibels (dB).

After data collection, cycle elements were added to the dataset as a new column of corresponding, manually-recorded start and stop times. Thus, each observation whose timestamp fell within the start and stop time for a particular activity cycle was assigned a label for that activity (i.e. travel, acquire, fell, or delay). Data were then imported into the R open source statistical programming environment (R Core Team 2018) for analysis. The entire raw dataset, representing all three fallers, consisted of 354,430 observations. Of these, 19.0% were acquire, 49.0% were fell, 14.7% were travel, and 17.3% were delay.

Most sensors in the Pixel record measurements in three dimensions, making the data sensitive to phone orientation on the body. One way to develop models that are orientation-independent is to calculate the magnitude of each sensor (Siirtola and Röning 2013). Thus, rather than using the x, y, and z values from the acceleration, linear acceleration, and gyroscope sensors, the magnitude for each sensor measurement was calculated using Equation 1:

$$Sensor_{mag} = \sqrt{Sensor_x^2 + Sensor_y^2 + Sensor_z^2} \tag{1}$$

where $Sensor_{mag}$ is the overall sensor magnitude, and $Sensor_x$, $Sensor_y$, and $Sensor_z$ are the values from the sensor in the x, y, and z directions, respectively. Thus, the variables selected from the raw data included acceleration magnitude (m/s^2), linear acceleration magnitude (m/s^2), gyroscope magnitude (rad/s), and sound level (dB).

To build activity recognition models, the raw data are usually segmented using a sliding window of a defined length of time and features are calculated from this segmented data (Khan et al. 2013; Attal et al. 2015; Shoaib et al. 2015;

Mehrang et al. 2018). This window is advanced in predetermined increments, defining a new subset of data from which features are extracted. In this study, four time domain features (mean, standard deviation, interquartile range, and skewness) for each of the four sensor values were extracted from the raw data using 10 different sliding window sizes (ranging from 1 to 10 s), for a total of 16 variables (Table 1). The window was advanced one row at a time through the raw dataset, calculating these four time domain features for all four sensor values at each subsequent position. This approach created a new dataset for each window size. These datasets were used to build the activity recognition models. For example, using a 3-s window, features were calculated for each row in the dataset using the previous 30 observations (representing 3 s of data). Calculations were performed two ways for each window size. In the first approach, calculations were restarted each time a faller switched activity (i.e. with gaps between cycles). In the second approach, calculations were performed continuously for each faller (i.e. without gaps between cycles).

Random forests

The random forest algorithm is an ensemble learning method that creates multiple classification and regression trees (CART) (Breiman 2001; Khalilia et al. 2011). A bootstrap sample of the original dataset (about two thirds of the data) is used to build the current tree and about one third of the observations (called out-of-bag (OOB) samples) are left out and used to estimate model prediction error as well as assess variable importance (Liaw and Wiener 2002; Genuer et al. 2010; Zhong et al. 2014). Specifically, these OOB observations are classified by the tree in order to provide an unbiased estimate of overall classification accuracy (OOB accuracy), meaning there is generally no need for cross-validation (Breiman 2001; Svetnik et al. 2003; Lawrence et al. 2006; Zhong et al. 2014). At each node in the tree, a random sample of the predictor variables is selected and used to find the best split (Breiman 2002; Liaw and Wiener 2002). Specifically, the Gini measure of impurity is used to select the split that has the lowest impurity (Breiman 2002; Khalilia et al. 2011). The Gini impurity metric ranges from 0 to 1 and measures the distribution of class labels in a given node, with 0 representing a node that contains only elements of the same class (Khalilia et al. 2011). Random forests have been used to develop highly accurate activity recognition models using wearable sensors (Bayat et al. 2014; Gjoreski et al. 2016; Weiss et al. 2016; Mehrang et al. 2018).

Table 1. Time domain features extracted from each raw variable, with acronyms used throughout the paper.

Raw variable	Feature extracted	Variable acronym
Acceleration magnitude	Mean	A_Mean
Acceleration magnitude	Standard deviation	A_SD
Acceleration magnitude	Interquartile range	A_IQR
Acceleration magnitude	Skewness	A_Sk
Linear acceleration magnitude	Mean	LA_Mean
Linear acceleration magnitude	Standard deviation	LA_SD
Linear acceleration magnitude	Interquartile range	LA_IQR
Linear acceleration magnitude	Skewness	LA_Sk
Gyroscope magnitude	Mean	G_Mean
Gyroscope magnitude	Standard deviation	G_SD
Gyroscope magnitude	Interquartile range	G_IQR
Gyroscope magnitude	Skewness	G_Sk
Sound level	Mean	S_Mean*
Sound level	Standard deviation	S_SD*
Sound level	Interquartile range	S_IQR*
Sound level	Skewness	S_Sk*

*These four variables were only included in models with sound.

