Monitoring Vegetation Height using Data Acquisition from Ubiquitous Multi-Sensor's Platform

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Abstract—**Vegetation height plays a crucial role in various ecological and environmental applications, such as biodiversity assessment and monitoring, landscape characterization, conservation planning and disaster management. Its estimation is traditionally based on in situ measurements or airborne Light Detection and Ranging sensors. However, such methods are often proven insufficient in covering large area landscapes due to high demands in cost, labor and time. Since, the emergence of wearable technology, ubiquitous sensors and Internet of Things offers an appealing framework for monitoring environmental parameters at extremely low cost, which, in turn, contributes to the development of affordable real-time vegetation monitoring system. This is especially relevant to rural environments and underdeveloped countries. We proposed a methodology for data acquisition from a ubiquitous sensor wearable platform and developed a machine-learning model to learn vegetation height on the basis attribute associated with pressure sensor. The proposed methods are proven particularly effective in a region where the land has forestry structure. The results of linear regression model (r2 = 0.81 and RSME = 16.73 cm) and multi-regression model (r2= 0.83 and RSME = 15.73 cm), indicate a promising alternative in vegetation height estimation when in situ or Light Detection and Ranging data or wireless sensor network are not available or affordable, thus facilitating and reducing the cost of ecological monitoring and environmental sustainability planning tasks.**

I. INTRODUCTION

Vegetation height is a key indicator for many terrestrial ecosystems which can be associated with habitats and their biodiversity and biomass [1], [2]. Besides, Vegetation height can be utilized for classification of land cover or estimating forest age and habitat quality. Indeed, it is an essential input parameter for ecosystems and highly correlated with vegetation biomass [2] , which is the fundamental element of the carbon cycle and a substitute for fuel loading estimation [3].

Vegetation has many forms, one of them is referred to as Herbaceous vegetation or short vegetation, which is found to play an important role in determination of confined livestock grazing and climatic variability as agents of vegetation change [4] . Traditionally, (short) vegetation height is measured using handheld devices such as hypsometers (for mature trees) or measuring poles (for seedlings and low vegetation) through field campaigns [5], [6]. However, these methods are time consuming, incur high labor cost, and are therefore limited in scope to mapping at fine scales. Measuring vegetation height requires a huge amount of effort. Alternatives to these approaches, numerous technologies are available, in the case where the possibility and availability of situ measurement are unattainable, include imaging and radar-based methodologies. LiDAR, referred to as a 3D laser scanner, is recognized to be one of the most efficient alternate for recording vegetation data mostly using airborne sensors [7], [8], [9]. Lidar with its full waveform digitizing provides highly efficient measurements at a footprint level of observation for forest structure where several works have been reported.

Intuitively, pressure-based sensors may provide information on land cover such as soil properties, water content and vegetation properties (density, height etc.) where the relationship between soil and vegetation is not fully unknown. Indeed, soil compactness, texture, bulk density and organic / mineral composition directly influence plant growth, quality and abundance. For instance, Landhaeuser et al. [10]. studied the effects of soil compactness on the depth and lateral spread of marsh reed grass. Silva et al. [11]. found that animal trampling can cause soil compactness and degradation of soil structure, which negatively affect vegetation growth and height. Similarly, Botta et al. [12]. reinforced Silva et al.s findings and showed that even increased frequency of pedestrian or wheels passages can lead to an increase of dry bulk density, which in turn, affects vegetation height. The question can therefore be raised to investigate the extent to which soil patterns can be employed to estimate vegetation height. Especially, is it possible to perform such estimation using solely low-cost sensor platforms? With the recent advances in sensor technologies, including IoT framework, cloud computing and wearable technology, several breakthroughs in low cost and efficient environment monitoring technology become accessible to a wider audience (non-specialist group). Indeed, one notices, for instance, a range of wireless sensor network deployed for habitat and environment monitoring applications, see, e.g., the review paper [13]. on the use of smart and low-cost sensors in agriculture, food and related applications. Zhou et al. [14]. put forward a scalable field cost effective IoT powered phenotyping platform, referred CropQuant, for crop monitoring and trait measurement in a way to predict vegetation growth.

