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Tree tilt monitoring in rural and urban landscapes of Hong Kong using smart sensing technology

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ABSTRACT

Urban trees are beneficial to our environment and important to human inhabitants. However, they are exposed to natural and anthropogenic stressors, such as strong windstorms, extreme wind events and accidents; inducing tree falling which can cause personal damages, economic losses and infrastructural destructions. The current study is the first of its kind, presenting a tree monitoring system, and using smart sensing devices installed on more than 8000 trees in Hong Kong's rural and urban landscapes. A description of the key components of the system, followed by big data analysis and three case studies of strong wind events over the past 2 years, are presented. A network of smart sensing devices was deployed to develop a large-scale, long-term, smart tree monitoring framework; to help identify potentially hazardous trees in urban areas, particularly during extreme weather events. The changes in tree tilt angle under natural wind loading were recorded. Patterns and responses of tree tilt angles were analyzed, with prediction using time series models based on the Seasonal Autoregressive Integrated Moving Average (SARIMA) and Extreme Gradient Boosting time series forecasting (xGBoost). The results showed the highest correlation for 1-hour forward forecasting, by applying xGBoost model on tree tilt data and weather observations (R^2=0.90). On the other hand, SARIMA model produced one-step-ahead prediction with correlation (R^2) ranging from 0.77 to 0.93, while lower correlation ($R^2 \leq 0.55$) was observed for long term prediction (15 days) of the tree tilt angles. Finally, a dashboard and mobile applications of tree monitoring systems were developed, to transfer knowledge and engage the public in understanding associated hazards with tree failures in the urban area.

1. Introduction

Urban trees are important. They exhibit a wide range of ecosystem services that have long been unveiled and increasingly reported (Fares et al., 2017; Grote et al., 2016; Nowak et al., 1996), which benefit our environment and human inhabitants in multi-faceted dimensions. These include reducing urban heat island effect, enhancing biodiverse habitat for wildlife, increasing the aesthetic value of the street view, and relieving mental distress (Gómez-Baggethun et al., 2013). Yet, trees growing in urban and surrounding areas are subject to considerable environmental stress, requiring proper maintenance to avoid potential hazards, no matter to life or property, in order to cultivate a sustainable urban ecology. During strong windstorms and extreme wind events, accidents relating to failures of urban trees cause personal damages, economic loss and infrastructural destruction (Lopes et al., 2009; Mortimer and Kane, 2004; Peltola, 2006). Therefore, continuous monitoring of the stability of urban trees is imperative in ensuring a sustainable urban design. Numerous tilt sensors have been developed, attaching to tree trunks which continuously collect dynamic data, to measure the tilt angle of root plate movement and wind-induced tree failures (Ancelin et al., 2004; Gardiner et al., 2000; Hale et al., 2012; James et al., 2013a, 2013b). A monitoring system based on analysis of dynamic tree tilt movement data can help devise effective management practices, to reduce tree failures and associated risks in a cityscape during extreme wind events (Heinonen et al., 2009).

To assess and predict tree falling, tree tilt monitoring in association with weather observation is mandatory. Apart from tree species, health and growing conditions (Bartens et al., 2010; Cannon et al., 2015), the critical wind speed for tree failure varies with structural attributes of a tree, such as diameter, age, height, inclination, size, canopy spread, and wood density (Lopes et al., 2009). Trees with lesser diameter at breast height (DBH) are more susceptible to strong winds. Thus, the

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height / diameter ratio of a tree is a critical physical attribute associated with the risk of tree failure (Petty and Swain, 1985). On the other hand, trees behave like a vibrant system, and the tree anchorage holds soil firmly so the root supports the tree trunk and foliage. Weak anchorage in the root system may cause tree falling hazards. This can be detected by measuring the turning momentum or capturing the tilting data of a tree, using a variety of accelerometers, inclinometers, sonic anemometers and Laser Doppler Interferometers (Bartens et al., 2010; Cannon et al., 2015; Dahle et al., 2017; Eloy, 2011; Giambastiani et al., 2017; James et al., 2013a, 2013b, 2014; Moore et al., 2005; Moore and Maguire, 2005). Long term data on tree tilt movements and their response to weather observations can provide important information for early detection of tree mortality, which can be help mitigate associated risks with tree failure, and protect public life and property (Pokorny, 2003).

Hong Kong is well-known for its unique landscape features, where most trees are grown in an intense urban environment or along hilly topography, amidst compact skyscraper buildings and crowded population. An assemblage of collated tree information from extensive field works and rigorous assessments have been conducted to assemble a systematic tree inventory, with listings based on trees under the purview of relevant government departments.

Typhoons are significant meteorological phenomena with strong wind speeds of 118.8 km/h or more (Neumann and Elms, 1993); they bring along heavy rains which in some cases, can induce flash-floods. Strong winds severely damage trees by uprooting, bole snagging, breaking of branches, and defoliating of leaves. In addition, tree failures in urban areas can cause damages to the surrounding environment, such as people, buildings, and transportation infrastructure. The magnitude of the damages is associated with prevailing wind direction, wind speed, as well as the position and health of the affected trees. Therefore, it is important to understand the consequences of high wind speed and their association with tree cover damages.

On average, five to six tropical cyclones threaten Hong Kong every year, with a peak occurrence period during the months of August and September. Over the last 75 years, 12 super-typhoons passed over Hong Kong. On 16th September 2018, super-typhoon Mangkhut hit Hong Kong with a maximum wind speed of 185 km/h; this was regarded as the most severe typhoon in Hong Kong (HKO, 2020). More than 55,000 trees were uprooted due to the typhoon, and 7000 tons of wood waste were collected. Hong Kong also lost 11 out of its 500 historic and valuable trees (Fig. 1). On the other hand, 5,300 fallen trees were reported during the typhoon Hato in 2017 and approximately 1000 trees failures were recorded during the typhoon Vincent in 2012. In 2019, five major wind storms or tropical cyclones hit Hong Kong, viz., Tropical Depression Mun from 2nd to 4th July (maximum wind speed of 55 km/h), Tropical Storm Whipa from 30th July to 4th August (maximum sustained wind of 85 km/h), Severe Tropical Storm Bailu from 21st to 26th August (maximum wind storm speed of 117 km/h), Tropical Storm Podul from 27th to 30th August as a tropical depression with the maximum wind speed of 85 km/h near its centre, and Tropical Depression Kajiki from 1st to 4th September, being the fifth tropical cyclone formed as a tropical depression, with the maximum wind speed of 55 km/h (HKO, 2020). In this study, tropical typhoons, cyclones and tropical depressions are considered windstorms with different wind surges or wind speeds; the damage to trees is associated with wind speed and direction of a storm. Aside from apparent impacts such as tree failures, these windstorms can also affect tree stability and result in weakening of root anchorage.