Two main parameters to consider when building random forest models are the number of trees to grow (n_{tree}) and the number of predictor variables randomly selected at each node (m_{try}) (Liaw and Wiener 2002; Genuer et al. 2010). Random forest models do not overfit as trees are added and estimates from OOB predictions tend to be more reliable as forests grow (Breiman 2001; Lawrence et al. 2006). However, prediction accuracy increases at a decreasing rate as trees are added (Breiman 2001; Lawrence et al. 2006) and Svetnik et al. (2003) suggest choosing a value of n_{tree} that achieves stabilization of the OOB error. Khalilia et al. (2011) found that n_{tree} did not influence classification results after > 20 trees were used and Oshiro et al. (2012) suggested that 64–128 trees are adequate for achieving a balance between performance and processing time. It has also been shown that changing m_{try} does not usually have a significant effect on results, with the default value (the square root of the total number of variables) often performing best (Liaw and Wiener 2002; Svetnik et al. 2003). However, Strobl et al. (2008) suggest varying m_{try} when predictor variables are correlated.

The importance of variables used in random forest models can be assessed using various criteria. A simple method is to count the number of times each variable is selected by all trees in the forest, while more advanced measures include Gini importance and permutation importance (Strobl et al. 2007). In terms of Gini importance, the mean decrease Gini (MDG) for each variable is derived by adding up all the decreases in the Gini impurity criterion over all trees in the forest and is normalized by the number of trees (Breiman 2002). For permutation importance, mean decrease accuracy (MDA) for each variable is derived by randomly permuting the variable of interest and then predicting the response for the OOB observations using this permuted variable along with the non-permuted variables (Liaw and Wiener 2002; Strobl et al. 2008). The prediction accuracy will be lower if the original variable was associated with the response (Strobl et al. 2008). Both MDA and MDG can be used to rank variables in terms of their importance (Liaw and Wiener 2002).

Development of random forest models

The *randomForest* function in the R *randomForest* package (Liaw and Wiener 2002) was used to fit random forest machine learning models to the filtered sensor data to predict the four work cycle elements. Random forests were chosen because they have previously been used successfully in activity recognition (Bayat et al. 2014; Gjoreski et al. 2016; Weiss et al. 2016; Mehrang et al. 2018), they tend to be less sensitive to training data quality and overfitting (Breiman 2001; Belgiu and Drăguţ 2016), and they have efficient computational times (Svetnik et al. 2003). Rather than split the data into training and testing datasets, models were created using the full datasets and the OOB error rate calculated internally by the algorithm (based on the one-third portion of data (OOB samples) left out when constructing each tree) was used to evaluate overall model prediction accuracy. Furthermore, prediction accuracy for individual cycle elements in all models was derived from the error rates for each element calculated by the algorithm. In all cases, accuracy is reported as a percent and was calculated as 100*(1 – error rate). In order to balance accuracy and computational time, all models in our study were created using 100 trees. Models were created using the default value of m_{try} (the square root of the total number of variables), as this has been shown to perform well in terms of prediction accuracy (Liaw and Wiener 2002; Svetnik et al. 2003). Models with and without sound were also compared (i.e. models with sound contained all 16 variables defined in Table 1, while models without sound contained only 12 variables). A total of 40 models were created using the 10 window sizes (1 to 10 s) and two variable sets (with and without sound) for the two sliding window calculation approaches (with and without gaps between cycles).

The relative importance of variables used in the models was assessed using two of the more common importance measures described above: MDA and MDG. The top three variables in terms of MDA and MDG were tallied for all 10 window sizes for each of the four combinations of variable sets and sliding window calculation methods: without gaps and without sound (NGNS), without gaps and with sound (NGS), with gaps and without sound (GNS), and with gaps and with sound (GS). Bar charts were used to illustrate the number of times each variable occurred in the top three.

Results

Figure 2 is provided to show an example of the raw sensor data. In this randomly-selected 1-minute sample, different patterns in the variables were visible when comparing cycle elements, most notably with the sound variable, which was fairly consistent for the acquire element but more variable for delay (Figure 2). Each faller also exhibited slightly different patterns. For example, the data for Faller 2 was more variable for the selected felling element while the raw sound data for Faller 3 was more variable for the selected travel element (Figure 2).

For most window sizes, the classification error rate leveled off after approximately 25 trees, suggesting that building our models with 100 trees was sufficient (Figure 3). The error rate also decreased as window size increased, with the 1-s window having much higher error rates (Figure 3).

