Smart Agriculture System of Flood Monitoring and Mitigation Using Live Data for Flood-Prone Area

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Abstract **– This research proposes a solution to improve the system for monitoring relevant environmental parameters using sensors for flood mitigation. Sensors are used to collect data regarding farm flood situation. The collected data are trained for a classification model to activate the solar-powered water pump to mitigate flood incidents in a flood-prone area. The system helps farmers to monitor real-time environmental parameters relevant to farming operations and flood including soil moisture level, water level, and water flow speed in a nearby canal that provides water to the farm. To reduce flood damage, the system assists to drain the excessive water to prevent prolonged submerging of the crop. The devices are designed to use the electricity from solar power, so the system is practically used outdoor where an electricity cord is difficult to setup. Experimental results show that the sensing data from the deployed sensors are accurate. The generated prediction models give the high performance with average of 1.0, 0.97, and 0.93 F-1 score for no-flooding, mild-flooding, and severe flooding respectively.**

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1. Introduction

Smart farming is a concept of using information technologies such as Internet of Things (IoT), robotics, drones, and AI to manage agriculture production aiming to increase the quantity and quality of products [1]. The technologies enable solutions to agricultural problems in two major areas as precision farming and farming automation. Precision farming refers to the use of sensors to obtain accurate real-time data for managing the plant effectively and selectively [2]. For farming automation, technologies help to automate a routine farming process using obtained information in decision-making aiming to reduce human labor in the field. These technologies are applied to solve many existing agricultural issues.

In Thailand, several smart farming applications have been studied and developed for industrial crops such as rice [3], [4], durian [5], mango, mulberry [6], tamarind, and macadamia [7]. These application systems are designed to solve the specific issues including farm data collection and management, recommendation of fertilization, pest and disease control, and water management [8], [9]. Among them, works towards water management [10] are one of the favorable topics in Thailand due to its frequent water problems including drought and flooding. According to the World Bank collection of development indicators, agricultural land in Thailand was reported at 43.28 % in 2018; thus, water is needed to manage accordingly for both irrigation-based farm and rainfall-based farm [11]. In Thailand, water tends to be insufficient in a dry season, and flood may occur in a rainy season, especially in a lowland area and an area near a river.

In fact, one of the major issues in Thai agriculture is the risk from flood in the flood-prone area. Since agriculture is highly dependent to water for raising crops, many farmlands are located near the water sources including river and irrigation canal. They are susceptible to the flooding problem as they are in a flood-prone area. Flood damage to agricultural area apparently causes economic loss and affects food security [12]. Crop submergence due to flooding can adversely affect crop growth and yield [13]. Flooding also significantly alters the level of nutrients in the soil including nitrogen, phosphorus, silicon, potassium, and organic matter in the soil.

There are several works aiming towards the flood problem as flood monitoring system and forecast system. Authors of study [14] apply IoT technology to collect information of water level in river and canal of the flood-prone area in Southern region of Thailand to develop flood monitoring system and warning when the flood occurs. They set up sensors in crucial spots in the water way to closely monitor the raising of water level. Furthermore, the data are used to train for forecasting the flood for earlier warning to the affected area. Study [15] also examined deploying sensors for surveillance system and reporting of flood damage. They aim to monitor flood situation and analyze for agriculture-based flood victims. Then the report of the flood situation is created as an evidence for affected farmer to get help and compensation from the related government sector. Their work shows a good result to monitor flood incident in real-time and forecast [16].

This research aims to develop a flood-countermeasure system for a farm in a flood-prone area in Thailand. The proposed system is designed to cover the process of detecting, deciding, and solving the flood problem for a small size farm. The designed system composes the use of IoT-based sensor to detect environmental parameters, decision-making from machine-learning, and solar-cell-based automated mobile machine to handle flooding. We expect the system to help in better management of flood risk in Thai flood-prone area in the future. The rest of this paper is organized as follows. Section 2 provides a brief background of the study area. Section 3 explains a design of our proposed system. Section 4 gives an experiment setting and result with discussion. Section 5 presents a conclusion of this paper and discussion.

2. Related Works

A substantial amount of study has been conducted recently on environmental monitoring sensor networks, notably in the field of flood detection systems [17].