The significance and value of a tree in an urban space are determined through its benefits to the society, and the risks associated with tree failures due to extreme wind events, tree defects and health status (Dwyer et al., 1991). Studies indicate in the coming decades, there will be an expected increase in intensity by 2% to 11% and in frequency by 6% to 34% for tropical cyclones (Knutson et al., 2010; Virot et al., 2016). Therefore, it is important to model and monitor the response of trees to windstorms, devise effective measures to stabilize trees in the urban landscape, and avoid damages to human life and infrastructure. There is precedence from previous studies in investigating tree failures and resistance to dynamic wind loading during windstorms and cyclones, and static pulling (Giambastiani et al., 2017; Lopes et al., 2009; Peltola, 2006).

Fig. 1. Tree mortalities after the typhoon Mangkhut hit Hong Kong on 16th September 2018.

This study aims to determine the thresholds and ranges of tree root-plate movement under natural, dynamic wind loading, by deploying a large-scale network of smart sensing devices for long-term monitoring of tree tilt angles. To the best of our knowledge, a comprehensive GIS-based system has not been developed to continuously monitor and model tree tilt movement in an urban landscape. The current study is the first of its kind, presenting a platform of tree monitoring system, using smart sensing devices installed on more than 8000 trees in the City of Hong Kong, with continuous monitoring and big data analyses capabilities. To share the knowledge of building this system for the benefit of the tree community with the intent that it can be replicable in other geographies; a description of the key components of the system is discussed, followed by big data analysis, and three case studies of strong wind events over the past 2 years. The investigation and analysis of the big data analysis framework are currently undergoing implementation at full scale; when the project comes to fruition, additional learning will be shared.

2. Material and methods

2.1. The system architecture of the smart sensing technology (SST) network

Customized sensors are designed to track the physical response of trees under different wind loading conditions, by measuring rotational angles, tree displacements and tree tilt angles within a tilt accuracy of 0.05°. These observations are recorded by integrating hardware components including accelerometer (Roll ± 90°, Pitch ± 90°), vibration sensor, micro-controller, ON/OFF switch, battery (8500mAh (LoRaWAN) / 19,000mAh (NB-IoT)) and antenna (Fig. 2). The dimensions of the sensors are 125mm(L) x 67mm(W) x 40mm(H) for LoRaWAN and 132mm(L) x 67mm(W) x 50mm(H) for NB-IoT sensors.

The emergence of the Internet of Things (IoT) paradigm is the key in enabling seamless and massive interconnection of smart devices, machines or things over the Internet (Fig. 3). Coupled with the Big Data Infrastructure and using a machine learning approach, the smart intelligent layer is essential for smart resources to be able to process infor-

Table 1
Distribution of the LoRaWAN and BB-IoT coverage in Hong Kong.

Type	Network Setup	Typical Range	Max Power Consumption	Signal Coverage in Hong Kong
LoRaWAN	Private / Public Network	5-10 km	0.025 W	Urban Area & On Requested Basis
NB-IoT	Mobile Operator	10-15 km	0.2W (max)	Same as Mobile Network Coverage

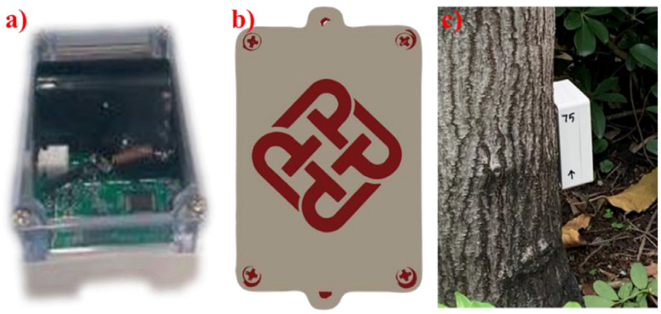

Fig. 2. Sensor structure insights and installed sensor on a target tree.

mation (Poza-Lujan et al., 2019). The ubiquitous framework of system architecture can be summarized in three-folds: data acquisition, data curation and data presentation; where this architecture has been proven to be able to make positive impacts and provide useful solutions for landslide management (Karunarathne et al., 2020).

A new generation of wireless communication systems - LoRaWAN and NB-IoT - were adopted to provide pervasive connectivity between the sensors and the database (Table 1). Despite the applications for both networks are diverse, LoRaWAN is considered the best on the low-cost applications front, whereas NB-IoT is applicable to those with high quality of service and low latency (Sinha et al., 2017). Our study has adopted dual-mode networks, i.e. LoRaWAN and NB-IoT for the pilot scheme; these networks provide complementary resolution in solving the problem of deteriorated network performance in some high-density terrains in urban Hong Kong.

The architectural framework at the level of data curation was developed with specialized technologies used for big data analytics and machine learning approaches (Fig. 3). The data processing backend not only handles streams of geographical data from individual trees within the whole territory, but it also produces models for deeper insights on the tree movement mechanism, and generates within a specific timeframe, reliable predictions for forecasting future failure-related incidents of a single, or clusters of trees.

The development of daily monitoring platform is based on the functional requirements provided by the tree managers working closely on urban trees. The front-end of the system, i.e. the application dashboard, can support users in obtaining quick review of tree conditions, and identifying high-risk-trees through dynamically data fetching, from data curation to the multi-model data presentation. This is done by overlaying interactive maps and azimuth-like data plots to exhibit relevant data features, powered by a tailor-made dashboard to extract insights through visualizing knowledge for the users, which is based on space-time environmental data and tilting data of trees (Benita et al., 2020).

2.2. Selection of trees and sensor installation

Tree height and DBH are the core factors in controlling tree uprooting (Giambastiani et al., 2017; Peltola et al., 2000). The stability of trees is correlated with physical parameters, e.g. height, diameter at breast height (DBH), canopy size, root plate diameter and root depth; as well as species, soil type and wind load (Giambastiani et al., 2017). The pulling test conducted by Peltola et al., (2000) suggested a significant correlation between tree stability and factors including tree height, DBH, stem weight, taper (i.e. ratio between height and DBH), root depth and crown size. They indicated that tapering trees, which have a lower height to DBH ratio, have a higher chance of stem breakage than uprooting.

Therefore, in this study, tall trees (i.e. > 5 m) and trees with large DBH (i.e. > 200 mm), were selected. The sensors were installed at the lower tree trunk of selected trees. Due to concerns of public safety, higher priority was given to roadside trees with heavy vehicle or pedestrian traffic, as well as trees in public facilities, such as parks and promenades. The sensors were installed in three location clusters; including Wan Chai district, which is one of the most commercialized areas in Hong Kong; Kwun Tong Promenade, which is near the coastline with relatively high wind speed; and Victoria Park, which is one of the largest parks in Hong Kong (Fig. 4).