Prediction accuracy for all models (created with 100 trees) increased as window size increased (Table 2, Figure 4). For both calculation approaches (with and without gaps between cycles), the OOB overall prediction accuracy was similar for models without sound, with the lowest accuracies (65.9% (NGNS) and 66.1% (GNS)) obtained using 1-s windows and the highest accuracies (98.1% (NGNS) and 98.6% (GNS))

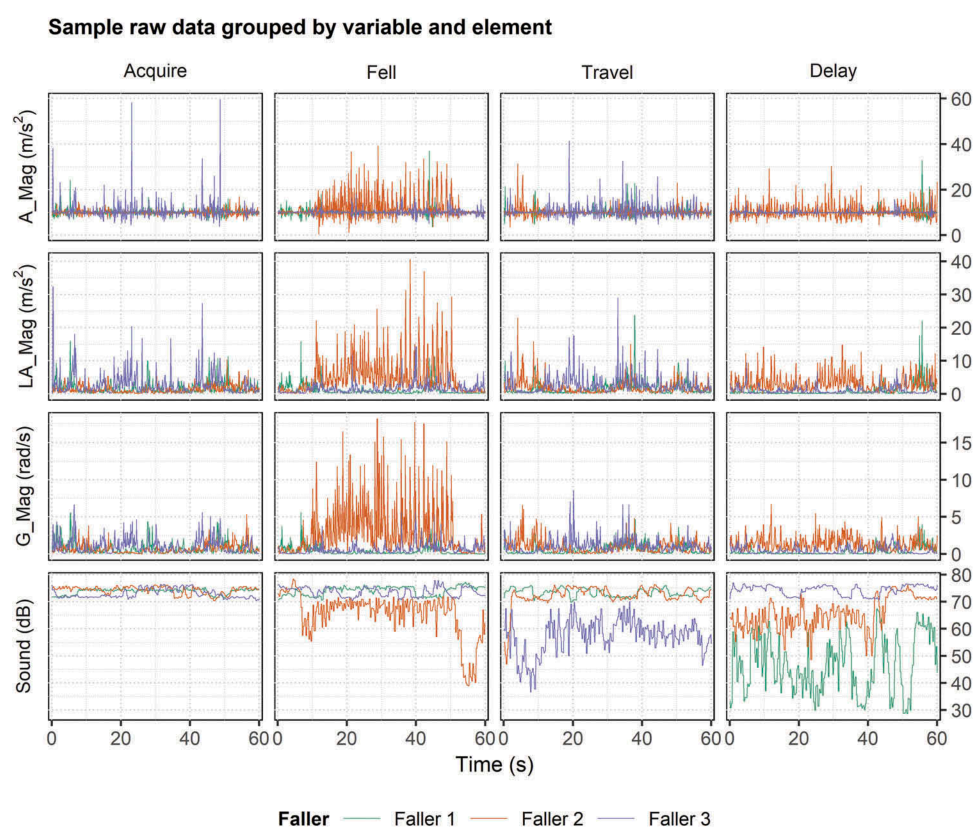

Figure 2. Example raw sensor data plotted for one minute of each cycle element (acquire, fell, travel, delay) chosen from a random cycle for each faller. Line color indicates the sensor variable (acceleration magnitude (A_Mag), linear acceleration magnitude (LA_Mag), gyroscope magnitude (G_Mag), and sound level (Sound)) and line type indicates the faller.

