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RESEARCH ARTICLE

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Wireless sensor networks and machine learning meet climate change prediction

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Summary

Climate change is one of the main challenges faced by the development of every country. For countries producing agricultural commodities, the climate affects the quantity and quality of products. Many methods have been proposed to keep track of climate. One traditional method is the weather station model, which indicates the temperature, wind speed, and direction and extent of cloud cover. However, this method of predicting climate change has low accuracy due to geographical variation, for example, mountainous or forested areas. Recently, a combination of wireless sensor networks (WSN) and machine learning (ML) has been considered for prediction with the Internet of Things (IoT), for instance, through a wireless body area network. For climate change prediction, we design and develop a control system that uses node sensors to collect data in sandhills and beaches, with data management conducted via a web application with three components. The first component is designed to collect data from the node sensors. The second component is mainly used to control the system through a web application. The third component uses linear regression in ML to analyze the data to predict weight and volume. The complete system has been tried and tested in real time on a 10-m^2 area of a beach at Binh Thuan province, Vietnam, where sensor node data were wirelessly collected over a cloud using a web application. This enabled assessment of the current state of the land at a coastal sandy beach, as well as prediction of the risk level of desertification and natural disasters.

KEYWORDS

linear regression, machine learning, predict, sensor, web application, wireless sensor network

1 | INTRODUCTION

Climate change poses one of the most significant threats to modern civilization. The impacts of climate change may be of an economic, social, or environmental nature and can also be positive, negative, or neutral.

Binh Thuan is a province on the southern central coast of Vietnam. It is dominated by sandy soil, and coastal sandhills occupy about 16% of the total area. It receives a large amount of sun and wind, and the sandy expanse of the region is facing

Abbreviations: ANA, antinuclear antibodies; APC, antigen-presenting cells; IRF, interferon regulatory factor.

TABLE 1 Distribution of coastal sandy areas in Binh Thuan province, Vietnam

#	Types	Surface area (hectares)	Percentage (%)
1	White sand dunes	7.710	6.1
2	Yellow white sand dunes	7.710	5.8
3	Red sand dunes	77.960	61.9
4	Sea sand soil	32.995	26.2
5	Total	125.935	100

many difficulties due to its dry climate, low educational level, and individual economic constraints. These difficulties include a lack of irrigation water, a lack of domestic water, and a significant risk of desertification. It is necessary to find a technical solution to these problems, to prevent them from worsening.

The province has the driest climate in the country. The average annual temperature is over 27°C, and the average annual rainfall ranges from 1000 to 1600 mm per year, which is half the values typically received by other areas in the south. The land in Binh Thuan has been becoming increasingly arid in recent years, partly due to the sea breeze and groundwater extraction. Since the area is so dry and sandy, flying sand is a regular occurrence, which further augments the rate of desertification. Sand dunes can form due to the continual wind present in the area, and sand from these dunes quickly flows downslope away from the coast. Furthermore, fierce sandstorms can occur across these dunes and are capable of burying villages and fields across thousands of hectares. Table 1 indicates the distribution of coastal sand in Binh Thuan province, Vietnam. This movement of sand can affect regional production, especially of crops such as cotton and grapes.[1,2]

Desertification usually affects the fertility of an area. For example, the town of Bac Binh, located in Binh Thuan province, used to be known for its vibrant crops and the large variety of animals inhabiting its forests. However, dramatic changes have occurred in recent decades. The forests are gone, and animals and plants are struggling to survive because water resources have dwindled. In addition, the overall quality of water resources, especially groundwater, has also decreased over the past 30 years. These negative impacts can be permanent and irreversible. For instance, soil degradation causes soil to be washed away, water supplies cannot be replenished, and lost forest areas cannot be recovered.[3-6]

However, advanced technology can offer benefits to people. In recent years, the Internet of Things (IoT) has started to play a significant role in daily life by enhancing the ability of users to modify their surrounding environment. In fact, IoTs are primarily used to predict and control factors concerning climate change and environmental matters. One of their advantages is the possibility to provide governments with information regarding the effects of climate change on the environment.[7-9]

Desertification usually affects the fertility of an area. For example, the town of Bac Binh, located in Binh Thuan province, used to be known for its vibrant crops and a large range of animals living within its forests. But in recent decades, there has been quite a dramatic change. The forests are gone, and animals and plants are struggling to survive because water resources have dwindled. The overall quality of water resources, especially groundwater, has also decreased in the past 30 years. These negative impacts are sometimes permanent and irreversible; soil degradation causes soil to be washed away, water supplies cannot be replenished, and lost forest areas cannot be recovered.[3-6]

Advanced technology, however, can bring benefits to to people's lives. In recent years, IoT has begun to play a significant role in daily life, increasing our ability to modify the environment around us. IoTs are mainly used to predict and control processes concerning climate change and environmental fields. They are ideal because they can provide governments with information regarding climate change effects on the environment.[7-9]

The main focus of this article is to assess environmental change and sand movement in specific regions and provinces of Vietnam and to provide farmers with information and recommendations to assist them in adapting to the changing climate conditions with the use of WSN technology solutions. We would also like to raise awareness of the importance of education relating to local habitats, the preservation and protection of water supplies, and the responsibility of provincial authorities to prevent deforestation. More specifically, we acknowledge the importance of ML. A number of drawbacks and limitations that should be considered when using ML techniques in WSN applications are presented in Table 2.

The contributions of this study are as follows:

- The design and development of a novel advanced sensor structure for monitoring the movement of sand in Vietnam at a low cost, based on state-of-the-art WSN technology.
- The implementation of transfer techniques for LoRa technology. Data measured and collected by node sensors at a study location can be transferred to a web application, from which farmers and local governments can access it anytime.

TABLE 2 The pros and cons of combining machine learning and wireless sensor network

Model	Combining Machine Learning (ML) and Wireless Sensor Networks (WSNs)
Pros	• WSNs usually monitor dynamic environments that change rapidly over time. • WSNs may be used to gather new knowledge about unreachable or dangerous locations in real time. • System designers prefer robust ML algorithms that are able to calibrate themselves to newly acquired knowledge. • WSNs are usually deployed in complicated environments where researchers cannot build accurate mathematical models to describe the system behavior. While some WSN tasks can be prescribed using simple mathematical models, they may still require complex algorithms to be solved. Under similar circumstances, ML provides low-complexity estimates for the system model.
Cons	• WSNs use a considerable percentage of their energy budget to predict accurate hypotheses and extract the consensus relationship from data samples. • A trade-off is present between the computational requirements of the algorithm and the accuracy of the learned model. • The higher the required accuracy, the higher the computational requirements, and the higher the energy consumption.

- A system based on linear regression in ML, which analyzes sensor data in conjunction with the weather to predict sand movement in the near future. Governments and farmers can use this technology to gain a better understanding of the environment, and to protect dwindling resources.
- The first article to propose the use of a WSN to provide a reliable reference for comprehensively understanding the influences of climate change in Vietnam.
- The successful deployment of this system in Binh Thuan province, Vietnam, where the results prove its usefulness in evaluating climate change damage.

This article is organized as follows: Section 1 provides a comprehensive introduction; Section 2 discusses related work; Section 3 presents the proposed diagnostic system; Section 4 presents relevant results; and Section 5 offers a discussion. Section 6 concludes the article.