In a nutshell, our study aims to overcome the challenges of such operational costs, time and labor experienced in remote sensing technologies and WSN deployment challenges, by utilizing the low-cost sensor in the form of wearable device. The goal is to introduce a new perspective in data acquisition and analysis from a low cost multisensory handed device through a wearable platform, for estimating the vegetation height.

II. Materials and methodology

A. Study area

This study has been conducted in an 8-type soil variety area in Oulu region, Finland. see Fig. 1, which highlights distinct vegetation height levels. Typically, Normalized Difference Vegetation Index (NDVI) is a standard way to measure healthy vegetation. Higher (lower) NDVI values indicate healthy (poor) vegetation quality. Besides, the existence of several repositories and open data where NDVI values are publicly available provides us with efficient tool to guide the selection of the study area in a way to ensure useful differentiation. Accordingly, we have selected the study area based on NDVI index and the google earth location to ensure the variability in vegetation height at each site. However, the exact variation is quite difficult to estimate solely using the NDVI index. Table I. features the exact coordinates of the study area, vegetation type and structure covered that were observed during the experiment. The description of the structure of vegetation observed in each area; namely, structure type A, B and C; is reported in Table II.

TABLE I. Detail Of Study Areas Locations Including Vegetation Types And Structures

Study Area	X coord.	Y coord.	Veg. type	Struct. present
Site 1	65.0693	25.483	Sand	None
Site 2	65.0701	25.480	Grassland	A, B, C
Site 3	65.0712	25.478	Grassland	A, B, C
Site 4	65.0726	25.471	Grassland	A, C
Site 5	65.0714	25.465	Grassland	A, B
Site 6	65.0633	25.475	Grassland	A, B, C
Site 7	65.0646	25.472	Grassland	A, B, C
Site 8	65.0644	25.467	Grassland	None

TABLE II. Vegetation structures presents in study areas

Structure type	Description
A	Mixture of Woody and Herbaceous Plants
B	Woody plants dominate Herbaceous plants
C	Herbaceous plants

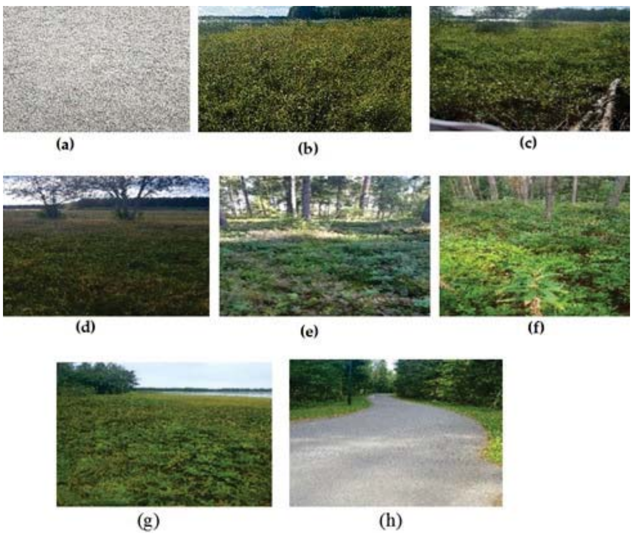

Fig. 1. Study areas near kuivasjrvi, Oulu, Finland; (a) Site 1; (b) Site 2; (c) Site 3; (d) Site 4; (e) Site 5; (f) Site 6; (g) Site 7; (h) Site 8

B. Wearable platform design and description

The wearable platform developed with the synergy of three sensors, namely, flexi force sensitive resistor, temperature and humidity, and Bluetooth module is utilized for strengthening the overall building of the wearable platform see Fig. 2, while Bluetooth module is employed solely for transmission purpose. An android application is also developed to store the readings obtained from the sensors on a mobile application.