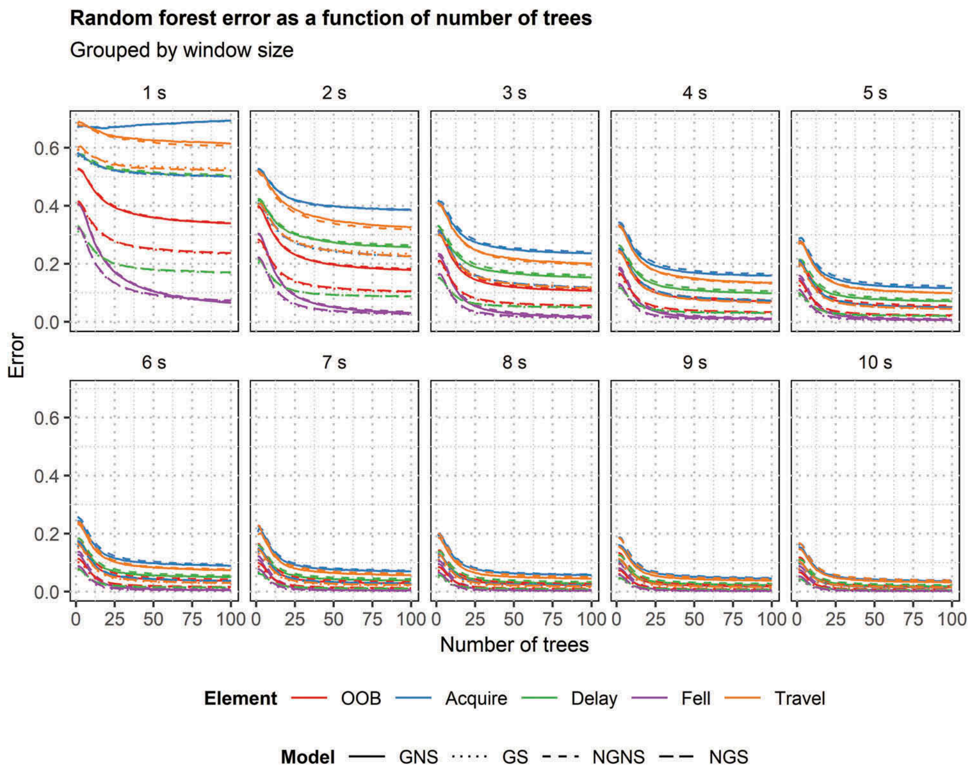

Figure 3. Random forest error plotted as a function of the number of trees in the model. The plots are grouped by the 10 window sizes. Line color indicates overall model (OOB) error as well as error for the four elements (acquire, fell, travel, delay). Line type indicates the four combinations of variable sets and sliding window calculation methods (GNS, GS, NGNS, NGS).

obtained using 10-s windows (Table 2, Figure 4). Including sound increased OOB prediction accuracy, with accuracies of 76.3% (NGS) and 76.5% (GS) for 1-s windows and accuracies of 99.3% (NGS) and 99.6% (GS) for 10-s windows (Table 2, Figure 4). Thus, the two calculation methods did not result in a noticeable difference in OOB prediction error, but the inclusion of sound decreased OOB error in all models.

In terms of individual cycle element prediction accuracy, *felling* had the highest classification accuracy for all models and window sizes. Neither the calculation method (with and without gaps) nor the inclusion of sound had a noticeable effect on *felling* prediction, with accuracies ranging from 92.7% – 93.4% (1-s windows) up to 99.6%–99.9% (10-s windows) (Table 2, Figure 4). *Acquire* had some of the lowest prediction accuracies, ranging from 30.7% – 49.9% (1-s windows) up to 96.1%–99.0% (10-s windows), with the inclusion of sound increasing *acquire* prediction accuracy for both calculation methods (Table 2, Figure 4). Prediction accuracy for *travel* ranged from 38.6% – 47.9% (1-s windows) up to 96.2%–99.1% (10-s windows), with sound increasing *travel* prediction accuracy for both calculation methods (Table 2, Figure 4). Prediction accuracy for *delay* ranged from 49.4% – 83.1% (1-s windows) up to 97.9%–99.6% (10-s windows) and including sound increased *delay* prediction accuracy for both calculation methods (Table 2, Figure 4).

Figure 5 shows the variables ranked in order of importance based on the MDA and MDG indices for all models for the 1-, 5-, and 10-s windows. In order to determine which variables were most important across all combinations of models and window sizes, the top three variables (for MDA and MDG) from each model were recorded and tallied (Figures 6 and 7).

Only four of the 12 variables used in models developed without sound (NGNS and GNS) occurred in the top three in terms of MDA for all models: LA_Sk, G_Sk, A_Sk, and A_Mean (first and second panel, Figure 6). Of these, LA_Sk, G_Sk, and A_Sk seemed to have the greatest importance (i.e. the greatest number of occurrences in the top three most important variables) for datasets calculated with and without gaps (first and second panel, Figure 6). Of the 16 variables used in models developed with sound (NGS and GS), only five occurred in the top three in terms of MDA for all models: S_Mean, LA_Sk, G_Sk, A_Sk, and A_Mean (third and fourth panel, Figure 6). Of these, LA_Sk and S_Mean occurred most frequently in the top three for datasets calculated with and without gaps (third and fourth panel, Figure 6). For the NGS models, A_Sk also occurred frequently in the top three (third panel, Figure 6), while for the GS models, both A_Sk and G_Sk occurred frequently in the top three (fourth panel, Figure 6).

Only six of the 12 variables used in the models developed without sound (NGNS and GNS) occurred in the top three in terms of MDG for all models: A_SD, A_IQR, LA_SD, G_SD, G_Mean, and LA_Mean (first and second panel, Figure 7). Of these, A_SD, A_IQR, and LA_SD seemed to have the greatest importance (i.e. the greatest number of occurrences in the top three most important variables) for datasets calculated with and without gaps (first and second panel, Figure 7). Of the 16 variables used in models developed with sound (NGS and GS), the same

Table 2. Prediction accuracy (percentage) for each cycle element (A = acquire, D = delay, F = fell, T = travel) as well as overall model (OOB) accuracy. Models were created for window sizes ranging from 1 to 10 s using 100 trees. Data is grouped according to model type (NGNS, GNS, NGS, and GS).