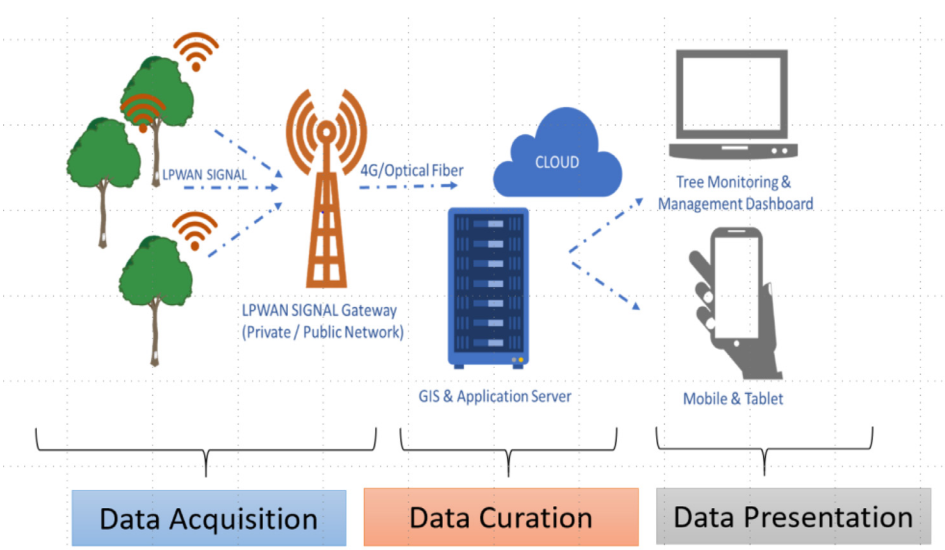

Fig. 3. An overview of the system architecture smart sensing technoology (SST) network architecture.

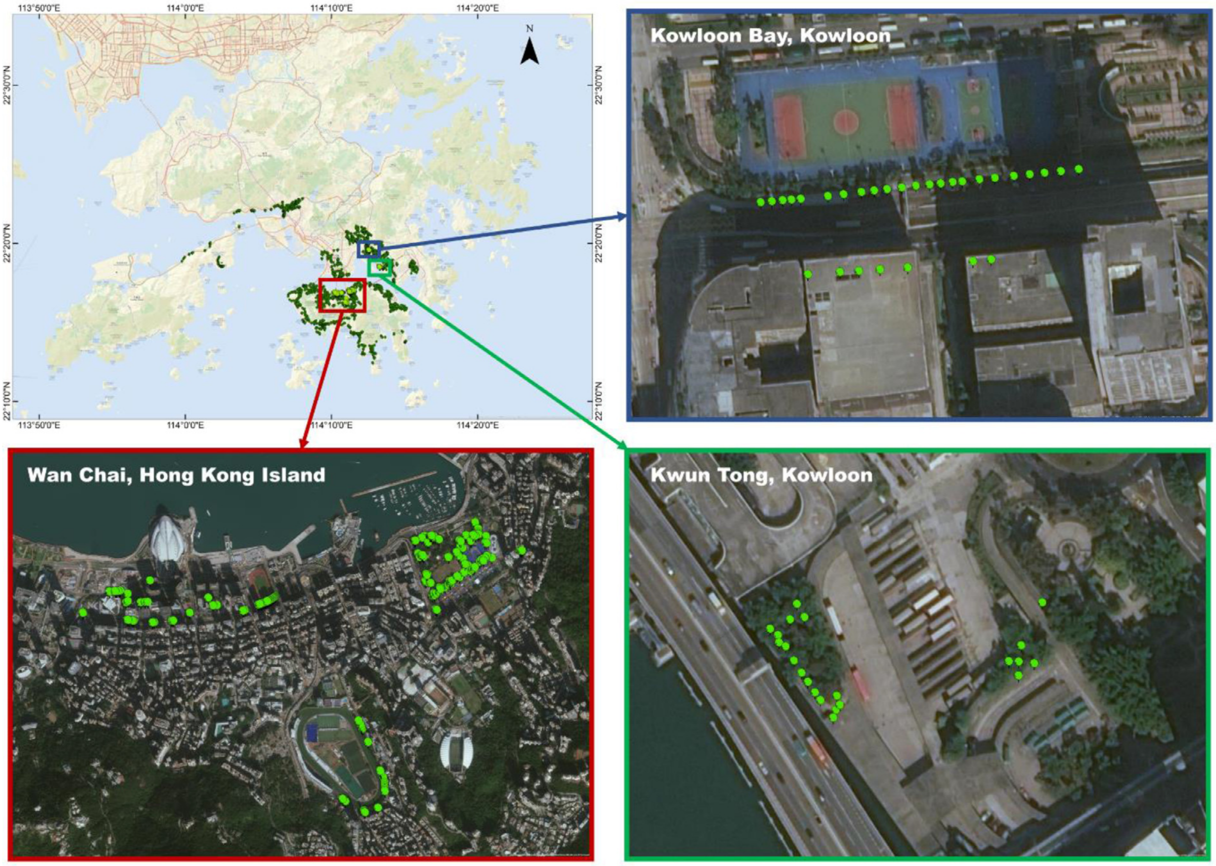

Fig. 4. Map of the distribution of all targeted trees in Hong Kong and the selected trees in the three location clusters.

2.3. Attributes associated with each target tree

For each targeted tree, data on a range of attributes were stored under five major categories, viz., Tree, Sensor, Environment, Point-of-Interest (POI), and Tree Trajectory (moving pathway visualized as an azimuth). The physical characteristics, tree species, DBH, height, crown spread, and tree health conditions such as root and trunk health status, were visually assessed by a certified arborist. Sensor EUI and serial numbers corresponding to each individual tree were stored. The 'Environment' contains information about the surrounding environment, including air quality and wind speed, as well as demographic information such as population density in the district. The POI denotes the proximity of an individual or cluster of trees to the nearest residential and commercial areas, and calculates the dynamic correlation which analyzes the tree failure pattern in the urban landscape heterogeneity. The 'azimuth visualization' interpolates the tree moving trajectory in terms of tilting angles and the movement direction, where the track record of the movement pattern of a tree can be clearly illustrated. The tree tilt measurements associated with physical attributes, species, geolocation, health status, geographical association and environmental surrounding, were analyzed in the study. This helps unveil the underlying causes of tree failures due to strong windstorms in Hong Kong.

2.4. Data collection and refinement – The Big Data

Tree tilting angles were recorded regularly with a one-hour interval in a normal day, and more frequent readings (5-minute interval) were taken when the Hong Kong Observatory issued rainstorm or typhoon signals. The data packages with the information on collection time, roll angle and pitch angle, were transmitted from the sensors via the gateway through either LoRaWAN or NB-IoT networks, depending on the communication module used in the sensor. Then, the tree monitoring system collected the data from the platform of networks, and recorded the data in the tilt angle database for further analysis. Since the initial angle measurement varied because of the installation works and the natural tree leaning, post-processing was conducted on the fly to initialize the angle measurements. The trees were assumed to be stable after the day of installation, and the reading of roll and pitch angles after the first day of installation were considered to be the initial values. For measurements taken after initialization, the current measurement was subtracted by the initial values as listed in Eqs. (1) and (2):

$$Roll = Roll_{current} - Roll_{initial} \tag{1}$$

where *Roll* is the corrected roll angle, $Roll_{current}$ is the instant roll angle and $Roll_{initial}$ is the initial roll angle at the time of sensor installation.

$$Pitch = Pitch_{current} - Pitch_{initial} \tag{2}$$

where *Pitch* is the corrected pitch angle, $Pitch_{current}$ is the instant pitch angle and $Pitch_{initial}$ is the initial pitch angle at the time of sensor installation.