These studies sought to address a variety of issues and demands, taking into account the unique characteristics and setting of each application. To gather information relevant to various parts of flood monitoring, such as tracking rainfall or river gauging, many sensors have been used in these networks. To enhance flood prediction, early warning, and overall catastrophe management, the goal in each situation is to precisely monitor and evaluate crucial parameters. A review of the pertinent literature is provided in this part, along with a list of significant developments and suggestions for additional research.

A remote water-level monitoring system developed by Xiuhong *et al.* [18] was successfully implemented in Poyanghu Lake. A field sensor, a base station, a data center, and a WEB-releasing module make up the system. In addition to offering early warning of anomalous occurrences and protection in some risky situations, it can accomplish real-time remote monitoring. Two fundamental concerns about various adaptive systems to natural catastrophes were helpfully addressed by a different research [19]: What are the key requirements to providing a reliable WSN-based system (e.g., a river monitoring system)? and What steps can be taken to develop a flexible and dependable WSN-based system? The authors of that article developed a dependable river monitoring system based on WSN and IoT, which was effectively implemented in the Brazilian city of Sao Carlos. In the end, the strategy was implemented for several platforms.

To monitor and control flood events, a different research [20] suggested the use of flood detection and warning system called FLoWS. Using an Arduino Uno and a GSM module, the suggested system may also send SMS and MMS alerts to the public and authorities about locations that are impacted. Additionally, the Android application for the system enables the public and municipal authorities to view real-time graph data on flood levels. In paper [21], an IoT perspective on flood monitoring issues in crowded locations was covered.

The "Crowdsourcing" smartphone app was created in [22] to provide flood information to locals who are engaged in disaster prevention in flood-prone regions. The sensors are incorporated with this app using SMS. Prior to alerting people, the built mobile application may also be utilized to communicate with servers, which process data to determine the proper alert level. Then, the sensor-equipped mobile app is used as a flood risk management tool. A web- and belief rule-based expert system with sensors was integrated by Islam *et al.* [23] to forecast floods in real time based on river flow and rainfall. Additionally, the method makes it easier to monitor the elements that make floods more intense in a particular location.

Cutting-edge IoT tools offer a singular chance to foresee dangers and track severe occurrences in real time, like floods. They are perfect for collecting a great number of complex data because of their versatility. These "smart technology devices" can reduce risk by gathering flood data and acting as an early warning system when arranged in networks. The Calderdale Flood Sensor Network, which was created in the UK following the community's catastrophic floods in 2015, is one real-world example [24]. This IoT installation established several monitoring stations to keep an eye on the area's growing water levels by utilizing LPWAN network connectivity.

A thorough examination of LoRaWAN performance with different parameter values is presented in another work [25]. The purpose of the study is to shed light on how various configuration decisions affect network performance and to provide recommendations for improving LoRaWAN installations. The researchers carried out in-depth tests using various spreading factors, coding rates, payload sizes, and transmission power levels in order to accomplish this. Their research demonstrated the trade-offs between each parameter's related communication range, energy consumption, and network capacity. Network operators may configure their LoRaWAN networks to achieve the best possible performance in terms of coverage, dependability, and energy efficiency by being aware of these trade-offs.

In the context of the IoT, a retransmission-assisted resource management method known as R-ARM for LoRaWAN is given in [26]. The writers tackle the difficulties that LoRaWAN networks face, such as few resources and erratic network circumstances that might impair performance and wasteful use of resources. R-ARM uses retransmission as a tactic to balance network load and provide dependable communication in an effort to enhance resource management. R-ARM uses effective channel allocation, spreading factor optimization, and adaptive transmission power regulation to improve LoRaWAN network performance. The suggested method lowers energy usage and latency while simultaneously boosting the network's capacity and dependability. All things considered, the R-ARM method offers a viable way to manage resources in LoRaWAN-based IoT networks.

In our study, we focused to develop a flood-countermeasure system for a farm in a flood-prone area in Thailand. The proposed system is designed to cover the process of detecting, deciding and solving the flood problem for a small size farm. The designed system composes of the use of IoT-based sensor to detect environmental parameters, decision-making from machine-learning, and solar-cell-based automated mobile machine to handle flooding. We expect the system to help in better management of flood risk in Thai flood-prone area in the future.