Model	Window (s)	OOB	A	D	F	T
NGNS	1	65.87	30.73	49.36	93.21	39.41
NGNS	2	81.76	61.30	73.62	96.61	68.16
NGNS	3	88.79	76.03	83.88	97.99	80.34
NGNS	4	92.45	83.50	89.41	98.67	86.78
NGNS	5	94.46	87.80	92.46	99.03	90.18
NGNS	6	95.79	90.71	94.51	99.24	92.32
NGNS	7	96.64	92.73	95.66	99.34	93.80
NGNS	8	97.30	94.12	96.70	99.45	94.89
NGNS	9	97.77	95.30	97.29	99.53	95.66
NGNS	10	98.13	96.10	97.86	99.58	96.20
GNS	1	66.08	30.69	49.82	93.41	38.58
GNS	2	82.17	61.46	74.30	96.98	67.42
GNS	3	89.28	76.36	84.70	98.31	79.92
GNS	4	92.96	84.08	90.16	98.96	86.49
GNS	5	94.94	88.35	92.88	99.30	90.17
GNS	6	96.26	91.09	94.98	99.49	92.62
GNS	7	97.16	93.06	96.20	99.63	94.35
GNS	8	97.77	94.36	97.22	99.68	95.53
GNS	9	98.23	95.55	97.76	99.77	96.25
GNS	10	98.57	96.48	98.22	99.79	96.83
NGS	1	76.28	49.90	82.89	92.65	47.87
NGS	2	89.51	77.37	91.17	97.26	77.33
NGS	3	94.42	88.10	94.97	98.49	88.30
NGS	4	96.67	92.65	96.95	99.10	93.42
NGS	5	97.77	95.09	97.95	99.39	95.55
NGS	6	98.38	96.26	98.60	99.55	96.99
NGS	7	98.78	97.21	98.95	99.65	97.71
NGS	8	99.04	97.82	99.23	99.70	98.15
NGS	9	99.23	98.39	99.36	99.76	98.41
NGS	10	99.33	98.65	99.50	99.76	98.56
GS	1	76.54	49.93	83.09	92.93	47.13
GS	2	89.74	77.38	91.32	97.47	76.77
GS	3	94.75	88.42	95.11	98.80	88.03
GS	4	96.88	92.76	97.03	99.30	93.17
GS	5	97.98	95.14	98.04	99.59	95.57
GS	6	98.64	96.48	98.75	99.74	97.13
GS	7	99.01	97.36	99.07	99.82	97.94
GS	8	99.28	98.01	99.31	99.87	98.52
GS	9	99.49	98.61	99.52	99.92	98.84
GS	10	99.60	98.95	99.59	99.93	99.06

three variables always occurred in the top three in terms of MDG for all models: S_Mean, S_SD, and S_IQR (third and fourth panel, Figure 7). In all cases, S_Mean, S_SD, and S_IQR were ranked first, second, and third, respectively, for datasets calculated with and without gaps (third and fourth panel, Figure 7).

Discussion

Our results show that activity recognition models based on smartphone sensor data can characterize cycle elements and delay time for hand fallers with random forest model OOB accuracies ranging from 65.9% to 99.6%. These numbers are consistent with previous smartphone-based activity recognition models developed in other fields (Anjum and Ilyas 2013; Reddy et al. 2010; Siirtola and Röning 2013; Bayat et al. 2014; Shoaib et al. 2014).

Prediction accuracy increased with increasing window size, which is also consistent with previous work (Mehrang et al. 2018). Prior studies have achieved high accuracies with window sizes of 1–13 s (Anjum and Ilyas 2013; Lau et al. 2010; Reddy et al. 2010; Wu et al. 2012; Siirtola and Röning 2013; Bayat et al.

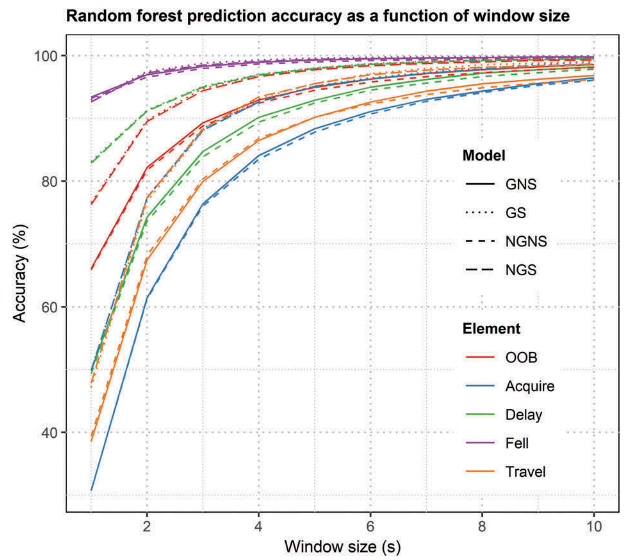

Figure 4. Random forest prediction accuracy for each of the 10 sliding window sizes. Models were created using 100 trees. Line type indicates the four combinations of variable sets and sliding window calculation methods. Line color indicates the accuracy of the four cycle elements as well as the overall model (OOB) accuracy.