The roll and pitch angles present rotational angles along the x-axis and y-axis respectively; the resulting tilt angle can be calculated by applying the trigonometric formula (Eq. (3)) with an assumption of no self-rotating movement along the tree trunk at z-axis:

$$Tilt = \sqrt{(\tan(Roll))^2 + (\tan(Pitch))^2} \tag{3}$$

where *Roll* and *Pitch* are the corrected roll and pitch angles from Eq. (1) and Eq. (2), respectively, and *Tilt* is the tilt angle of the tree.

This study analyzed more than 2,000,000 tree tilt angle measurements (with data collected from 31st May, 2019 to 30th June, 2020) from the 230 SST sensors. The real-time data were continuously recorded and transfered to the system for big data analysis, to monitor and forecast the state of tree tilt condition.

2.5. Tree tilt analysis

2.5.1. Seasonal decomposition

Seasonal decomposition aims to examine the trend, and seasonal or periodic patterns of a signal. In this study, the time series of the tilt angle from the trees were analyzed by applying an additive model with seasonal decomposition (Eq. (4)). Since the raw data were not corrected at equally spaced points of frequencies, time series of tilt angles were preprocessed to the regular sampling frequency, by resampling the time series and setting of the seasonal decomposition analysis. In the preprocessed time series, the tilt angle was resampled to 5 min intervals using linear interpolation; the default length of the cycles was set to 1 day (24 h) and the trend was extrapolated for forecasting.

$$\mathrm{Signal}(t) = \mathrm{AV}(t) + \mathrm{Trend}(t) + \mathrm{Seasonal}(t) + \mathrm{Residual}(t) \quad (4)$$

where, Signal(t) is the input signal, AV(t) is the average value in the time series, Trend(t) is the increasing or decreasing value in the series, Seasonal(t) is the repeating cycle in the time series, and Residual(t) is the random variation in the time series.

2.5.2. Wavelet transform

In the wavelet technique, a signal is transformed into multiple lower resolution levels by applying a combination of scaling and controlling factors of a single wavelet function (Percival and Walden, 2000). The wavelet analysis filters out the high or low-frequency part of a signal, by changing the resolution of the signal. For each wavelet transformation, half of the signal components with higher frequency are discarded according to Nyquist's rules, while the points of the filtered signal are reduced by half. For tilt angle analysis, the discrete wavelet transform (DWT) was used. The tilt angle was resampled to 5 min intervals using interpolation. If the original signal were sampled at 5 min intervals and the first Detail Coefficients generated from wavelet analysis were removed, then the signal components with a period of less than 10 min would be eliminated.

2.5.3. SARIMA (seasonal autoregressive integrated moving average) analysis

SARIMA is an advanced form of the general ARIMA model. It incorporates a seasonal component of time series in the data analysis. In this part of the study, all tilt angle readings from the tilt sensors were resampled to 1-hour interval (Eq. (5)). The order of the hyperparameters was limited from 0 to 2, while the number of time steps (m) was set to 24 (one day). Two SARIMA models were adopted for the study - one step ahead prediction (one hour ahead) model and long-term prediction (15 days ahead) model. The one step ahead model aims to predict tree tilt angle for the next hour, to detect sudden and potential changes of trees, such as falling, sensor interference and malfunction.

$$SARIMA(p, d, q)(P, D, Q)m \quad (5)$$

where, p, d, and q represent the three parameters of the general ARIMA. p is the auto-regressive aspect representing past values; d is the integrated part which controls the amount of time series differencing in the model; and q corresponds to moving average part in the model. To incorporate seasonal components, three additional components were added to the basic ARIMA model: seasonal autoregression (P), seasonal differencing (D), and seasonal differencing (Q); with the number of time step (m).

2.5.4. xGBoost (Extreme Gradient Boosting) time series forecasting

Extreme Gradient Boosting (xGBoost) is an optimized, supervised machine learning technique based on the principle of gradient boosted decision tree algorithm (GBDT). It uses multiple decision trees and an additive training approach to solve classification or regression learning problems. The independent variables (features) are manually decided, and the quality of selected features is one of the key factors affecting the performance of the machine learning model. Three extra features were created for the xGBoost model, which comprised lag/backshift operation, exponential moving average, and weather observations. xGBoost supports GPU (pipeline) computing to speed up the model training and evaluation process. The time series (tilt angle) were also resampled with a 1-hour interval before model training and evaluation. However, in xGBoost model (refer to Fig. 5), an hourly forward chaining method in xGBoost model was used for model performance evaluation, which means the value of last tilt angle was predicted successively while all previous data were assigned into the training set, until the required length of the testing set was generated. In this study, 3 different tilt angle forecasting models which predict the tilt angle after 1, 2 and 3 h, were created and then evaluated. To optimize the model performance for xGBoost, hyperparameters were fine-tuned as they largely affected model performance. The key hyperparameters used for the xGBoost were 'eta': model learning rate (step size per each boost training), 'max_depth': maximum depth of a tree, and 'gamma': minimum loss reduction required for making a partition of a leaf node; subsample: 'Ratio of the sample (rows)' used for model training, and 'colsample_bytree': ratio of features (columns) used for model training. For all models, the number of boosting round was set to 400, while a GPU was used to speed up the training process.

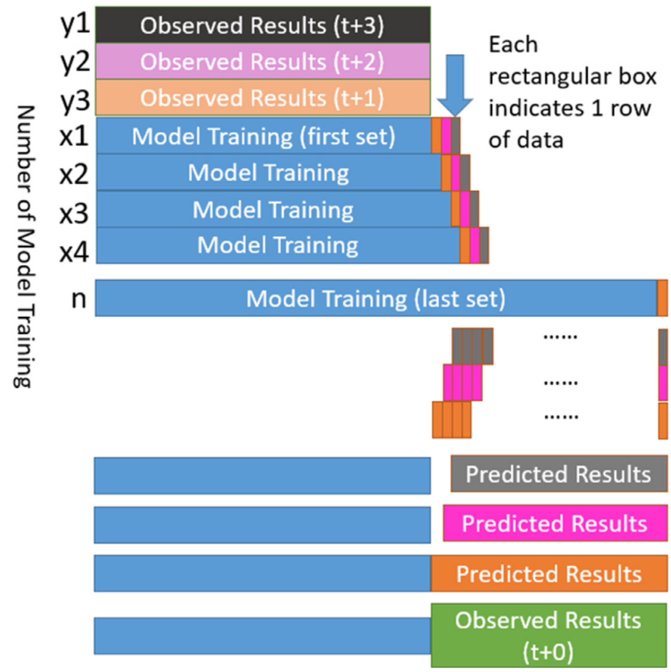

Fig. 5. An hourly forward-chaining method in xGBoost model performance evaluation.