2 | RELATED WORKS

In recent years, a large amount of research has been conducted on sand movement in wind tunnels. For example, sand dyed in fluorescent colors was embedded in an artificial wind tunnel, and a video camera recorded its dispersal over time. The distribution of the colored sand, both in the downwind and crosswind orientations, was then examined. The results were very insightful and demonstrated that an artificial model can be used to accurately predict sand movement in a real environment.[9,10]

The survey performed in Tomasz[11] introduces the method of monitoring coastal dunes for scientific purposes. The description of the technique is focused on the specific aims of the research, in addition to the morphological coastal forms and vegetation cover types. The precision of measurement techniques and collected data is also noted.

Another experiment made use of both the Global Positioning System (GPS) and traditional beach surveying methods and a beach monitoring method using kinematic GPS surveys was developed shortly afterwards. This method involves collecting specific GPS locations from a specialized moving vehicle so that an exact model of a two-dimensional beach surface can be generated. The results indicate that the GPS analysis is in sync with traditional shore-normal surveys to a level of 1 cm, and repeated GPS measurements employing a moving vehicle reveal the precision to be accurate to 1 cm. Moreover, repeated and continuous sampling by the GPS surveying technique reveals changes in shorelines and beach morphology that conventional shore-normal profiles do not usually detect.[12] The application of GPS surveying systems, merged with traditional systems, provides an enhanced understanding of beach changes, sediment transport, and storm impacts and gives native people living in the region valuable information about their changing environment.[13,14]

Remote sensing has long been applied to study sand dune movement.[15] As a result, a methodology has now been generated and examined to map various sand dune habitats. The original objective was to present an operational device that could map environments and monitor changes at specific sites around England. This technique has provided a different way to monitor change in coastal nature areas and assists the management and preservation of protected sites.[16]

Other studies have used optically sensed images to provide accurate measurements covering a wide area.[17] By employing this method, it is feasible to identify and classify three spatial properties of sand dunes in the studied areas. These characteristics include the spatial distribution of sand dunes relevant to other morphological units in the study region, the speed and magnitude of sand dune migration rates, and the direction and orientation of sand dune migrations. In Diego et al.,[18] we developed a sand dune encroachment vulnerability index to assess the susceptibility of Nouakchott to sand dune encroachment. This index is based on the geophysical characteristics of a given area, and when used in conjunction with a geographic information system (GIS), it can help regional governments with the task of implementing preventive measures.

The article in Pozzebon et al.[19] proposes a WSN framework, which is believed to be a novel solution to remotely measure sand level movement for beaches or dunes in real time. The study proposes a low-cost sensing structure, which can measure level changes and send data via Zigbee communication technology. Moreover, the specified sensor is integrated into a collection of sensors that, when arranged in a grid layout, can obtain the same data at multiple points, thus enabling the description of changes in a studied region. This technology is proving to be an excellent device for investigating coastal erosive processes.

Other research has proposed the use of a sensing structure that is able to orientate and position itself according to wind direction and directly measure the volume of wind-transported sand by collecting samples and estimating its weight. The experiments were conducted remotely without the need for human participation. This was possible because the structure is equipped with a Zigbee wireless communication module, which periodically sends readings to a local gateway. Data are then prepared by a microcontroller and transferred to a remote data store center with the use of GSM technology.[20]

A study conducted in Iran sought to examine and predict climate change effects with a focus on temperature and rainfall.[21] According to the simulated example presented in the study, rainfall exhibited a decreasing trend, while temperature exhibited an increasing trend. Other research has considered consumer waste connected to climate change,[22] particularly consumer waste generated when people dine out in restaurants. An online survey was conducted in which several hundred young adults were asked questions, each of whom had dined out in a restaurant during the previous month. Using an equation developed in the study, it was found that climate change awareness positively influences an individual's attitude and intention to reduce the waste that they produce. A fundamental review of the study problems discussed in this research is provided by Zhang and Reggiani,[23] which points out how the performed studies support the improvement of scientific understanding by policymakers. However, all of these solutions only provide theories for the prediction of climate change.

By applying modern mathematical models, some studies have proposed methods for accurately predicting climate change effects.[24-27] The optimization Maxent model presented in Li et al.,[24] which is based on the method of maximum entropy, is a useful example of kind distribution. However, the range of appropriate variables within an environment, along with type parameters, is an essential factor that must be considered when applying this model. A model for predicting rainfall in water-scarce regions can be seen in Alotaibi et al.,[25] which the authors view as an effective aid to water resource management. This method involves machine learning. However, the general model is very complex and combines many machine learning elements. The article in Zhu et al.[26] aims to establish the historical streamflow response to climate change and to forecast future response based on artificial intelligence models. However, future hydrological projections featured high uncertainty. Another climate change model was constructed using a neural network and was termed a radial basis function.[27] Again, this study combines many machine learning elements to establish the connection between climate change and extreme weather, although the impacts of climate change have not been quantified simply with the connection between climate change and extreme weather.

Many studies have attempted to analyze the risk posed by climate change to agriculture in developing countries like Vietnam.[28-31] However, to date, no clear-cut information has been provided. Moreover, these authors do not introduce any technology to measure the impact of climate change in Vietnam.

After reviewing a number of relevant studies that feature advanced technology and algorithms, with the advantages and disadvantages of three different models listed in Table 3, we consider it necessary to provide a more efficient way to understand the impacts of climate change. This especially holds true for certain coastal areas of Vietnam, where people would benefit from having a cheap and simple way to analyze the changes in their environment.

We propose a visual monitoring method for tracking sand levels and sand movement in coastal areas. The ever-changing status of sand dunes can be monitored using WSN technology, combined with a microcontroller. This would be invaluable for farmers by helping them to plan ahead. Furthermore, this method expands and builds upon the technology/methods proposed by existing studies but at a lower cost. We also introduce a web application to enable farmers or government

TABLE 3 Advantages and disadvantages of the different methods used to measure sediment transport

#	Model	Advantages	Disadvantages
1	Visual	• Low prices and complexity levels. • Equipment is not needed.	• Results are not always evident. • Requires challenging storage of large amounts of map data.
2	Global Positioning System (GPS)	• Can be used to image the time, location, and characteristics of dust plumes. • High accuracy and tested on extensive coverage.	• High prices and complexity levels. • Equipment is needed, and stations are moderately complex to set up and maintain.
3	Wireless sensor networks (WSN)	• Low costs, highly accurate prediction, and real time. • Can be applied to more extensive coverage and used at any time, position, and for real-time monitoring.	• Requires technical assistance to design and set up. • Results depend on a suitable sensor.