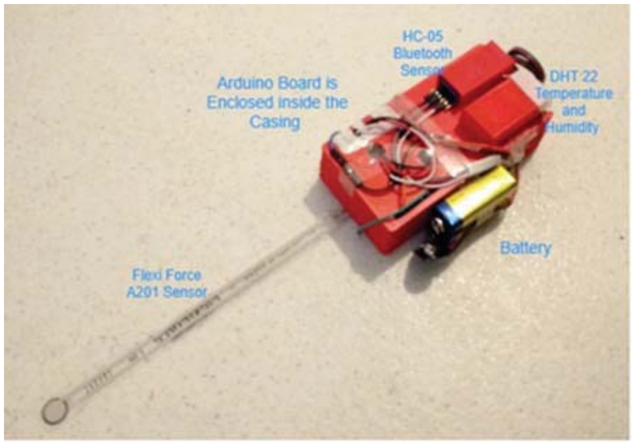

Fig. 2. Wearable platform representation: image view of the developed system

We have chosen DHT 22 temperature and humidity sensor, due to its high reliability, good stability and compatibility with Arduino platform. The DHT22 sensor consists of two parts: a capacitive humidity sensor, which is responsible for measuring the humidity, and a thermistor that measures the temperature of its surroundings. The sensor has the capacity to measure the temperature in the ranges from -40 to +125 degrees Celsius with +-0.5 degrees accuracy, offering excellent quality, fast response, anti-interference ability and cost-effectiveness. This enables us to read the temperature from the sensor and display it in the serial monitor. Flexi force sensor, also referred as the force sensitive resistor, is used for calculating the pressure value. It operates on changing its resistance when the external force, pressure or stress is applied. Tekscan flexi force A 201 became nowadays quite a standard and among most popular instruments for measuring force in wearable platforms. A fixed value resistor of 1Mohm is connected in a series with the FSR resistance. The connection of FSR with Arduino is established by joining one end to the power pin and the other end to the fixed value resistor ground, the point where the resistor is connected to analogue pin of Arduino board. In order to determine the force of unknown loads, the equation for the best fit is to be derived. For this purpose, a set of input-output voltage measurements should be carried out. Next, voltage-force graph is plotted, and the best linear fit is identified. In agreement with manufacture recommendation, a Voltage vs Force graph is plotted in order to find the best linear fit. Bluetooth module. We employed the HC-05 Bluetooth module because of its simplicity and capability of transferring the data over a short distance. The module can easily be interfaced with Arduino board. The logic voltage level of data pin of HC-05 is 3.3V. Therefore, the connection of data line between Arduino TX and RX needs to connect through a voltage divider in order to not burn the module. On other hand, the pin of Bluetooth can be connected directly to the

Arduino board. An android mobile application is developed using Android Studio, for the purpose to record the reading from the developed multi-sensor platform. The application uses the Bluetooth communication for acquiring the real time sensor data from the HC-05 Bluetooth module and further, stores the data information.

III. Vegetation survey

A. Field measurements and height estimation

One of the traditional practitioner-based approach for vegetation height measurement, referred to line-point intercept method, is carried out using the field measurement method proposed by Jeffery et al. [15], with some alteration. In this respect, the cover is measured along a linear transect line and is based on the number of hits on a target species out of the total number of points measured along that line. In our case, vegetation height is measured as the height of the tallest plant part within a 30 cm diameter cylinder projected tangent to transect. It is measured vertically from the soil surface at the center of the cylinder, see Fig. 3, for illustration purpose.

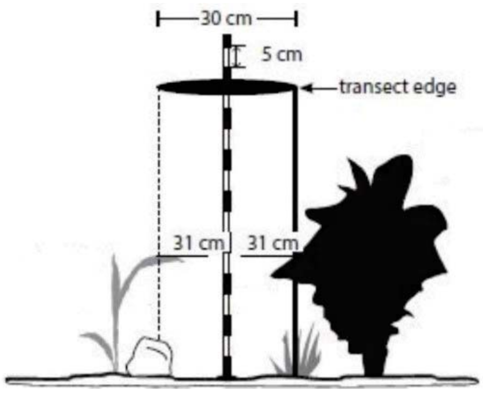

Fig. 3. Vegetation field measurement using transcend

Given the geometrical constraints on the study area and considering the density of the plants (canopy cover), we chosen to carry out the aforementioned transcend based measurement five times at regular interval in the region of the study where the plant density is deemed important. More formally, five distinct measurements of vegetation height Hi is carried out at each interval of 2.5 meters. We then estimate the average maximum vegetation height of canopy cover, over the five measurements:

$$Avg.VH = \frac{1}{5} \sum_{i=1,5} H_i \qquad (1)$$

The primary assumption by doing so is that we reasonably assume that each of the study field is rather associated with a minimum number of vegetation heights (up to three), corresponding to average transcend measurements according to (1) in each vegetation type / structure. This is motivated by the fact that the plants type (either grassland or forest) and structure type (A, B or C) in each site of study are roughly homogeneous in terms of height; therefore, it makes sense to consider the vegetation of the same structure (A,B, C) to be of the same height. This subsumes at least three pre-requisites. First, the average operation (1) is carried out for each structure type present in the study site (up to three, corresponding to A, B, C structures). Second, the fine-grained variation of the vegetation height is not the prime concern of the study. Third, there exists a mechanism (simple GPS locations and/or visual patterns), which maps the location to the structure type at each site in order to build the ground truth model, which is required for the subsequent analysis. The preceding enables us to build the ground truth in terms of vegetation height for each of the eight study sites. The overall structure of the ground truth data-set is highlighted in Table III. Especially, for simplicity purpose and

TABLE III. Ground truth structure of each study area

Variables	Description
Vegetation type	Grassland or Forest
Structure type	A, B or C structure
Bounding box	Latitude and Longitude of the top-left and bottom-right of the approximate rectangular region
Vegetation height	Average vegetation height measured using transcend method

location matching, we modelled the region in the same site of the same structure type, and thus of the same vegetation type, by a rectangular region. The latter can therefore be represented using a bounding box.

B. Platform Data acquisition

Several experiments were performed for the acquisition of sensor data, where around 10 meter of distance is covered by walk at each designated site. During this walk, the wearable platform is attached to the foot. In total eight tests were performed at each study site and each test is carried on different path for finding the variation in the sensor data. The general execution plan is shown in Fig. 4, which provides fined experimental details. Armed with the developed footwear platform, the user performs normal walking task at each site ensuring that all structure types present in the site are covered. At each walk step, the sensory information is transmitted to mobile station, and thereby to cloud platform to enable further preprocessing.

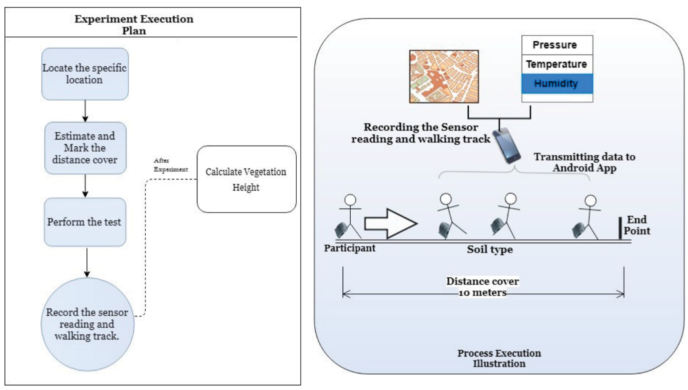

Fig. 4. General execution plan of the experiment setup

Especially, we mainly focus on pressure sensor output as the temperature and humidity sensor exhibits no variation due to the fact that measurements were almost instantaneous so that there is no variation of temperature or humidity data at the time of the measurement both within the same site and across sites. Given the samples of pressure data acquired during the walking process at each site / structure type, one determines its statistics in terms of average pressure value, minimum value and maximum value. These three entities (average, min and max of pressure values) are taken as independent variables in our study to infer vegetation height. The description of these parameters is listed in Table IV. In total, 62 samples or observations are collected during experiments, where the division is as follow: 8 experiments in Site 1(soil type: sand), no vegetation structure variation, 8 experiments in Site 2 soil type: sand), all the three vegetation structure A, B, C are present. 5 in Site 3, 8 in Site 4, 7 in Site 5. 7 in Site 6, 8 experiments in Site 7 and 8 in Site 8. The dataset is split into training and testing dataset, where 80 perecnt of data is used for training the linear regression models and 20 percent is used for testing the model.