3. Results and discussion

3.1. SARIMA model for tilt angle analysis

Ten tree samples in the countryside (Tai Tong Country Park) and six tree samples in the urban area (Kwun Tong and Wai Chai districts) were selected for tree tilt angle analysis. For the one step ahead forecasting, weather observations data from HKO were applied to the model as an exogenous variable. Since 'the distance between the countryside tree samples and Shek Kong automatic weather station', and 'the distance between the urban tree samples and Kwun Tong, and Wai Chai automatic weather stations', are the shortest, temperature records in these weather stations were extracted. The period of the training model was from 1st January, 2019 to 31st March, 2019 (3 months) and the testing

Table 2
Metrics of the tilt angle predictions using the SARIMA model.

Tree_ID	Best hyperparameters from grid search (p,d,q)(P, D, Q)m	RMSE of the testing set data	R square of the testing set data
Countryside Trees (one step ahead)			
Tc1	(1,0,1)(1,1,0)24	0.088	0.815
Tc2	(1,0,1)(0,1,1)24	0.063	0.934
Tc3	(1,0,1)(0,1,1)24	0.078	0.926
Tc4	(0,1,0)(0,1,1)24	0.074	0.881
Tc5	(1,0,1)(0,1,1)24	0.043	0.899
Tc6	(0,1,0)(0,1,1)24	0.136	0.868
Tc7	(1,0,0)(0,1,1)24	0.098	0.865
Tc8	(1,1,0)(0,1,1)24	0.033	0.861
Tc9	(1,1,0)(0,1,1)24	0.035	0.911
Tc10	(1,0,1)(0,1,1)24	0.062	0.895
Urban Trees (one step ahead)			
Tu1	(1,1,0)(1,0,1)24	0.007	0.767
Tu2	(1,1,0)(1,0,1)24	0.011	0.910
Tu3	(1,1,0)(0,1,1)24	0.019	0.928
Tu4	(0,1,1)(1,0,1)24	0.007	0.818
Tu5	(1,1,1)(0,0,0)24	0.046	0.881
Tu6	(1,1,1)(1,0,1)24	0.015	0.923
Long Term Prediction (15 Days) countryside tree			
Tc1	(0,0,0)(0,1,1)24	0.164	0.363
Tc2	(0,0,1)(0,1,1)24	0.163	0.555
Tc3	(0,0,1)(0,1,1)24	0.192	0.548
Tc4	(1,0,0)(0,1,1)24	0.17	0.383
Tc5	(1,0,0)(0,1,1)24	0.108	0.354
Tc6	(0,0,1)(0,1,1)24	0.333	0.211
Tc7	(1,0,0)(0,1,1)24	0.193	0.477
Tc8	(0,0,1)(0,1,1)24	0.073	0.34
Tc9	(0,0,1)(0,1,1)24	0.095	0.341
Tc10	(0,0,0)(0,1,1)24	0.156	0.338

period was from 1st Aprril, 2019 to 24th April, 2019 (24 days). Table 2 represents the results for one-step-ahead prediction models for the countryside and urban trees, as well as results for long term prediction (15 days models). Time series plots of representative tree samples are given in Fig. 6. For the countryside trees, the R^2 ranges from 0.815 to 0.934 while the RMSE ranges from 0.033 to 0.136. The results of the models for urban trees also show high correlations with R^2 ranges from 0.767 to 0.928, which are relatively lower than that of countryside trees. However, the results from the long-term prediction model do not show a very high correlation, with R^2 ranging from 0.211 to 0.555 and RMSE ranging from 0.333 to 0.073.

3.2. xGBoost tilt prediction with weather observations

Three to seven tree samples in the countryside (Tai Tong Country Park) were selected for tree tilt angle analysis, using the xGBoost tilt prediction models integrated with weather observations. Also, the features generated by lag/backshift and exponential moving average (EMA) were applied to the model. The weather observations data were obtained from the Hong Kong Observatory (HKO). The automatic weather station installed at Shek Kong was selected to extract the weather data, as the Shek Kong Station was nearest to the countryside tree samples in the Tai Tong Country Park. The training and testing period for the model was from 1st June, 2019 to 30th June, 2019 (1 month), and hourly forward-chaining was from 1st July, 2019 to 5th July, 2019 (5 days). Table 3 and Fig. 7 show the results for the xGBoost modelling. For the first hour forecasting, the highest R^2 are 0.897 and 0.863, for models with weather data observation, and without weather data observations, respectively. Notably, the highest correlations for both models decrease from first-hour forecasting to the third-hour forecasting; the R^2 decreases from 0.897 to 0.800 for the models with weather data, and from 0.863 to 0.664 for models without weather data. Similarly, the RMSE increases gradually from 1-hour to 3-hours forecasting. This indicates the shorter the forecasting period, the higher the predicting power.

Table 3
Metrics of the tilt angle predictions using xGBoost model.

Tree ID	1-hour forecasting		2-hours forecasting		3-hours forecasting	
	RMSE	R^2	RMSE	R^2	RMSE	R^2
with weather observations						
Tw1	0.093	0.865	0.109	**0.816**	0.114	**0.800**
Tw2	0.060	**0.897**	0.085	0.798	0.101	0.714
Tw3	**0.035**	0.802	**0.044**	0.689	**0.051**	0.585
Tw4	0.132	0.766	0.151	0.694	0.153	0.686
Tw5	0.095	0.816	0.104	0.781	0.115	0.735
without weather observations						
T1	**0.065**	0.854	0.096	0.683	0.109	0.595
T2	0.115	0.813	0.141	0.715	0.155	0.657
T3	0.068	**0.863**	**0.090**	**0.762**	**0.107**	**0.664**

4. Implementation of the tree monitoring framework in extreme weather events

During extreme weather events in Hong Kong, methods and analysis framework developed for this study were implemented to monitor tree tilt angles. Two extreme weather events were studied in this paper, to evaluate the effects of the wind and rain storms, on tree tilt angles and tree tilt directions. The events included tropical storm Wipha and tropical depression Kajiki, both happened in 2019.

4.1. Tropical storm Wipha

Wipha is a tropical storm which affected Hong Kong from 30th June, 2019 to 2nd August, 2019, with closest distance of 310 km from Hong Kong. During the storm, the Hong Kong Observatory recorded a maximum mean hourly wind speed of 88 km/h and gusts speed of 131 km/h at the Tai Mo Shan weather station. The storm also led to heavy rainfall, with over 250 mm in the entire city and exceeding 350 mm in some areas. The wind direction was mainly from the east (red background color in Fig. 8). During this period, the trees swayed in response to the wind force applied to the trees; with continuous wind from the east,