3. Methodology

The main objective of the proposed system is to prevent the flooding in an agricultural area. The system comprises of modules for detection of flood using sensors, decision-making, and automated controlling of a water pump to handle the flood. With the lack of electrical input in a field, the deployed electrical devices are powered by the mobile solar-cell.

In the flood-prone area, sudden flood may occur from two causes as heavy rain and overflowing water from a water source such as river, canal, and irrigation canal. According to Figure 1, the system is designed to detect the risk of flooding using the sensors to detect parameters related to flooding. History records from the detected parameters of flood incidents are used to train for decision-making model using machine learning technique. The water pump is then automatically activated following the decision-making model to drain out the excess water in a field to prevent damage from flooding. All the devices are communicated following IoT protocol.

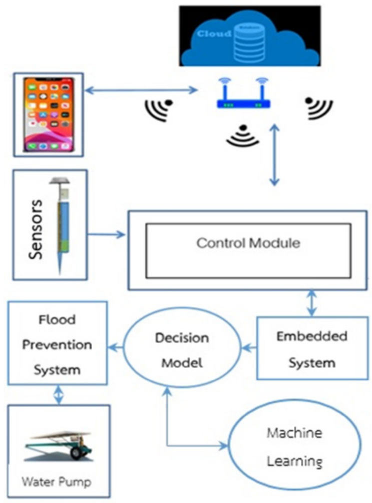

Figure 1. An overview of the flood prevention system in a flood-prone agricultural area

3.1. Study Area

Figure 2 shows the location of the study area, which is located in Tub-Nam Sub-district, Bang-Pa-Hun District, Phra Nakhon Si Ayutthaya Province Thailand. The Tub-Nam Sub-district is an agriculture-based area where farmers reside in their own farm. The agriculture in the area uses the water from rain, natural canal, and irrigation canal. The major canal in the area is Bang Kung canal, which connects water flow from Chao Phraya River.

The Bang Kung canal then spreads the water flow to smaller canals including Mon canal, Pho canal, Krata canal, Phoo-Tao canal, Saan canal, and Tub-Nam canal. The major agriculture products of Tub-Nam Sub-district are rice and sweet potato. Since farms in the area rely mostly on canals to provide agricultural water, the possible issues of the Tub-Nam Sub-district are flood from overflowing water from the canal and erosion of the water bank in the rainy season. Additionally, drought can also happen in the area if the water from the Chao Phraya River is low. However, the frequent issue for the agricultural business is the repetitive flood from overflowing water from the nearby canal. The flood is likely to happen in every rainy season annually, for 2-3 times per year. The flood normally lasts for 3-7 days, and the submerge level is around 30-60 cm. The flood that covers the agricultural field damages the crop products. It submerges the crop causing them to gradually rot, especially near harvesting period. Flood management is thus essential to provide a better quality of life to farmers in the area.