TABLE IV. LIST OF INDEPENDENT VARIABLES AND TARGETED VARIABLE

Attributes	Method of Acquiring	Importance
x1 = Maximum Pressure	Sensors platform	Independent
x2 = Minimum Pressure	Sensors platform	Independent
x3 = Mean Pressure	Sensors platform	Independent
y = Vegetation Height	Point intercept method	Target

IV. ESTIMATING VEGETATION HEIGHT USING WEARABLE PLATFORM

For the purpose of estimating the vegetation height from the pressure measurement, a multi-regression based approach is devised in order to assess the relevance of the underlined independent variables in this estimation process where the vegetation heights estimated in the field measurement through transcend method are used to determine the parameters of the regression model as highlighted in Fig. 3. Table IV summarizes the set of attributes related to pressure measurement and found relevant in this study. On the other hand, for the purpose of simplicity and good results obtained elsewhere, we used a multilinear regression model. More specifically, considering the interaction effects of the attribute variables, the regression model boils down, for a response variable y, to the following

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \quad (2)$$

where β_i *(i=0 to 3)* are the parameters, to be determined using the training dataset, of the model, interpreted as regression coefficients.

Nevertheless, instead of carrying out the regression analysis across all attributes, we have also considered the effects of downgrading the scale of the training by restricting the training to one predictor variable only. Therefore, the question that arises is

To which extent can a single attribute xi (i=1,3) estimate the vegetation height?

Equivalently, the preceding boils down to estimating the extent to which a single linear regression model of xi is statistically speaking a good fit to estimate the vegetation height of the training dataset. Mathematically, this corresponds to the following fitting equation, where xi stands for x_1, x_2 or x_3.

$$y = \beta_0 + \beta_1 x_1 \quad (3)$$

Intuitively, the three attributes may show distinct fit with the training dataset. It is therefore interesting to explore such trend. This corresponds to a backward elimination-based strategy where instead of treating the three attributes simultaneously, leading to a multi-regression model of three parameters, we will only restrict to the most significant attributes as testified by the simple regression fitting outcome. Besides, for scaling purpose, we set β_0 to one, and therefore, leaving only β_1, β_2, and β_3 to be estimated using the (multi) regression model (s). The next section details the result of this investigation.

V. DISCUSSION AND RESULTS

A. Correlation analysis

For validating and verifying the results, we later applied statistical analysis, in order to find out whether the associated attributes show any significance level of correlation with the targeted variable.

First, in order to show the effect of each individual attribute (max-pressure, min-pressure and mean-pressure) on (average) vegetation height as estimated in the field measurement, the variation of vegetation and each attribute with respect to various site locations is plotted in Fig. 5. The latter indicate, any increase (decrease) or the vegetation is translated into either an increase or a decrease of the attribute value, except for the site location A (sand), where both vegetation height and pressure values are meaningless. On other hand, the direction of variation (either increase or decrease) with respect to that of vegetation height indicates a positive or a negative correlation of the given attribute with respect to vegetation height. In this course, Fig. 5a highlights a rough negative correlation of maximum pressure with vegetation height. Although a slight deviation can be observed in site F, C, E and D, where the maximum pressure slight decreases as vegetation height. Though, it does not affect the overall trend of negative correlation. Indeed, the calculus of the Pearson correlation coefficient between the attribute variable and vegetation height indicates a correlation value of r = -0.9451 with p-value 0.0013. Likewise, from Fig. 5c, the mean pressure indicates a similar pattern as for the maximum pressure attribute, with a Pearson correlation coefficient r = -0.9219 and p-value = 0.0011. However, such trend is less visible in case of min-pressure attribute as highlighted by the corresponding Pearson correlation coefficient r = -0.79 but p-value = 0.02.

The results summarized in Table V indicates that there is a weakly significant inverse relationship between the min pressure and vegetation height r (61) = -0.39, n = 62, p ¡ 0.001. In contrary, a strong statistically negative correlation observed between the maximum pressure and vegetation height r (61) = - 0.86, n = 62, p <0.001. Similar relationship holds for mean pressure output and vegetation height where it was found r (61) = -0.85, n = 62, p <0.001. Tables V also exhibit the regression coefficient when a linear fit between the underlined independent variable (max pressure, min pressure or mean pressure) and vegetation height is enforced. Clearly, the small value of Person coefficient indicates again the min pressure attribute should be discarded and would not predict the vegetation height appropriately.