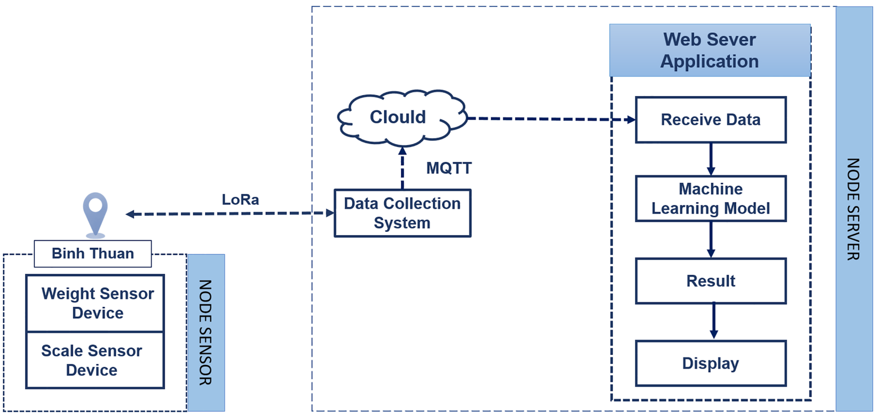


FIGURE 1 Explanation of the WSN system

agencies to directly monitor sand movement at any time or location. Finally, we propose an algorithm to predict the amount of sand movement within a given area based only on wind speed.

3 | MATERIALS AND METHOD

3.1 | An overview of the system

This article aims to design and implement a system, with sensors integrated into the WSN, which can monitor sand movement by using a web application. A methodology flowchart and general explanation of the WSN system are provided in Figure 1. This research included four steps: The first step was to collect 1-week worth of data covering four separate times of the day, concerning wind speed and sand movement in the study area. The second step involved clearing the area to install equipment. The area was large, with a rather complex erosion process. The third step was to design a WSN system with a two-component sensor node architecture and server node architecture. The first component of this step consisted of the sensor node and server node and the entire policy applied technology such as light sensors, load cells, microcontrollers, and wireless data transmission devices through LoRa technology between sensor nodes and servers. The second component was a web application, which allows an administrator to control the system. In addition, information from the WSN device can be viewed by the administrator to manage temperature control, while the MQTT protocol and web application display functionality. Finally, the last step involved using a mathematical equation to predict future sand movement based on wind speed. Since governments and farmers require accurate weather predictions for agriculture projects, this part of the procedure was very important. The details of the study area, along with the data collection and system architecture, are described in the following sections.

3.2 | Study area

Binh Thuan province is the driest province in Vietnam. Climate change is significantly affecting this area, due to a shift in the rates of rainfall and sand movement. Some researchers hold the opinion that the loss of forest land, the extension of irrigated areas, and the change in sand movement constitute the most severe environmental problems faced by the

FIGURE 2 Aerial image of the study area in Binh Thuan province, Vietnam

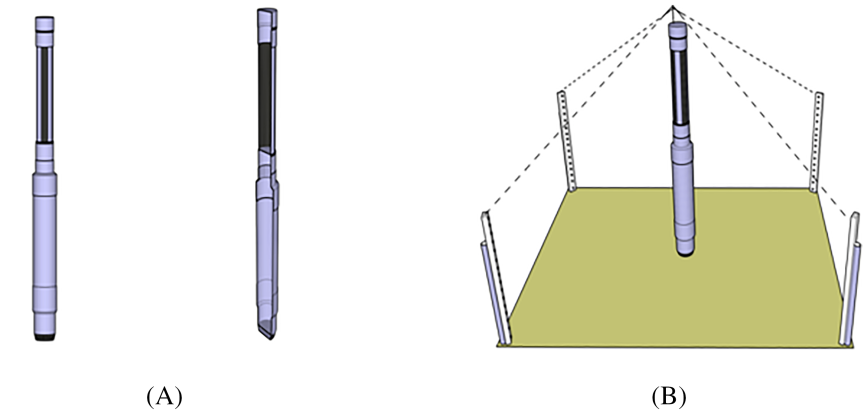


FIGURE 3 3-D simulation of the system: (A) 3-D model of the central cylinder; (B) 3-D model of the central cylinder, together with the other four cylinders

current generation. To evaluate the effect of sand encroachment on agricultural land, the study area in this section is located between latitudes 10°55′ and 2°2′N and longitudes 108°16′ and 56°8′E and is displayed in Figure 2.

3.3 | Data collection

Historical wind speed data for the research site can be found at the National Centre for Hydro-Meteorological Forecasting (NCHMF), a Vietnamese government organization (https://www.nchmf.gov.vn/). Additional information can be found on climate websites such as https://www.windfinder.com/. For this study, due to the potential influence of environmental variation on analysis outcomes, positions in all administrative regions were chosen. In addition, due to possible impacts by other factors, such as the scale of different climate positions, equipment accuracy, and management, the quality of data changed considerably between each situation.

3.4 | System architecture

This subsection details two mechanical devices whose function is to collect sand that has been moved and displaced by the wind. The first, rather simple, device is a PVC plastic cylinder with a hole in its side. Sand blows into the hole and falls to the base of the cylinder, from where it can be measured and examined. The cylinder is 10 cm in diameter and 120 cm in height, with two 8 × 60 cm rectangular holes on both sides cut approximately 20 cm above the base. The front hole is exposed and open to the elements, while the back hole is completely covered with a polyester veil with a 60 m mesh. This veil is fine enough to filter out grains of sand but allows smaller particles (such as silt and clay) to pass through. The second device consists of four different plastic cylinders, all of which are carefully arranged around a central cylinder, which has a square hole of its own. A 3-D model of this device can be seen in Figure 3.

To measure sand mass, we have designed a unique plastic basket, which is essentially a 15 cm high 3-D-printed cylindrical container. The upper lip of this container flares out so that it fits within the lower part of the mechanical structure. This particular shape has been specifically chosen to reduce the amount of friction between the basket and the inner walls of the rotating part of the plastic tube. Conflict in this part of the device would be a problem, as it could affect its precision

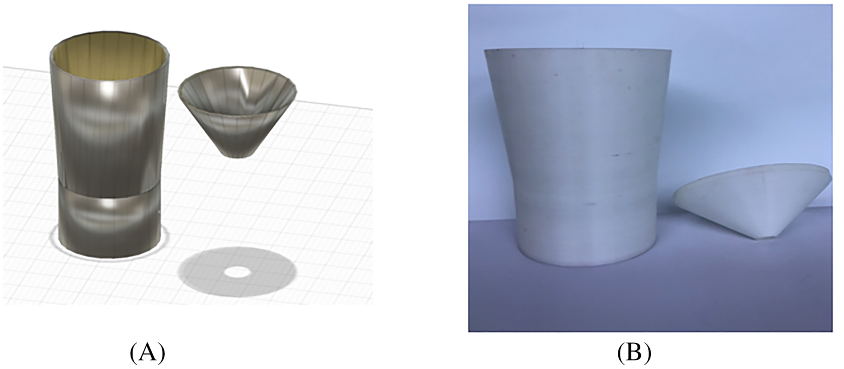


FIGURE 4 Prototype of the sensing structure: (A) 3-D model of the basket; (B) the real basket and funnel used to collect sand

TABLE 4 Module components used for the sensor node architecture

Devices	Amount	Function
IC 74HC595	1	Manage 4 level
IC 74HC151	8	2 ICs/ 16 levels
A photo-resistor	64	1 photo-resistor manage 1 level
Resistor	64	Reduce the electric signal and return to the IC, safe and increase lifetime battery
ATmega 328P-AU	1	Microcontroller
ESP8266 Node MCU	1	Wi-Fi
E32 TTL 433 MHz	2	LoRa
HX711	1	24-bit ADC converter
DHT11	1	Temperature

and accuracy, so it was paramount to prevent this from happening. The upper section of the basket has been shaped like a funnel to direct collected sand toward the middle of the basket's base, therefore optimizing even placement inside the basket, to allow the load cell to accurately measure its weight. Once the basket is full of sand, it has to be emptied manually. This is achieved by removing the lid of the rotating structure (which is firmly attached to the weather vane), then lifting the basket up to the top. This task does not require the removal of any mechanical parts and thus does not interfere with data collection (although any weight measurement will be inaccurate while the basket is not in its usual position). A load cell with a maximum limit of 5 kg was used in this article. A 3-D model and a real archetype of the plastic, 3-D-printed basket is shown in Figure 4.