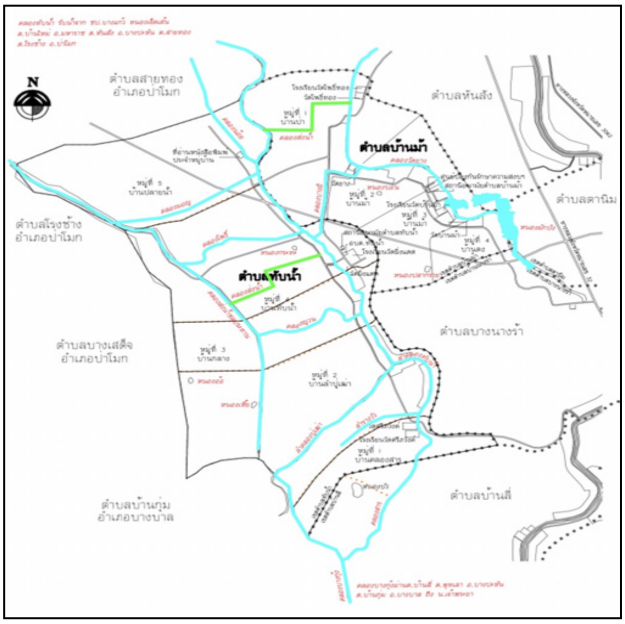

Figure 2. Map of Tub-Nam Sub-district

3.2. Mobile Solar Cell

The system is designed to be used outdoor in an agricultural field. Electricity is essential to power the devices of the system; thus, we design the mobile solar-cell cart to convert the energy of light directly into electricity to power the devices. The solar panel consists of 10 panels of 340w polycrystalline solar panels. The panels are located on mobile cart as shown in Figure 3. The cart is designed to be tugged by human and agricultural vehicles. The cart includes a power inverter to change direct current (DC) to alternating current (AC) to provide electricity for our devices including sensors and a water pump.

The 10 solar panels are estimated to generate electricity of 3400 watts per hours. The generated electricity is stored in a connected series of 19 batteries.

The selected batteries in this work are Lithium-Ion PowerBrick+ battery 12V-100Ah.

Figure 3. Mobile solar cell cart

3.3. Flood Risk Detection

To detect the risk of flooding, sensors are deployed in a farmland. In this work, 3 types of sensor as water level sensor, water current sensor, and soil moisture sensor are used**.**

1. *Water level sensor:* detecting water level in a nearby canal. A water level sensor is to collect water levels data in real-time. In this work, we select the ping sensor type to measure a distance between sensor and water surfaces. The sensor system consists of two components as a transmitter and a receiver. A transmitter is to send a wave to locate a water surface and measures a water level by travelling time, while a receiver is to receive a transmitted data to collect. The sensors are deployed in a nearby canal and in a field. Its accuracy is ¬±0.25% and runs on the power of 12 volts DC source.

2. *Water current sensor:* detecting a velocity or flow of water. The selected water current sensor consists of a plastic valve from which water can pass and a water rotor. Once the water flows through the rotor, a voltage difference is induced in the conductor due to the rotation of the rotor. The change in voltage can be observed in the speed of the motor and is calculated as output as a pulse signal to represent a measurement of the rate of flow of water. The measurement range is 25mm/s to 4000mm/s bidirectional with resolution of 1mm/s and accuracy of ±2%. The sensor runs on the power of 12 volts DC source.

3. *Soil moisture sensor*: a measurement of the moisture content of the soil in agriculture field.

A soil moisture detection sensor composes of two components. The first component is a two-legged lead with a pin that puts into the soil. The second component is an amplifier/ A-D circuit which links to the main connector to communicate with other devices.

The sensor reads both upper and lower soil moisture in the agricultural field and sends the reading data to measure soil moisture. The sensor runs on the power of 12 volts DC source.

When the environmental parameters are read through the remote sensor, they are transmitted via mobile GPRS communication to the control center for data processing. With the outdoor environment, all devices are well housed in a heavy-duty metal cabinet (Figure 4) with two fans installed for ventilation in cabinet to prevent overheat in operational temperature.

Figure 4. Mobile solar cell cart

3.4. Database and Decision-making Model

Real-time data from the remote sensors are stored in MySQL server, and C/C++ language code is used to code and directly send data through IoT. For decision-making model, the data are processed to find a mean value to represent environment parameters in hour manner. The collected data is processed to manually annotate with a class. There are three classes as no-flood, mild flood (30 cm flood and below), and severe flood (over 30 cm flood) depending on the actual circumstance of the field. The annotated data are then used to train for classification model using k-nearest neighbors (KNN) algorithm.

The features for training are not only the acquired data from sensors but also calculated data between times and places. The features are given in Table 1.