2014; Shoaib et al. 2014; Mehrang et al. 2018), and our results suggest that windows of 4–10 s result in acceptable accuracies of at least 80%. Datasets calculated with gaps between cycle elements had slightly higher model prediction accuracies for most elements, although these differences were small. This makes sense, as datasets calculated without gaps between cycles contained some values that were derived from two activities.

Including sound increased accuracy in nearly all models, particularly for shorter window sizes, and most notably for the acquire, travel, delay and overall model OOB error rates. Interestingly, sound had a less noticeable effect on the felling element error rate, possibly because the accuracy of predicting felling was high (≥ 92.7%) for all models. While we expected that chainsaw sound would be important for predicting felling, there appear to be sufficient movements detected by the phone's inertial sensors to accurately distinguish this element from others. These may be associated with a more consistent and stable physical posture as the faller is hunched over to make felling cuts, or possibly vibrations from the saw as it cuts solid wood.

Practical applications of activity recognition-based analytics include reporting production and delay time (utilization rate) for current conditions, mean time per tree felled, and mean distance traveled between trees for self-evaluation and improvement, with comparative analyses displayed at hourly to annual time scales. When coupled with emerging data-sharing technologies that function in remote areas (Becker et al. 2017; Wempe and Keefe 2017; Zimbelman et al. 2017; Zimbelman and Keefe 2018), sudden inertial shock or lack of movement could also trigger smart safety alert notifications to co-workers that an accident may have occurred.

There are several limitations of our study that are important to note. First, the sample size of only three chainsaw operators is small. To develop activity recognition models