3.4.1 | Sensor node architecture

The device's sensor and server node architecture are explained in further detail in the following paragraph.

The sensor node includes components such as a volume scale that uses a light sensor, a sand mass measuring device which uses a load cell, an IC that controls the level, and a microcontroller that reads the data.[32-38] Sea breezes cause humidity and condensation within the device, which the node needs to account for while controlling the operation of the circuit, the LoRa wireless transmission system, the IC that controls the scales, and the sand mass condensation equipment. The module components used in this article are shown in Table 4. The selected main board was an ATmega328P-AU, which is based on an 8-bit microcontroller with a 32-Kb flash memory. The main features of this microcontroller are as follows:

- Operates from a DC-5V source.
- Integrates a connector pin to load code for microcontroller via UART standard and push the reset button if needed.
- Connects and reads ADC data (24 bits) from a HX711 unit.
- Commands the translation IC to control an optical impedance measurement scale via a channel aggregation ICs.
- Enables UART communication via virtual serial port with a LoRa data transmission module.

The HX711 module communicates with a weight sensor that converts the weight to be measured into an electrical/analog signal. And then the module converts it to a digital signal and transmits the signal to the microcontroller for processing and dispatch. The LoRa module communicates with the microcontroller via the virtual serial port, before sending the data collected from the sensors to the server. The IC 74HC595 is sent out by the microcontroller to issue orders to control the amplitude scale, which measures the amplitude of the sand. In this way, it is transferring the amplitude signal to the microcontroller. The amplitude scales are controlled by a 74HC151 channel aggregation ICs and an ATmega328P-AU microcontroller. In order to, the sensor information is read by the microcontroller only every 4 s, not continuously. The sensor node can control up to four amplitude ranges simultaneously and incorporates the extension of the function pins for communication between the microcontroller and the computer.

The ATmega328P-AU microcontroller reads the signal of the ADC HX711 module from the DT pin of the module, connects to the SCK pin of the HX711 module, and uses a clock to adjust the sampling rate of the ADC module. When communicating with the microcontroller and ADC 24-bit HX711 module, it is necessary to adjust the values for sampling and to read the level of the returned voltage that corresponds to the change in weight. For the mass sampling process to be successful, the gain is set for the HX711 module by exporting the corresponding number of pulses from the microcontroller via HX711 via the SCK pin. Because channel A of HX711 is used to read the weight value, and the lowest possible voltage resolution is desired, gain is chosen that is equal to 128, which is equivalent to an output of less than 25 pulses for HX711. The next relevant parameter to set is the sampling rate of HX711. A sampling rate of 10SPS is preferred because the application does not require the sampling rate to be too fast. For real-time sampling, 10SPS is negligible and avoids interference at 80SPS. Measurement errors can be overcome by utilizing a high average sampling frequency.

To determine the mass value, we flatten the ADC reading from the HX711 and then take a sample of 100 g. Because each Loadcell and HX711 module has a different resistance value (even if the weight value is equal, different raw values are given when they are connected to the ADC 24-bit module). Four steps are followed to find the measurement value in grams:

- Step 1: Read the rough value divided by 24 bits in HX711 denoted by RD_n;
- Step 2: Create a loop with the average number of samples divided by variable t to obtain a stable ADC division value;

$$RD_{average} = \frac{\sum_{n=0}^{t} RD_n}{t}, \tag{1}$$

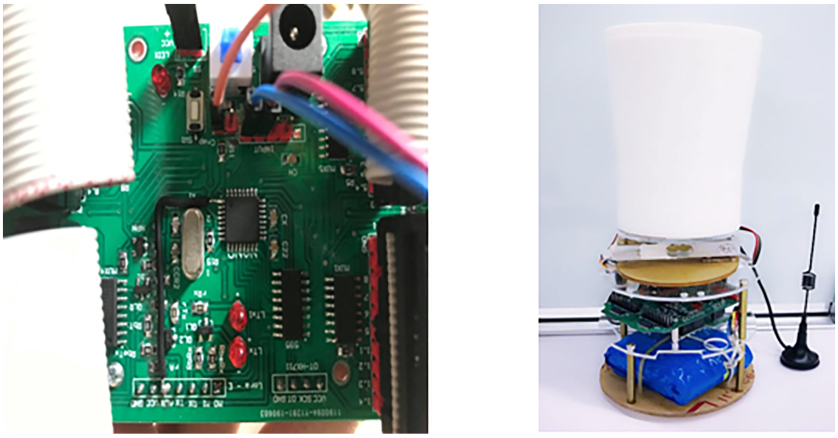
  t denotes the number of sampling times selected by the user. The number of samples can be 16, 32, 64, or 128 and is selected according to the need for accuracy. A value of 128 will provide a stable value and error in milligrams but will consume the resources of the microcontrollers.
- Step 3: Subtract the average ADC value from itself and set the value to zero to serve the standard unit of the amplitude scale.
- Step 4: To select the division value according to the scale of 100-g amplitude, a 100-g test sample was placed on the system. The system then features the $RD_{100g} = 45\,100$ values.

$$\text{Value decision} = \frac{RD_{100g}}{100} = 451, \tag{2}$$

After the correct calculation of the sharing value, it is entered into the program so that it is always available, even if the device needs to restart. The microcontroller also has the function of inputting values from the serial book to perform a resampling of the weight values. Next, we introduce the sensor node structure and learn about the features of the components that make up the system. We designed a two-layer circuit with a central microcontroller, ATmega328P-AU, with the device components described in Table 4 embedded into the central circuit that have the ability to measure the amount of sand transported by the wind, as well as moving surface sand. Subsequently, we integrated the circuit with the plastic basket shown in Figure 5.

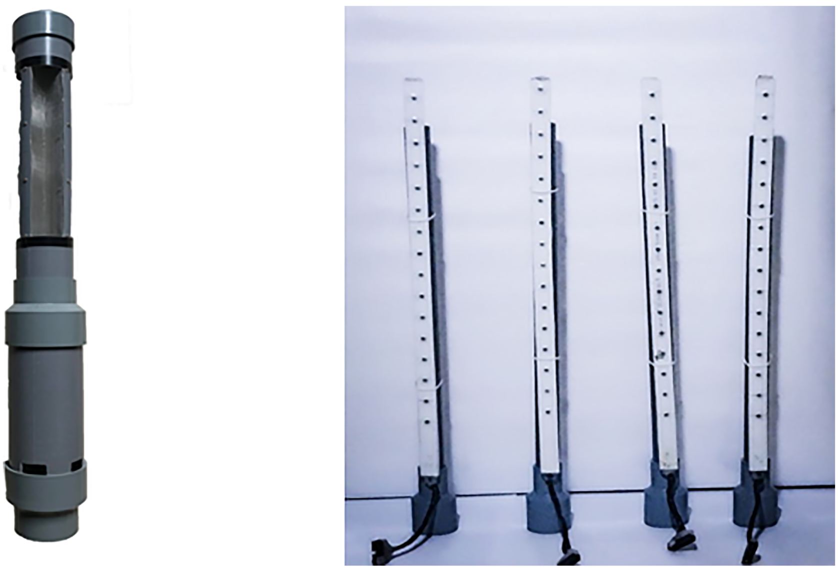
After printing the basket using a 3-D printer, we placed the circuit board and basket into the PVC tube; as shown in Figure 6. amplitude scale block is designed to measure the amplitude of the sand, because the change in coastal sand amplitude may increase or decrease depending on ebb and flow. This is especially the case in areas where landslides often occur. Landslides are also covered by sea sand, so the amplitude scale can measure the fluctuation of the amplitude depending on weather conditions in specific locations.