Table 1. Feature for training a classification model

Features	Data type	Acquisition	Definition
wu	integer	sensor data	current water level (cm.) in the upstream of a canal
dwu	integer	calculation (dwu = wu – wu′)	difference in water level comparing to past 1 hour (cm.) in the upstream of a canal
wd	integer	sensor data	current water level (cm.) in the downstream of a canal
dwd	integer	calculation (dwd = wd – wd′)	difference in water level comparing to past 1 hour (cm.) in the downstream of a canal
wf	integer	sensor data	current water level (cm.) in the field
dwf	integer	Calculation (dwf = wf – wf′)	difference in water level comparing to past 1 hour (cm.) in the field
wc	integer	sensor data	current water flow (mm./s.)
dwc	integer	calculation (dwc = wc – wc′)	difference in water level comparing to past 1 hour (mm./s)
s	integer	sensor data	current soil moisture
sd	integer	calculation (sd = s – s′)	difference in soil moisture comparing to past 1 hour (mm./s)
Flood type	class	annotating for reference	defined classes (no-flood, mild flood, and severe flood) for classification

The features are trained using KNN for multiclass classification since this work has three classes. KNN algorithm stores all known cases and determines a class of a new case based on a distance measure to the known cases [ref] as shown in Figure 4.

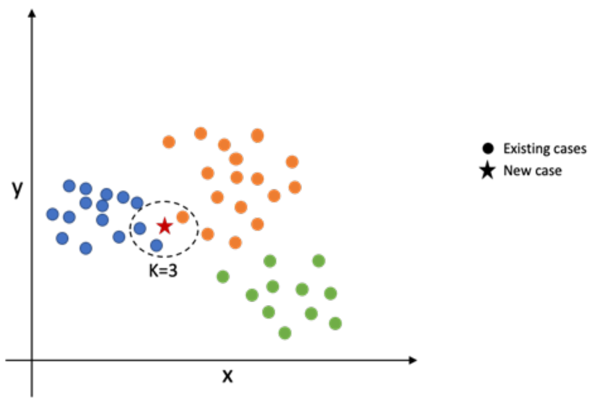

Figure 5. KNN for multiclass classification for classifying flood classes

The new case is classified by a majority vote of its defined K number of neighbors by a distance function. The K number in this work is set to K=3. The selected distance function in this work is Euclidian distance given shown in Equation 1.

$$d(x, y) = \sqrt{\sum_{i=1}^{k} (x_i - y_i)^2} \tag{1}$$

With x, y are two points on a plane.

$d(x, y)$ is the distance between x and y.

With the classification model, we can classify the incident of floods. Since the data of every field differs, automated classification is the most suitable method to define flood incidents specific to the assigned field. The classification result of mild flood and severe flood then will be used in flood draining process.

3.5. Flood Draining

To prevent crop fields from being damaged by flooding, installing a drainage system to remove excess water is a useful method. In this work, the water pump is a pipe-type (as shown in Figure 5) using electricity from solar energy. The draining pump in this work uses a 3-horsepower motor (2.2 kilowatts) with 1,450 RPM which can constantly drain water for 1.54 m3/min.

Since we are designed to automatically manage a water level, a pump using fuel cannot be used because of a complexity on engine starting and a refilling of fuel which needs to be done manually. Because a water pump uses centrifugal force to send fluid to the outside while it spins causing fluid to be drawn from the center continuously, it is necessary for a pump input to be ready in a most depth flood area for the whole time to prevent damage of a device when it is activated.

To prevent accidents that the pump may activate without water and damage itself, we install a water detecting sensor at the tip of the drain side. The pump will not be allowed to activate unless the installed sensor can sense the water. The drained-out water is designated to the downstream of the canal to prevent returning of the drained water.

For condition to activate the water pump, classification results of the decision-making model are used along with the current obtained sensing data. The mild flood will activate the pump until the current water level in the field is equal to the water level of the previous no-flood classification result. For the severe flood classification, the pump is activated considering water current, water level in a canal and water level in a field based on each field threshold.

Figure 6. The pipe-type water pump to drain flood

4. Experiments and Results

There are 2 experiments to test the potential of the proposed system. First, we statistically measure the results of the monitoring sensor data comparing to monitoring from farm owner. Second, the performance of the classification model is examined. Third, we evaluate the performance of the overall system.

4.1. Statistical Evaluation of Environmental Parameter Detection

In this experiment, we asked 5 farm owners to monitor environment parameters regarding water level and water current for a total of 30 times using their own measurement tools and recorded them. Then we compare farmer monitoring results and the sensing data results using one way ANOVA. The statistical analysis of the results is given in Table 2.