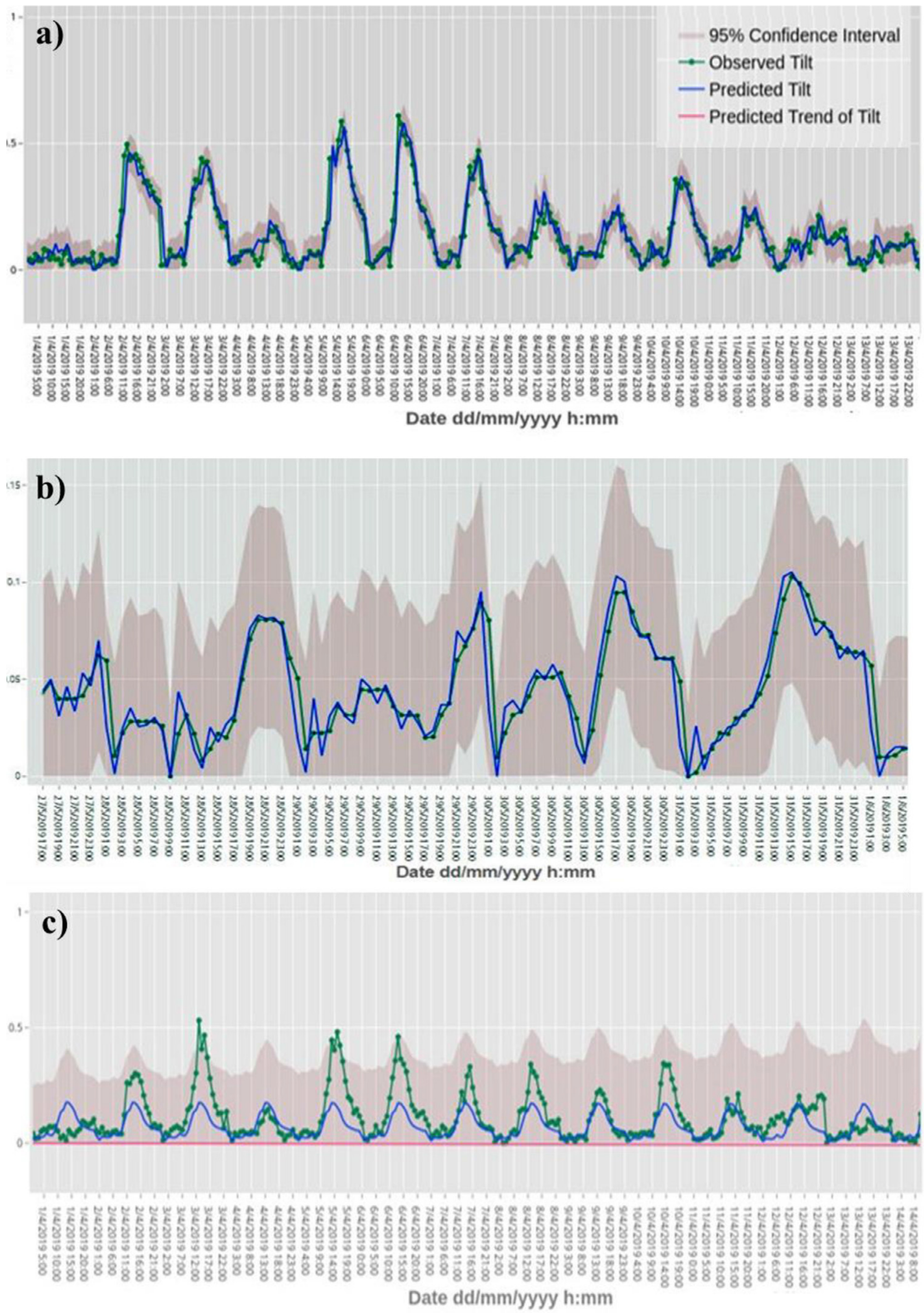

Fig. 6. Tilt angle prediction using SAMIRA model, (a) one step ahead for countryside tree, (b) one step ahead for the urban tree, (c) long term prediction for countryside tree.

the respective tilt angles kept increasing. During the event, most of the recorded tilt angles were within 0.6 degrees. Fig. 8 shows the tilt measurements and the radar chart of a *Senna siamea (syn. Cassia siamea)*, with a height of 14 m, canopy diameter of 7 m and DBH of 378 mm. The tilt angles were mostly between 0 to 0.15 degrees before the storm event (i.e. the vertical lines indicating the tropical cyclone warning signals), and they kept increasing during the storm period, reaching 0.35 degrees. The radar chart shows the trees that swayed in random directions before the typhoon (light red dots); and with a strong wind from the east during typhoon, they swayed towards the west (dark red dots). The results indicate the tree tilt angle would keep increasing if strong winds were coming from the same direction for a relatively long period (e.g. two days); the tree would bounce back to the original position if there were winds from opposite direction, or winds came at the same direction but at lower wind speed.

4.2. *Tropical depression Kajiki*

Tropical depression Kajiki influenced Hong Kong from 1st September, 2019 to 3rd September, 2019, with the closest distance of 330 km from the south of Hong Kong. Tropical depression Kajiki was weaker than the tropical storm Wipha, causing a maximum average wind speed of 63 km/h and general rainfall of over 50 mm. The tree tilt angles were relatively small compared to that of Wipha. Most measurements fell within the range of 0 to 0.2 degrees, being only one-third of Wipha's. Fig. 9 shows the tilt angle measurements of a *Delonix regia*, with a height of 12 m, canopy diameter of 12 m and DBH of 470 mm. The analysis shows the variation of the tree tilt measurements; the change in tilt directions were insignificant with small magnitude. The results suggest a tree would be stable when applied by a relatively weak wind force.