As mentioned, the device includes four amplitude scales to calculate the volume of sand in an area. After extensive testing, we find that the ideal setup for the four scales is to have resistors with 16 levels on each scale. The principle of operation for the amplitude scales is straightforward: We arrange the optical support along a plane with 16 photo-resistor impedance, equivalent to 16 measurement levels. If any position is obscured or exposed, the amplitude scale sends a value that corresponds to the level measured there.



(A) (B)

FIGURE 5 Prototype of the sensing structure: (A) two-layer circuit board with a central microcontroller; (B) real module with a basket on the top, load cell in the middle, and a two-layer circuit board with LoRa module transmission



(A) (B)

FIGURE 6 Mechanical structure with a tube made from PVC thermoplastic polymers: (A) a pilaster PVC tube, which is placed in the center region; (B) four pilaster plastic tubes used to measure the volume scale in a region

A photo-resistor is a type of resistor that changes with light intensity. When intense light shines in its direction, it reduces the resistance value and vice versa. Photosynthesis comprises a high-impedance semiconductor; when photons in high-energy light rays strike electrons in a molecule, the semiconductor turns into a magnetic conductor and reduces the resistance. In low light or dark environments, the resistance value can reach 2 $M\Omega$ and can be reduced to about 100 Ω in the presence of intense light. A photo-resistor impedance is usually made from cadmium sulfide (Cds) and cadmium selenide (CdSe). Due to the smothering nature of airborne sand, an optoelectronic device is very suitable for this application. The type of resistance used is 5 mm, and the distance between the scales is 30 mm.

Marine environments, high temperatures, and the presence of corrosive components such as sand and seawater can easily damage the sensors of the device. With this in mind, the housing column was inserted into a plastic tube to preserve and protect it. The tube is completely sealed, and no sand can enter it, so the photo-resistor is fully protected. Even if a thin layer of sand manages to adhere to the column, its accuracy is unchanged, because the photo-resistor can detect the proximity of sunlight through a thin layer of sand.

The ATmega328P microcontroller details with 74HC151 functions, listed in Table 5, and scale system can perform the following tasks:

- Control 74HC595 to turn the scales on and off;
- Read output sample signals to scan measured level values through 74HC151;
- Read comparative messages returned from 74HC151;

TABLE 5 ATmega328P-AU details with IC 74HC151 functions

ATmega 328P pinout	IC 74HC151	Function
2	Y	Read the value of the returned result from the comparator signal IC
A3	S0	Output a scan signal to the scale value at pin A
A4	S1	Output a scan signal to the scale value at pin B
A5	S2	Output a scan signal to the scale value at pin C
10	DS	Control signal level
11	SH	Export the control bits
12	ST	Transfer the signal bits
13	EN	Enable IC operation

- Output 74HC595 IC control signals in a premade array of messages through pins 10,11,12,13, thereby enabling sequential operation of the controlled IC74HC151 for readability. In addition, the levels of the microcontroller scale must connect the output signals to pins A, B, and C of 74HC151, as well as read the comparative message returned from pin Y of 74HC151. This saves the signal pins of the microcontroller, thereby reducing the size of the hardware. To be able to activate 74HC595, we output pin 13-EN level 1 to allow the translation register of the IC to work and delete all data existing in the previous entry.

Pin 10-DS is responsible for displaying high or low values, depending on the requirements of use for initializing the program, to ensure that all 74HC151 are turned off equivalent to the output pins of 74HC595 of level 1. The microcontroller creates a loop to carry out the data to be exported to all eight registers of 74HC595 and then output by an upward edge at the ST CP pin position. The IC 74HC151 will be set from 1 to 8, respectively:

- Scale 1 is IC 1 and 2;
- Scale 2 is IC 3 and 4;
- Scale 3 is IC 5 and 6;
- Scale 4 is IC 7 and 8.

After introducing the sensor node structure and outlining the various features that make up the system, we considered a method for determining the volume of sand displaced by wind. This is done in four steps, with different techniques to read data values according to Equations (1) and (2). Next, we introduced a simplified method to determine the displacement of sand volume, based on the square calculation formula introduced in Equations (3)–(8). After introducing the features of the sensors and adjusting the parameters, as well as methods for determining the displacement volume according to the wind, we started to design a practical model with a central cylinder to measure the amount of collected sand.

After obtaining all of the amplitude values from the scales, we calculate how much the volumetric value varies from the original design level. Following the original design, four scales are set up vertically and are situated perpendicularly to each other, forming a rectangular shape, with the distance between the pillars dependent on the measurement conditions shown below. The height of the four sides a, b, c, d are set to be equal to the height of the four scales. To calculate the total volume of the rectangular cube, we divide the volume of the rectangle into two parts, with two different ways to choose a triangular prismatic cube, V_1 and V_2, and then average the two volumes. We then obtain an average volume of sand displacement. Figure 7 depicts the geometry that may be used to calculate the volume of a triangular cylinder.

We divide the rectangular cube into four quadratic prismatic blocks: (*EHF.ADB*||*HFG.DBC*) and (*EFG.ABC*||*EGH.ACD*). The formula for calculating the volume of a triangle cylinder is

$$V_{XYZ} = S \times L, \tag{3}$$

where

- S is the area of the base of the prism;
- l is the height of the prism.

The formula for calculating the area of the base is

$$S = \frac{1}{2} a \times h, \tag{4}$$

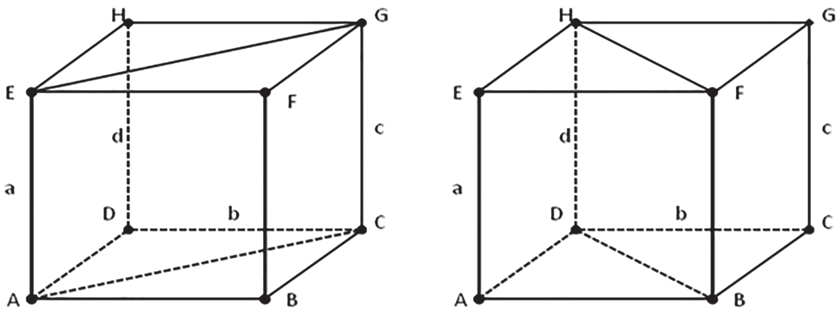


FIGURE 7 Rectangular prism with all sides adhering to the equation dimensions. Pilaster plastic tubes are attached to the four corners to take measurements in a given region

TABLE 6 Equations to calculate the volume of triangular blocks

Triangulars	Formula
EHF.ADB	$V(EHF.ADB) = S\left(\frac{a+b+d}{3}\right)$
HFG.DBC	$V(EHF.ADB) = S\left(\frac{c+b+d}{3}\right)$
EHG.ABC	$V(EHF.ADB) = S\left(\frac{a+b+c}{3}\right)$
EGH.ACD	$V(EHF.ADB) = S\left(\frac{a+c+d}{3}\right)$

where a is the length of the base and h is the height of a triangle.