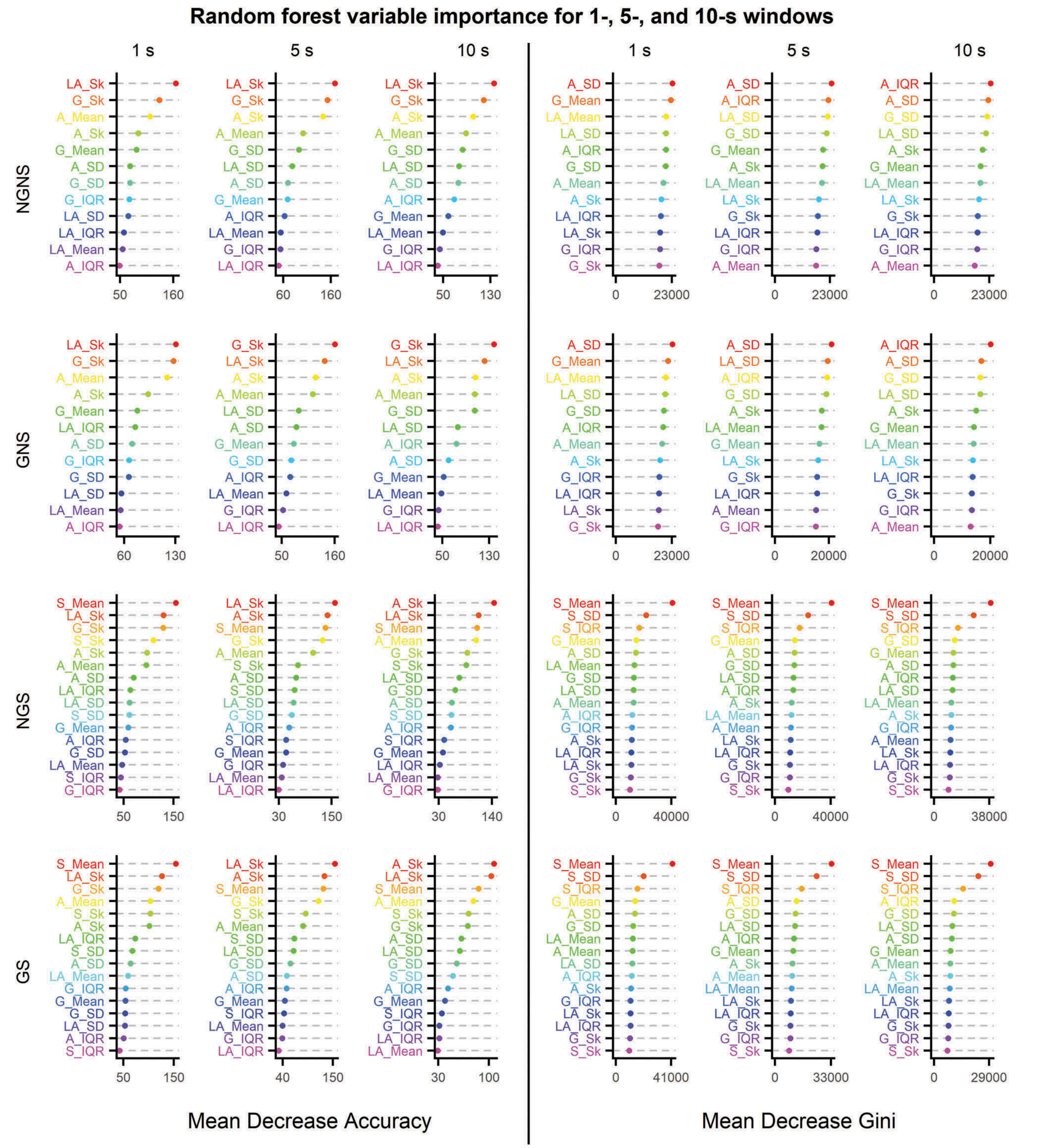

Figure 5. Plots of random forest variable importance for mean decrease accuracy (MDA) and mean decrease Gini (MDG). Only plots for the 1-, 5-, and 10-s windows are shown. The first row shows models created using data calculated without gaps and without sound (NGNS), the second row shows models created using data calculated with gaps and without sound (GNS), the third row shows models created using data calculated without gaps and with sound (NGS), and the fourth row shows models created using data calculated with gaps and with sound (GS).

that provide robust predictions in a range of stand and site conditions and with a variety of chainsaw makes and models, a larger sampling effort and modeling analysis should be conducted internationally across a range of stand conditions, topography, weather, operators, and saw types to account for these sources of variability (e.g. Keefe et al. 2014; Bell et al. 2017; Di Fulvio et al. 2017).

Use of uncalibrated smartphone microphone decibel levels is a second limitation of our study. Decibel levels range widely from the sound of a chainsaw at idle to a fully unthrottled saw. Microphone calibration scales decibel levels more appropriately (Swanepoel et al. 2014). Subsequent studies should evaluate the impact of calibration on activity recognition model accuracy and

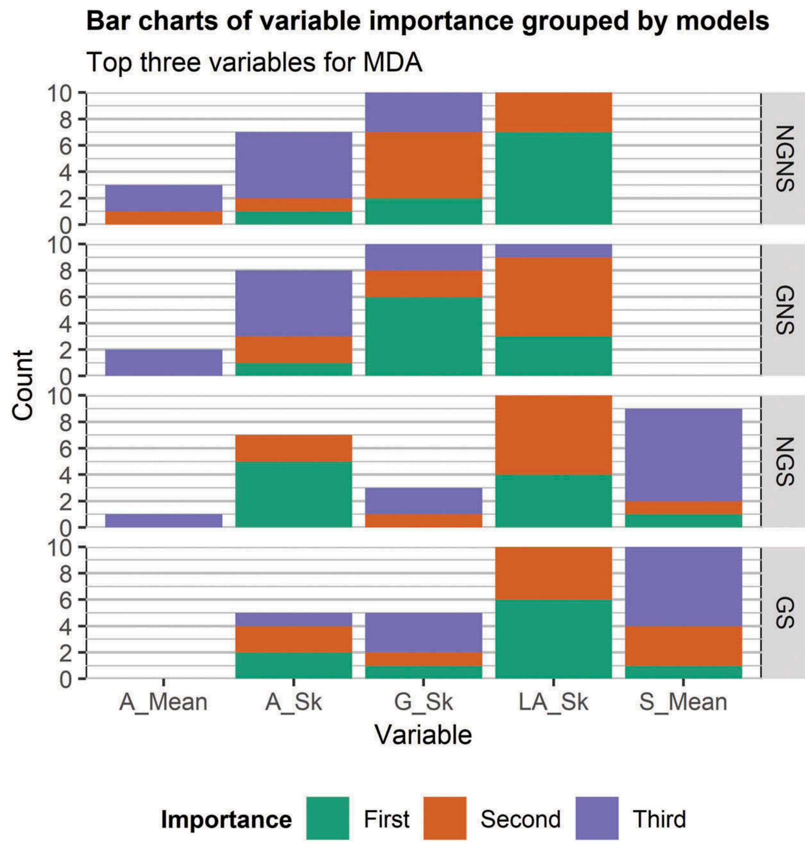

Figure 6. Bar charts of variable importance in terms of mean decrease accuracy (MDA). The height of each bar indicates the number of times each variable occurred as either the first, second, or third most important variable for the model type (NGNS, GNS, NGS, and GS) across all 10 window sizes. The color indicates how often the given variable was in either the first, second, or third most important spot.