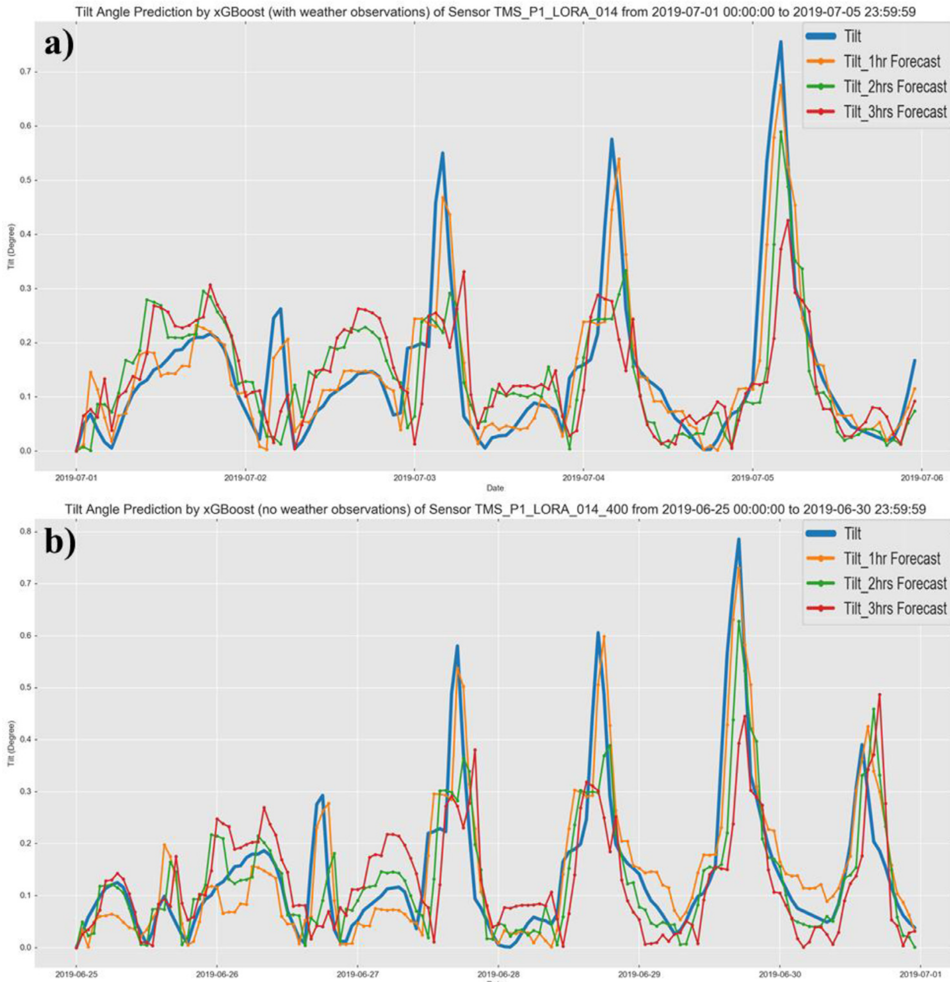

Fig. 7. Tilt angle prediction using xGBoost model, (a) model with weather observations, (b) model without weather observations.

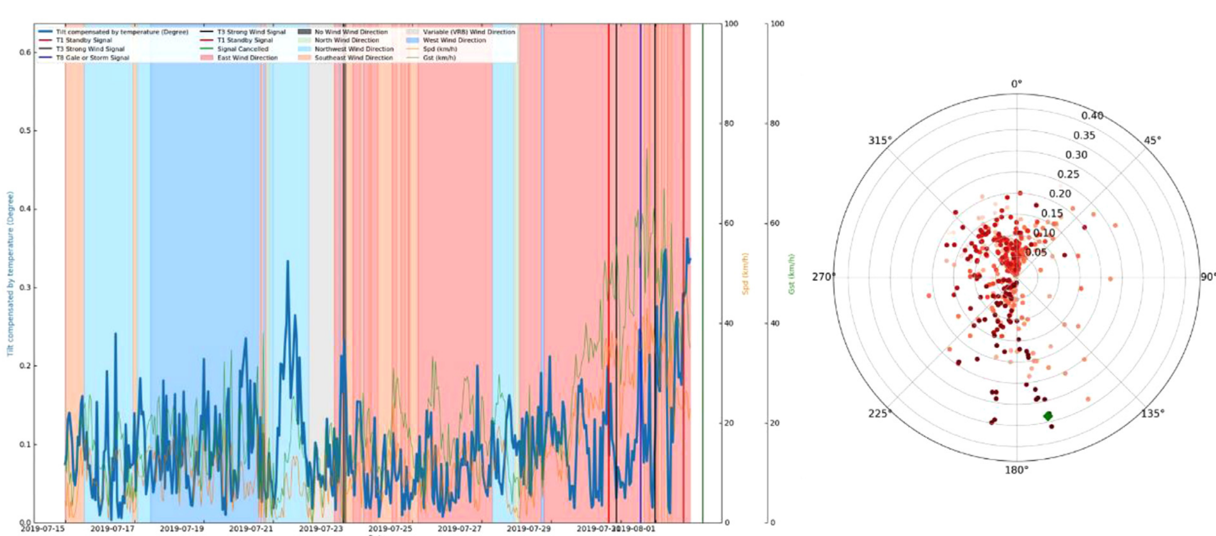

Fig. 8. Graphs representing tree tilt angle and tilt direction during the tropical storm Wipha.

5. A GIS-based platform for tree monitoring system

An interactive, web-based tree tilting monitoring dashboard was developed; based on a Geographic Information Systems (GIS) platform, by incorporating the attributes, data and analysis which comprise the tree monitoring system (Fig. 10). With the tree coordinates, individual trees were displayed on the map and a user could identify respective tree locations. Different colors of tree icons, from green, yellow, orange to red, present different categories of tree tilt angles, whereby a green icon denotes normal trees with tilt angle smaller than one degree; a red icon denotes abnormal trees with tilt angle greater than five degrees, with others being different colour levels at a 1-degree increments (refer to

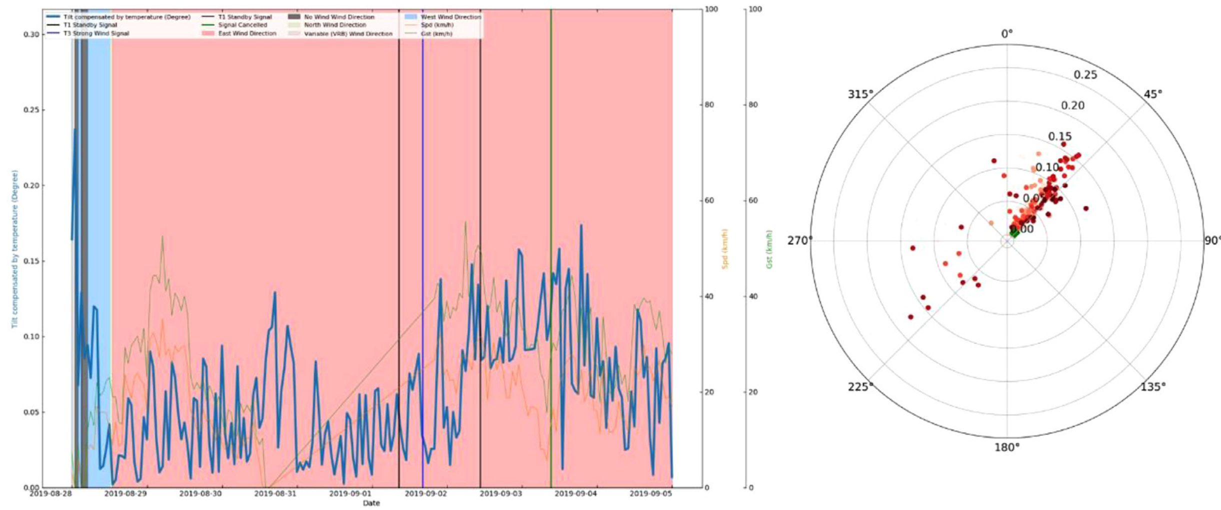

Fig. 9. Graphs reresenting tree tilt angle and tilt direction during the tropical depression Kajiki.