However, due to the setting of the scales forming a square, the two triangles of the base always have the same area; thus, we have

$$S = S_{ABD} = S_{DBC} = S_{ADC}. \tag{5}$$

Due to the nature and properties of sand, the lengths of the three sides of the triangular prism are almost equal. In order to calculate the average measurement of the lengths, the area of the base is divided equally into four parts. We then have a formula for calculating the volume of triangular prisms.

Then, we get

$$V_1 = V_{EHF.ADB} + V_{HFG.DBC} = S\left(\frac{a+b+d}{3}\right) + S\left(\frac{c+b+d}{3}\right), \tag{6}$$

$$V_2 = V_{EHG.ABC} + V_{EGH.ACD} = S\left(\frac{a+b+c}{3}\right) + S\left(\frac{a+c+d}{3}\right), \tag{7}$$

where the equations of $V_{EHF.ADB}$, $V_{HFG.DBC}$, $V_{EHG.ABC}$, and $V_{EGH.ACD}$ are shown in Table 6.

Since the volume of the rectangular cube is equal to the average of the two volumes, we can change the volume of sand to be

$$\begin{aligned} V_{mov} &= \frac{1}{2}(V_1 + V_2) = \frac{1}{2}\left[S\left(\frac{a+b+d}{3}\right) + S\left(\frac{c+b+d}{3}\right) + S\left(\frac{a+b+c}{3}\right) + S\left(\frac{a+c+d}{3}\right)\right] \\ &= \frac{S}{2}\left[a+b+c+d\right]. \end{aligned} \tag{8}$$

Finally, we set that the total weight movement is equal to the values from Equations (2) and 8, as shown in Table 6.

3.4.2 | Server node architecture

The server node architecture is designed with a single circuit using a 5-V source with two communication modules (LoRa E32 and ESP8266),[38,39] as shown in Figure 8, and placed far from other devices to avoid interference. In this circuit, the LoRa module can receive data from the station before transferring the data to the Wi-Fi module. Then, the Wi-Fi module forwards the data to the web application. This data transfer is performed by using the hypertext transfer protocol request to a Java web application, which controls the data acquisition. It is subsequently stored in a MySQL database, in addition to its visualization.

3.5 | Web application for online data collection

A web application has been developed with Java programming to manage data on sand movement caused by wind. This web application also aggregates the temperature, sand movement, and wind speed to obtain weather forecast data for NCHMF, which is a governmental organization in Vietnam https://www.nchmf.gov.vn/. The application provides the forecast information in JSON and HTML formats. It reads the forecast data (JSON format) of the particular situation employing API, then stores it in a MySQL database on the server, which is included in the prediction algorithm.

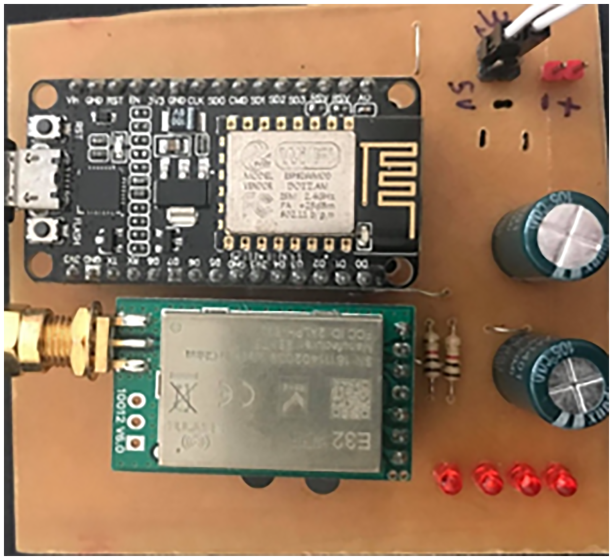


FIGURE 8 Prototype of the server node

TABLE 7 Collected data during the data acquisition campaign, achieve by a sensor node at Binh Thuan Province, Vietnam

Samples	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Wind speed (m/s)	8.06	8.10	8.13	8.29	8.51	8.56	8.83	8.95
Total (g)	46.09	48.68	52.20	66.95	89.60	94.18	120.16	132.12
Samples	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Wind speed (m/s)	9.14	9.17	9.31	9.33	9.46	9.93	9.96	10.03
Total (g)	150.92	160.16	170.22	183.06	229.50	236.02	239.38	240.38
Samples	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Wind speed (m/s)	10.08	10.11	10.22	10.27	10.29	10.38	10.47	10.85
Total (g)	247.29	255.29	257.75	264.06	265.39	273.18	280.94	320.18

3.6 | Predict sand movement by using linear regression in machine learning

Regression analysis is a staple of classical statistical modeling. In very general terms, regression is concerned with describing and evaluating the relationship between a given variable and one or more other variables. More specifically, regression attempts to explain movements in a variable by reference to movements in one or more other variables. The model $y(t) = \alpha + \beta x(t) + u(t)$ is known as the classical linear regression model (CLRM). Data for $x(t)$ are observable, but since $y(t)$ also depends on $u(t)$, it is necessary to be specific about how the $u(t)$ are generated and shown in Brooks.[40] Though it may seem somewhat dull compared to some of the more modern statistical learning approaches described in later paragraphs, linear regression remains a useful and widely applied statistical learning method.

When studying and monitoring a specific area, data are collected at 24 sampling intervals throughout the week. The datasheet includes the amount of sand measured by the central pole, the moving volume of sand measured by the four surrounding posts, and the corresponding wind speed. Based on the data table, the higher the wind speed, the greater the extent of sand volume movement. These factors influence each other, so linear regression is a suitable model to use.

Linear regression is a regression algorithm whose output is a linear function of the input.[41,42] This is the most straightforward algorithm in the group of supervised learning algorithms. Regarding the problem with the table of values shown in Table 7, a dataset of 24 sampling times a week is produced in the study area to determine the displacement of sand. By examining the wind speed values x_1, along with the sand movement x_2, we can predict the future sand movement in a given study area. But what would the prediction equation $y = f(x)$ yield? Here, the factor x is a column vector containing the input data, and the factor y is a positive real number.

We know that sand movement increases with higher wind speed. With this knowledge, we can design the output model to be a simple function of the input. Then, we can see that the output model is a simple function of the input. In the general case, if a d-dimensional feature vector describes each data point $x \in \mathbb{R}^d$, then the output prediction function is written as follows:

$$y \approx \hat{y} = f(x) = \omega_1 x_1 + \omega_2 x_2 + \ \ldots \ + \omega_d x_d = \mathbf{x}^{\mathbf{T}}\omega, \tag{9}$$

where, $\omega = [\omega_1, \omega_2, \omega_3]^{\mathbf{T}}$ is a weight vector , which is to find. Since, the relationship $y \approx f(x)$ in Equation (10) is a linear relationship.