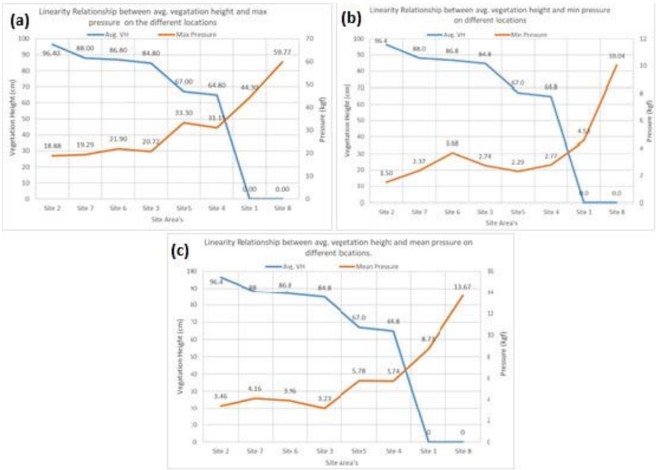

Fig. 5. Linearity Relation between; a) average maximium pressure(kgf) and vegetation height(cm); b) average maximium pressure(kgf) and vegetation height(cm); c) average maximium pressure(kgf) and vegetation height(cm)

TABLE V. PEARSONS CORRELATION COEFFICIENT WITH TARGET VARIABLE AT 95% CONFIDENCE LEVEL

Variables	Pearson Corr.	Signi.	Regression Coef. β
Maximum Pressure	-0.86	<0.001	β = -2.11
Minimum Pressure	-0.39	<0.001	β = -2.80
Mean Pressure	-0.85	<0.001	β = -8.73

The experiments results shows that the higher pressure readings are observed when exposed to more stiff surface such as asphalt and sand. In contrary, the stiffness may vary in lands where different level of vegetation is displayed. The reading also shows that lands with higher vegetation height experience lower reading of pressure attributes. This is due to the fact that smaller stiffness around the surface is sometimes rooted back to the presence of irregularities and unbalanced cases, which in turn, causes difficulty in walking, and, thereby, ultimately, results in lower recording of the pressure values.

B. Multi regression estimation of VH

In order to comprehend the influence of the multiple attribute on the targeted variable (vegetation height), we applied a multi-linear regression model with statistical model selection. For this purpose, we trained the model more efficiently by applying backward elimination technique [16] and predefined threshold-based of 0.05. Results of previous section showed that the max and mean-pressure exhibited strong and statistically significant negative correlation with vegetation height when considered either average site values or the whole readings. Initially, the multi regression model with backward elimination method considered all the independent variables (min, max and mean-pressure) during the training phase. After, training the model, we computed the p-value for each attribute that is then compared to some predefined significance threshold, which triggers the decision to maintain or discard the underlying attribute variable. Especially, the analysis of variance (ANOVA) is conducted in order to identify the level of variability within the corresponding regression model and form the basis for tests of significance.

The Table VI indicates that the p-value of min-pressure attribute is quite large 0.229 as compared to significance level

TABLE VI. STATISTICAL SUMMARY AFTER FIRST ITERATION OF MULTI REGRESSION MODEL

Variables	Coefficients	P-value	t Stat	Stand. Err.
Intercept	123.587	<0.001	22.337	5.533
Max.	0.743	0.229	1.216	0.611
Min.	-1.067	0.014	-2.525	0.423
Mean	-5.287	0.010	-2.648	1.997

of 0.05 (threshold). This agrees with previously aforementioned results. While, the maximum and mean attribute p-value do not exceed the significant level. Thus, pointed out to be highly statistically significant and considered to be powerful predictor for our training model. Therefore, considering such elimination-based analysis, the next iteration is run without the min-pressure attribute. The results of this subsequent analysis are shown in Table VII.

TABLE VII. STATISTICAL SUMMARY OF FINAL ITERATION OF MULTI REGRESSION MODEL

Variables	Coefficients	P-value	t Stat	Stand. Err.
Intercept	123.978	<0.001	22.353	5.546
Max.	-1.266	0.002	-3.233	0.392
Mean	-3.885	0.021	-2.374	1.637

Finally, the evaluation of the multi-regression model is conducted based on root mean squared error (RMSE) and regression coefficient using the training dataset. The predictive performance of the linear regression and multi regression model in terms of two evaluation measures for single target variable is presented in Table VIII.