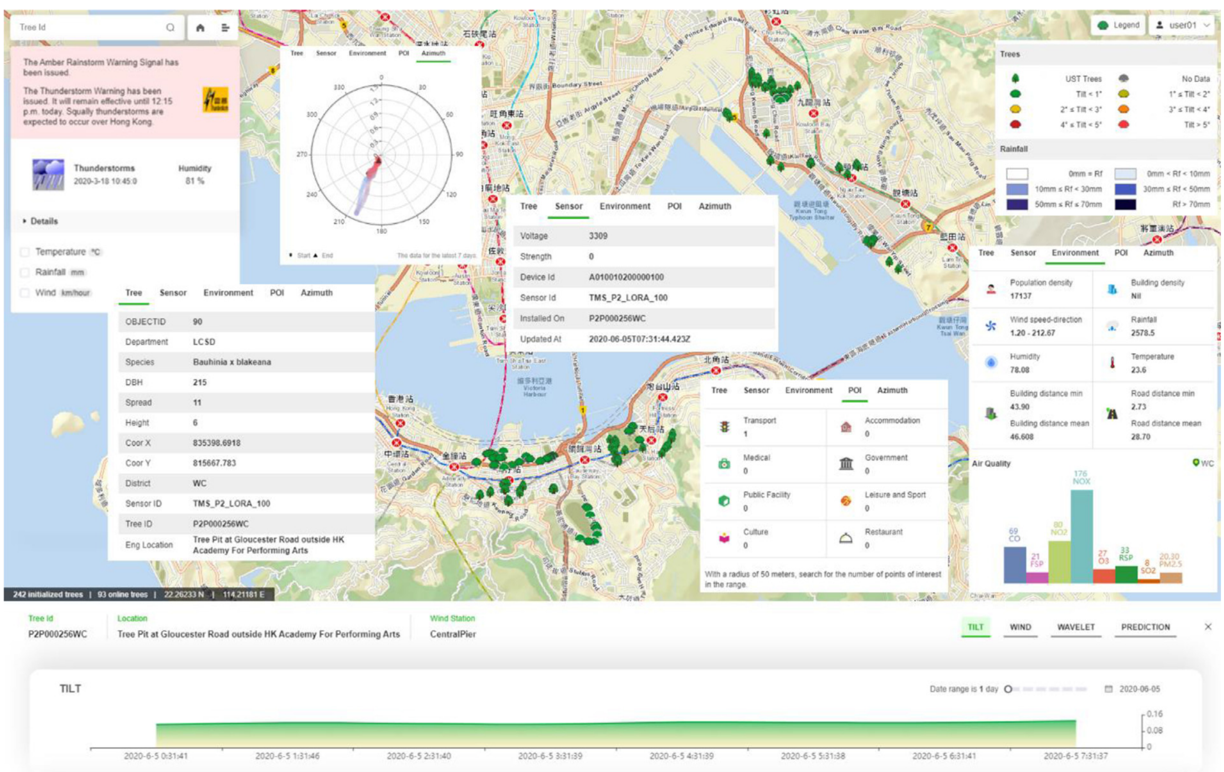

Fig. 10. GIS-based dashboard for real-time monitoring of tree tilt angle.

Fig. 10). A user can detect the trees with potential problems from the map interface, based on the colors of the tree icons and take appropriate actions. When a user clicks on a tree icon, the corresponding graphs of tilting angle, trend of tilting angle, periodic pattern, the remainder of tilting angle, wavelet analysis and prediction of tree tilting trend, are plotted for visualization and analysis.

Apart from the tilt angle data, the basic information of trees, sensor information, environmental factors, POIs and an azimuth graph, are available, when the user clicks on the tree icon for further information. The tree attributes collected in tree risk assessment exercise, for example, species, tree height, crown size and the DBH, are included in the basic information for the identification of trees. SST information based on sensors installed on the trees, including device ID, sensor ID, sampling interval and the status of the sensor, provide general information for the control of the SST device. ‘Environment’ tab lists the big data, which include the static data of historical weather data, air quality and the information of nearby population, buildings and roads. Further big data analysis can be conducted by considering these parameters. The ‘POI’ tab shows the number of nearby facilities, for evaluating the impact to the public if a tree failure were to occur. The ‘azimuth graph’ indicates the trajectory of a tree, which is useful for understanding the tree movement direction, since a healthy tree would bounce back to the original location after strong wind load (Sellier and Fourcaud, 2009).

Real-time meteorological data are also available on the dashboard, extracted from the website of the Hong Kong Observatory. The information covers the current weather warnings and signals, and district-specific information which include temperature, humidity, rainfall and wind speed. These data can help users understand the weather condition and the tilting response of trees. For further details, interested readers are encouraged to visit the study webpage http://www.jcsmarttree.com/ and send a request to the corresponding author for questions relating to data visualization information.

Apart from the deployment of the real-time tree monitoring system, a mobile application, “HKJC Smart Tree” was developed, to transfer the learnings of the study and the knowledge associated with the tree monitoring system. By making a menu of the target trees easier-to-navigate or more playful to interact with, the user experience of this application was potentially enhanced. More significantly, the users can socialize with their peers and personalize the experience on the spatially designated routes through the digital locative place, which drives the initiative to learn (Saker and Evans, 2020). The features and the instant visualization on the mobile application are considered an opportunity in enhancing the knowledge understanding and engagement with people who are conscious of tree management (Delmas and Kohli, 2020; Hernandez et al., 2020).

6. Conclusion

This study demonstrates the development and pilot implementation of a large-scale, real-time monitoring system for measuring tree tilt angle under natural wind loading. A network of smart sensing devices was deployed to develop the large-scale, smart tree monitoring framework in identifying potentially hazardous trees in urban areas, particularly during extreme weather events.

Patterns and responses of tree tilt angles were analyzed and predicted, using time series models based on Seasonal Autoregressive integrated moving average (SARIMA) and Extreme Gradient Boosting time series forecasting (xGBoost). Since the tree tilt angles are strongly influenced by exogenous factors, e.g. wind speed from weather observations, xGBoost models with weather data outperformed those without weather data. Overall, the predictive power of the model decreases with increasing forecasting period, and the best results were obtained for the one-hour prediction. The performance of xGBoost models is also significantly dependent upon the computational capacity, which can be enhanced by the use of GPU processing.

The model developed for tree tilt forecasting can effectively be used for detecting abnormal tilting of trees, by comparing the forecasted and the observed tilt angles. The dashboard and mobile applications of tree monitoring systems play a pivotal role in devising effective policies to transfer knowledge, and engage the public with the understanding of associated hazards with tree failures in urban areas. The system can help relevant stakeholders take timely actions in minimizing associated risks with tree failures. Furthermore, the modelling paradigm could incorporate seasonal patterns of the tree tilting, using big data modelling in Hong Kong, which is scalable and applicable to other cities in the world.

This study focuses on monitoring and analysis of the risks of tree uprooting due to root-plate failure as an initial step. Future studies are required to examine the breakage of tree trunk and branch failures under strong windstorm events. This will help enhance our understanding to further reduce losses due to tree failures in a city. Aside from natural wind loading, human influences such as construction work could also influence the stability of urban trees, due to weaker root systems in tropical or subtropical cities. In addition to the big data analysis framework developed and rigorous analyses performed, upon full-scale implementation of the system, further studies and in-depth data analyses will be conducted. Integration of relevant, physical attributes of trees with tilt angle measurements, would help evaluate, monitor, and define the thresholds for each species of trees to mitigate associated risks in tree failures.

Declaration of Competing Interest

None.

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