Similarly, with all data pairs, where N is the number of data in the training set, finding the best model is equivalent to finding ω so that the following function reaches the minimum value:

$$\mathcal{L}(\omega) = \frac{1}{2N}\sum_{i=1}^{N}\left(y_i - x_i^T\omega\right)^2, \tag{10}$$

where $\mathcal{L}(\omega)$ is the loss function of linear regression model with parameters $\theta = \omega$. The aim of Equation (10) is the smallest loss, which can be achieved by minimizing the loss in ω.

$$\omega^* = \text{argmin}\mathcal{L}(\omega), \tag{11}$$

where ω^* is the solution of the problem to be found, and the Equation (11) can be expressed as

$$\omega = \text{argmin}\mathcal{L}(\omega). \tag{12}$$

Before building the solution for the optimal problem of the loss function, we see that this function can be abbreviated in the form of matrix, vector, and norm as follows:

$$\begin{aligned}\mathcal{L}(\omega) &= \frac{1}{2N}\sum_{i=1}^{N}\left(y_i - x_i^T\omega\right)^2 \\ &= \frac{1}{2N}\left\|\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} - \begin{bmatrix} x_1^T \\ x_2^T \\ \vdots \\ x_N^T \end{bmatrix}\omega\right\|_2^2 = \frac{1}{2N}\|y - X^T\omega\|_2^2,\end{aligned} \tag{13}$$

where, $y = [y_1, y_2, \dots, y_N]^T, X = [x_1, x_2, \dots, x_N]^T$. Thus, $\mathcal{L}(\omega)$ is a function related to the square of the norm ℓ.

We see that the loss function has gradients at every ω. The optimal value of ω can then be found by solving the derivative equation of $\mathcal{L}(\omega)$ for ω to 0. Then the gradient of this function is relatively simple, as seen below:

$$\frac{\nabla\mathcal{L}(\omega)}{\nabla\omega} = \frac{1}{N}X(X^T\omega - y). \tag{14}$$

Since the gradient function is equal to zero,

$$\frac{\nabla\mathcal{L}(\omega)}{\nabla\omega} = 0 \Longleftrightarrow XX^T\omega = Xy. \tag{15}$$

If the square matrix is inverted, Equation (15) has a unique solution $\omega = (XX^T)^{-1}Xy$. Otherwise, if the square matrix is not inverted, Equation (11) has no solution or has minimal solutions. In general, the solution to the optimization problem in Equation (11) is as below:

$$\omega = (XX^T)^{\dagger}Xy. \tag{16}$$

Since the solution of the minimum problem of the loss function is

$$\bar{\omega} = \text{argmin}\frac{1}{2N}\|y - \bar{X}^T\bar{\omega}\|_2^2 = (XX^T)^{\dagger}\bar{X}y. \tag{17}$$

4 | EXPERIMENTAL RESULTS

The main objective of these experiments is to track sand movement using sensors and sometimes by utilizing weather forecast information. The secondary objective is to develop an algorithm that can predict future sand movement.

FIGURE 9 Prototype of the sensor structure installed in a real environment in Binh Thuan province, Vietnam

(A) (B)

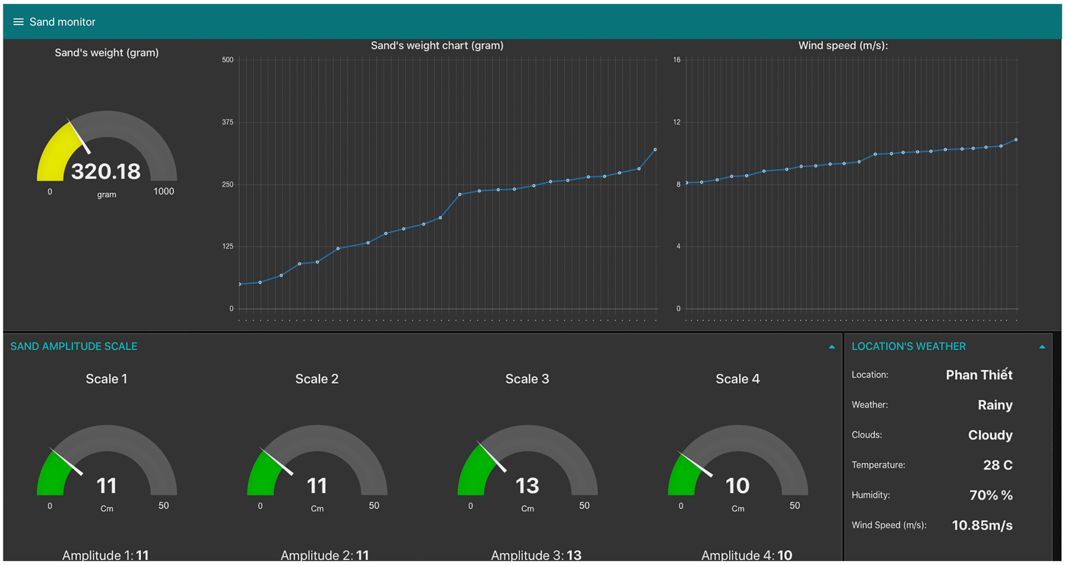


FIGURE 10 Screenshot of the web application

4.1 | Test in a real environment

As described in the previous section, a field data collection node was deployed in the sandhills of Binh Thuan province.The collected field data can be seen in Figure 9 and at the following YouTube link. The data were collected at the node sensor and sent to the server node via LoRa, then transferred to the web application via ESP8266. The sampling time of the sensor nodes was recorded four times per day. Figure 12 shows a screenshot of a web application-based interface for real-time monitoring, which displays the current sand movement and wind speed recorded by the sensor over one week. The node is powered by a rechargeable battery that lasts for two weeks.

A website was designed for this monitoring system, which displays the data acquired from the multiple sensors. Real-time data are displayed, in addition to an up-to-date dynamic line chart, as shown in Figure 10. The collected data are also stored in a database for further retrieval if required, which includes and sand movement, wind speed, and data transform the four scales. These experimental data should be invaluable for farmers when planning their work.

4.2 | An algorithm for sand movement prediction

The aim was to collect extensive data from an area of farming land using sensors and then to utilize the sensor data along with weather forecast information to develop an algorithm that can predict soil moisture in the near future. The algorithm uses a linear regression approach, as discussed in Section 3.6, to achieve a high degree of accuracy. Based on Equation (17), the linear data samples in Table 7 are plotted. The weight is evidently proportional to the wind speed, so the linear regression model can be used for this prediction. Considering that the 6-day data sample (as shown in Figure 11) is arranged almost in a straight line, the linear regression model is likely to produce good results. Applying Equation (17) returns the solution of the linear regression as $w = [[-755.49][99.45]]$.