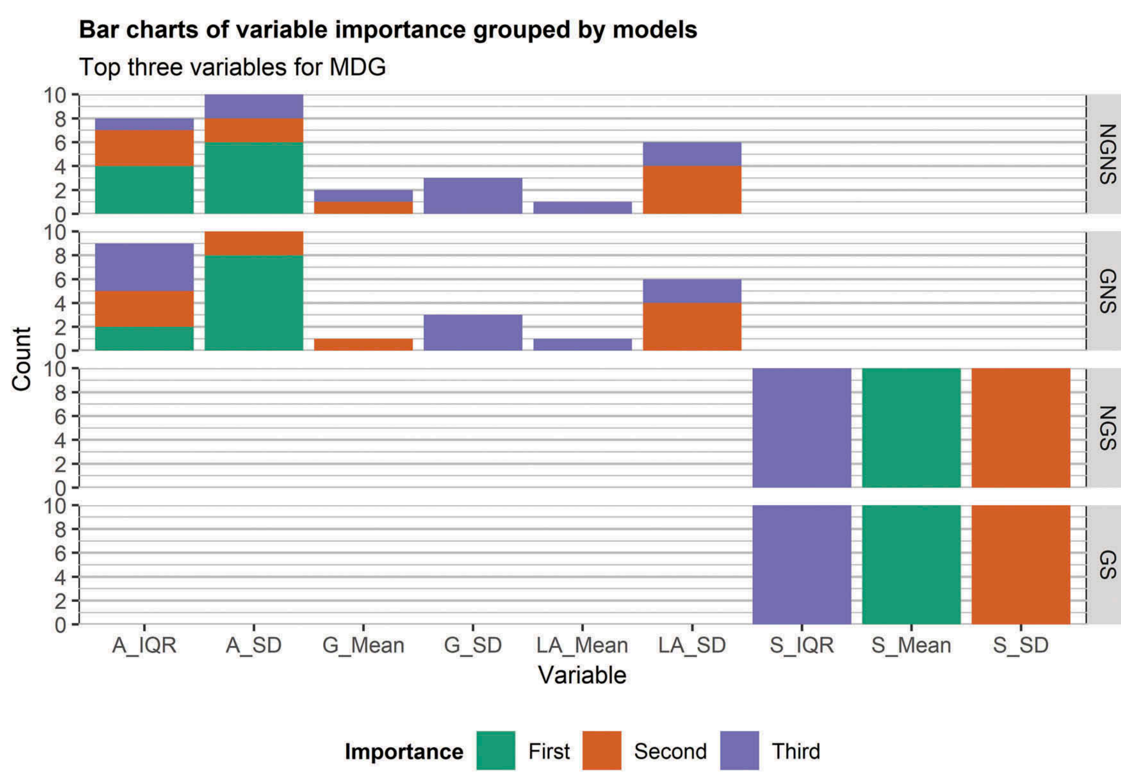

Figure 7. Bar charts of variable importance in terms of mean decrease Gini (MDG). The height of each bar indicates the number of times each variable occurred as either the first, second, or third most important variable for the model type (NGNS, GNS, NGS, and GS) across all 10 window sizes. The color indicates how often the given variable was in either the first, second, or third most important spot.

potentially use calibrated sound measurements. This is in part why we evaluated models with and without sound.

A third limitation of our approach is the development of random forest models with a categorical response that was not uniformly balanced among work cycle elements. Machine learning methods are subject to bias when the predicted classes are not distributed uniformly (Japkowicz and Stephen 2002). The proportions of elements in our study were 49.0% felling, 19.0% acquire, 14.7% travel and 17.3% delay. Higher OOB accuracy of the felling element may be related to the greater frequency with which felling occurred. However, it should be noted that all four elements were predicted with high accuracy when using longer (10-s) sliding window sizes to extract features (Table 2, Figure 4).

Use of smartphones to quantify work activities may raise privacy concerns for contractors. However, many are accustomed to equipment onboard computers recording productivity data (Strandgard et al. 2013). Recent logger surveys conducted in the western US (Newman et al. 2018; Wempe et al. 2019) have indicated low concern about privacy and general support for real-time mobile data-sharing, particularly when there are safety benefits (Newman et al. 2018; Wempe et al. 2019).

Future work should include coding the model developed in this paper, or a new model fitted to a larger dataset, into a phone app to validate predictions with independent data from different harvest blocks and operators. Development of activity recognition models based on smartwatches may be less obtrusive or burdensome for fallers. Conducting similar studies to develop activity recognition for other manual and motor-manual forestry positions may foster advanced analytics for forest operations. For example, a library of phone-based activity recognition models for tree planting, precommercial thinning, cable rigging crew functions, forest inventory, and timber sale layout would allow activity recognition-derived metrics to be correlated with inventory, GIS, and other data to model productivity, treatment and planning costs in ways not previously considered.

In conclusion, activity recognition models developed from common smartphone sensors using random forests predicted productive work cycle elements and delay for hand fallers with accuracies between 65.9% and 99.6%. Using longer sliding windows (10-s) to calculate time domain features consistently improved accuracy. When features derived from sound were included, they were often the most important predictors. However, models without sound also predicted cycle elements well. Models developed with time domain features calculated with gaps between elements performed slightly better than those without gaps. Development of sensor-based activity recognition models for motor-manual and manual work activities can provide advanced analytics for operational forestry through high-resolution, real-time summaries of work functions.

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