TABLE VIII. EVALUATING THE PERFORMANCE OF LINEAR REGRESSION AND MULTI REGRESSION FOR ESTIMATING VH

Variables	R^2	RMSE(cm)	Model
Max Pres.	0.81	16.73	127.03-2.12*x1
Max & Mean Pres.	0.83	15.75	122.91-1.25*x1-3.75*x3

The findings shown in Table VII, VIII indicates promising results and gives intuition for further research in data acquisition obtained through low cost sensors, where the use of multi-regression of max and mean pressure attribute yields a decrease in RMSE, and therefore, an increase in prediction capability.

C. Novelty and discussion on uncertainty of the work

Our findings showed a possibility to identify different level of vegetation height by utilizing the low-cost foot-wearable. Both linear-regression and multi-linear regression models employed in our studies are solely trained on the pressure sensor attributes (min, max and mean pressure values) and the obtained findings showed that the maximum, mean pressure attribute are highly correlated with vegetation height. Besides, both linear regressions using max-attribute and multi-regression (with mean and max pressures) shown good results in terms both RMSE values as well as statistical significance.

For the purpose of simplicity and accommodating the time constraint, we restricted our experimentation only to few areas covering different measurements of vegetation heights. In addition, the experiment is conducted only once at each site excluding the factor of daily variation of environmental conditions occurred due to the change in the temperature and humidity which might affect the soil moisture and vegetation structure.

Nevertheless, one should also point out that the experiments were mainly conducted with one single user wearing the ubiquitous sensor foot-based platform. This trivially makes the result pervaded by several uncertainty that are worth considering. First, users body weight straightforwardly influences the numerical values of the sensor pressure. Nevertheless, we believe that the influence of such phenomenon is very limited, as the interest is on the correlation of the pressure values with the vegetation height not on the exact value of the pressure values. Second, the walking patterns of the individual might also affect the pressure sensor readings. Although a full investigation of such effect would require a proper ergonomic analysis, the short interval between two measurements makes the impact of such factor likely limited as well. Third, other sensor placed in the ubiquitous platform, mainly, temperature and humidity, could not exhibit much variations. The foremost reason behind it, as already pointed out, is the short time span of recording the sensor measurement, which in turn, resulted in less variability in these measurements. However, the measurement can be considered in the condition, when the experiment is conducted for longer period of time, for instance.In future consideration, we are opted to involve sensor input from temperature and humidity sensor, which can be utilized in training the model for more efficient result. In addition, other modalities such as camera, can be added to the platform, which in turns, will be useful for investigating the spatial content of vegetation structure.

VI. Conclusion

In this study, data acquisition from the ubiquitous sensors wearable platform, for predicting the vegetation height were proposed and evaluated. The approach is based on developing a machine-learning model to learn the vegetation height from key attributes associated to pressure, temperature and humidity measurements. The idea is based on finding the key variation from the sensor measurement at different level of vegetation height. The approach uses multi-regression model that involves pressure related attributes (minimum-pressure, maximum pressure and mean-pressure). The correlation and statistical analysis showed that maximum-pressure and mean-pressure are more significant in predicting the vegetation height. Thereby, both single and multi-regression models were appropriately designed and tested.

In general, the results acquired from our approach are not meant to outperform or even approach some state of art approaches using more elaborated remote sensing or satellite imaging techniques, nonetheless, will pave the way for the development of low-cost ubiquitous technology. Indeed, in contrary with satellite imaging and advanced remote sensing technology that demand high operational costs, time and labor, our approach entitles new opportunities towards data acquisition at low cost, less time and labor demands. Similarly, the developed approach outperforms traditional in/situ measurements since it does not require any additional setup or labor cost. Individual equipped with foot/sensor platform can conduct the experiment straightforwardly. Besides, the proposed methodology is less time consuming because the device automatically gathering some aspects of the vegetation related parameters and hence, providing crucial information about its height when feed to developed linear regression model.

Although, this is a pilot approach and much work is still needed in order to construct more efficient machine learning model, considering users various modalities and possibly integrating other soil related sensors. In addition, our approach provides the feasibility for estimating minimalistic characteristic of forest structure nearly at very low cost and less labor demand.

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