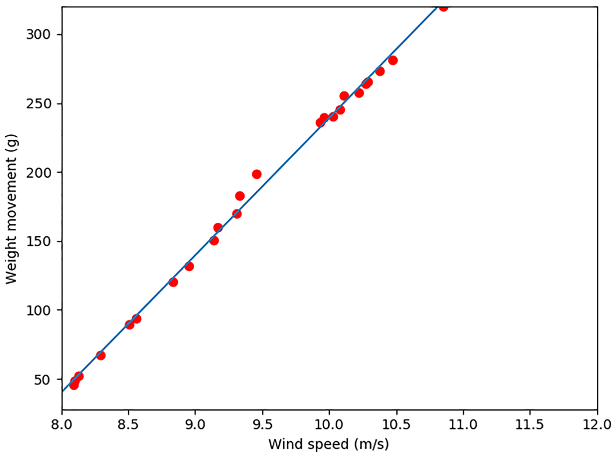


FIGURE 11 Linear regression equation model

TABLE 8 Comparisons between actual and predicted values

Samples	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Actual	46.09	48.68	52.20	66.95	89.60	94.18	120.16	132.12
Predicted	49.10	50.09	53.08	68.99	90.87	95.84	122.69	134.63
Samples	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Actual	150.92	160.16	170.22	183.06	198.50	236.02	239.38	240.38
Predicted	153.53	156.51	170.43	172.42	185.35	232.10	235.08	242.04
Samples	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Actual	245.32	255.29	257.75	264.06	265.39	273.18	280.94	320.18
Predicted	247.01	250.00	260.94	265.91	267.90	276.85	285.80	323.60

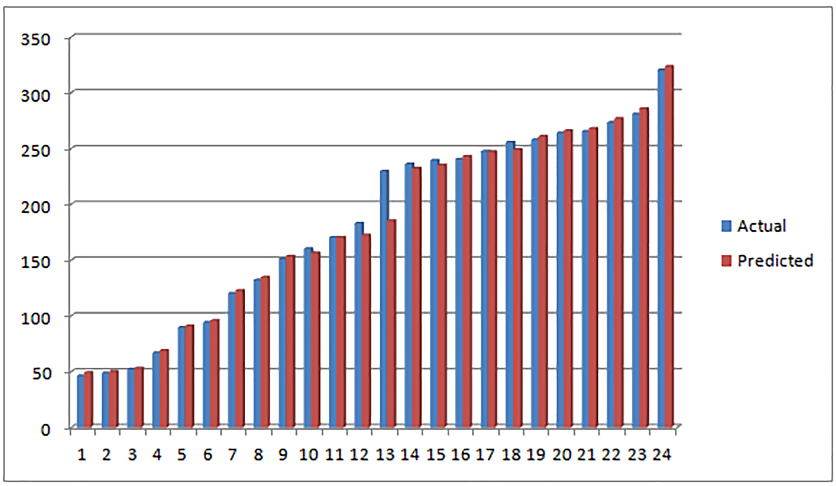


FIGURE 12 Comparisons between actual and predicted values shown on a bar chart

To find values, the *sklearn.linearmodel* from the Scikit–Learn library (https://scikit-learn.org/stable/) can be utilized with the use of Python programming, which is a popular library in ML. The solution of the linear regression of the *sklearn.linearmodel* was $w = [[-755.49][99.45]]$. Thus, by applying this model, we see that the results of the two calculation methods are the same. The outcome variables of the equation are weight and sand movement, while the input variable is wind speed:

$$\text{weight predict} = 99.45 \times \textit{windspeed} - 755.49, \tag{18}$$

Equation (18) enables the prediction of sand movement based on any wind speed condition. To check the accuracy of the model, sand movement data collected in a real environment were compared with the predicted sand movement data presented in Table 8. Results can also be compared on a bar graph, as shown in Figure 12. Our linear regression model is exact; the predicted percentages are close to the actual ones.

The final step was to evaluate the achievement of the algorithm. This step is particularly crucial to be able to compare the performance of different algorithms on a particular dataset in Table 8. For the linear regression algorithm, a commonly used evaluation metric, is the mean absolute error (MAE),[43] which is calculated as

$$MAE = \frac{1}{N}\sum_{j=1}^{N} \|y_j - y_i\|. \tag{19}$$

Applying Equation (19) returns an MAE value of 4.6, we can see that the value of MAE is 4.6. Accordingly, our algorithm was rather accurate but can still make reasonably good predictions. We conclude that our model returns fairly good prediction results.

5 | DISCUSSIONS

In a real working environment, the prediction of climate and weather change is complex and ambitious, because climate and weather predictive values result from a combination of spatial factors at a particular time. This research aimed to provide reliable evidence for the impacts of current climate change and extreme sand movement in certain regions and provinces in Vietnam. The aim of this research was to provide the public with a better understanding of the current situation of climate change, as well as useful information for the government. Based on the results achieved in the preceding sections, we now discuss matters such as design, application, efficiency, and economy.

- Design: The system has three components with different functions: to collect data from the node sensors, to control the system through a web application, and to apply the linear regression in ML to analyze the data to predict weight and volume. The first model consisted of a mechanic structure that can obtain the data from the sensor node. The second component was the web-based application, designed and implemented to monitor data change in real time. In this step, large-scale data from WSN were stored and employed for data analysis. The third component applied the most fundamental machine learning algorithm to analyze the data, in order to predict the weight of sand movement. Of course, the factors affecting sand movement are not limited to wind and rain. Hence, we will continue to improve and develop the system and will use multiple linear regression to monitor a wide range of variables.
- Application: The developed system was installed in Binh Thuan province, Vietnam. One key contribution of this work was to demonstrate the effects of a changing environment and climate. Moreover, it provides a way for local governments and farmers to track wind speed and sand movement in their area, without needing to be present at the site in question.
- Efficiency: The results show clear benefits for governments and farmers in relation to their work in agriculture. Accurate predictions of future sand movement reduce prices and enhance agricultural productivity. This case study offers significant potential for the use of digital technology applications in predicting climate change. We also hope that, after a successful pilot implementation, the project will be implemented on a large scale so that more people can benefit from what it has to offer.
- Economy: This research was conducted by designing a mechanical tool to monitor and predict sand movement by applying WSN and ML technology at a low cost. This research not only evaluated current conditions but also predicted future climate change. Furthermore, the relationship between climate change and extreme weather was recognized through the scientific method.

6 | CONCLUSIONS

In this paper, the combination of WSN and ML enabled the prediction of climate change to improve crop yields, enhance the quality of life, and reduce costs in several areas. This research is not only conducive to the improved allocation of fiscal expenditure by the government, through altering their perception, but may also help the public in their own efforts through having a correct perception. Climate change can only be solved through the joint efforts of the government and the public. For this reason, we have recommended WSNs for the monitoring of sand movement in this article. We have designed and implemented a system to measure environmental factors on a sandhill and on a beach. We have also applied the most fundamental machine learning algorithm to analyze data in order to predict the weight of sand movement. The developed system was installed at a location in Binh Thuan province, Vietnam with high efficiency and low cost. In future work, we will compare our system with existing approaches in the same and real experiments.

AUTHOR CONTRIBUTIONS

Conceptualization, methodology, writing-original draft preparation, writing—review and editing, visualization, and project administration were done by Tran Anh Khoa, Hoang Hai Son, VanDung Nguyen, Nguyen Hoang Nam, Nguyen Trung Tin, and Dang Ngoc Minh Duc; formal analysis, resources, and software were done Nguyen Quang Minh, Cao Nguyen Dang Khoa, Dinh Ngoc Tan, and Tran Anh Khoa.

CONFLICT OF INTEREST

There is no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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