Table 2. Comparison results of environmental parameter detection from manual and sensor

Environment Parameters	SS	df	MS	F	Sig
Water Level					
between groups	368	1	0.37	1.25	0.27
within group	17.12	58	0.30		
total	17.49	59			
Water current					
between groups	193	1	0.19	0.10	0.75
within group	109.44	58	1.89		
total	109.63	59			

The result indicates that the observation parameter from farmers and the sensing data are insignificantly different for both water level and water current (sig = 0.27 for water level and sig = 0.75 for water current). This shows that the sensors perform well to detect the actual environmental parameter in an outdoor field.

4.2. Evaluation of Classification Model

This study analyzes data from 5 farms in the study area. Therefore, we developed a total of 5 classification models. For each farm data, training data are to generate the model from 2021 while the testing data are data of mild flooding and severe flooding from 2022. The classification results are calculated for precision (P), recall (R), and F-measure (F1). The evaluation results of classification model are given in Table 3.

Table 3. Evaluation results of classification models

			Actual Incident				
	Prediction	No flooding	Mild Flooding	Severe Flooding	P	R	F1
	No flooding	183	0	0	1.00	1.00	1.00
Farm1	Mild Flooding	0	11	1	0.92	1.00	0.96
	Severe Flooding	0	0	5	1.00	0.83	0.91
	No flooding	181	0	0	1.00	1.00	1.00
Farm2	Mild Flooding	0	13	0	1.00	0.93	0.96
	Severe Flooding	0	1	5	0.83	1.00	0.91
	No flooding	186	0	0	1.00	1.00	1.00
Farm3	Mild Flooding	0	10	1	0.91	1.00	0.95
	Severe Flooding	0	0	3	1.00	0.75	0.86
	No flooding	186	0	0	1.00	1.00	1.00
Farm4	Mild Flooding	0	11	0	1.00	1.00	1.00
	Severe Flooding	0	0	3	1.00	1.00	1.00
	No flooding	183	0	0	1.00	1.00	1.00
Farm5	Mild Flooding	0	12	0	1.00	1.00	1.00
	Severe Flooding	0	0	5	1.00	1.00	1.00
	No flooding	919	0	0	1.00	1.00	1.00
All	Mild Flooding	0	57	2	0.97	0.98	0.97
	Severe Flooding	0	1	21	0.95	0.91	0.93

The classification results show that the classification of mild flooding yielded 0.97 precision, 0.98 recall and 0.97 F-measure score while severe flooding classification obtained 0.95 precision, 0.91 recall and 0.93 F-measure score.

The overall result indicates the classification performs greatly in all farm data. Since none of the datasets included any flooding incidents, our classification models did not produce any false positive or false negative results.

5. Conclusion

Flood is one of the frequent issues for agricultural production in Thailand. In some areas, flood is a repetitive incident that damages the crop product due to geographical setting. This work proposes a method to handle a flooding issue. The system is designed for a complete water management to assist farmers. The processes include a function to collect environment parameters, to classify the parameter for flooding prediction, and to solve flooding incident. The system is practically deployed in actual farms in the study area which is Tub-Nam Sub-district, Bang-Pa-Hun District, Phra Nakhon Si Ayutthaya Province Thailand. The proposed system shows the potential to help in water management to monitor and prevent flooding issue for an agricultural field.

The experimental results show that the sensor data is not different from manual detection as indicating sensor accuracy and reliability. Another experiment also shows that the collected sensing data can be used to generate a precise decision-making model to predict a flood incident. In a case of flood, the implemented automatic drainage pump is activated according to the sensor data and decision-making model to help prevent submerging crops. Furthermore, the deployed devices including sensors and draining pump are powered with the solar cell system so they are independent to home electricity cost. Specifically, this system generates a decision-making model based on an input of environmental parameter regarding individual farm; thus, the model is specified for the farm without the unnecessary noise resulting high classification performance. For the limitation of the proposed system, the draining pump can only prevent flooding for light flooding incident since the handing of the excess water is to drain out. In a case of a massive flood, the drained-out water will eventually flow back to the farm. In addition, the applied data transmission is via mobile GPRS communication which leads to occasional signal lost (0.5%) due to bad weather.

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