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Bespoke cultivation of seablite with digital agriculture and machine learning

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A R T I C L E I N F O

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A B S T R A C T

Climate change has driven agriculture to alter farming methods for food production. This paper presents a new concept for monitoring, acquisition, management, analysis, and synthesis of ecological data, which captures the environmental determinants and direct gradients suited to a particular requirement for specific plant cultivation and sustainable agriculture. The purpose of this study is to investigate a smart seablite cultivation system. A novel digital agricultural method was developed and applied to digitised seablite cultivation. Machine learning was used to predict the future growth conditions of plants (seablites). The study identified the illustrative maps of seablite origins, a conceptual seablite smart farming model, essential factors for growing seablite, a digital circuit for cultivating seablite, and digital data of seablite growth phases comprised the digital data. The findings indicate that: (1) An indicator of soil salinity is a quantity of sodium chloride extracted from a seablite sample indicating its origin of environmental determinants. (2) Saline soil, saline water, pH, moisture, temperature, and sunlight are essential factors for seablite development. These factors are dependent on climate change and were measured using a smart seablite cultivation system. (3) Digital circuits of seablite cultivation provide a better understanding of the relationship between the essential factors for seablite growth and seablite growth phases. (4) Deep neural networks outperformed vector machines, with 86% accuracy at predicting future growth of seablites. Therefore, this finding showed that the essential seablite development factors can be manipulated as key controllers for agriculture in response to climate change and agriculture can be planned. Basic digitisation of specific plants aids plant migration. Digital agriculture is an important practice for agroecosystems.

1. Introduction

Sustainable agriculture involves the cultivation of plants to produce food commodities for humans and animals. Plant cultivation is critical for regional economic assessments and boosts the local economy (Chaichana et al., 2024; Chaichana, 2023; Chaichana and Chakrabandhu, 2021; Chaichana et al., 2021). However, climate change will impact plant cultivation over the next five decades, and agricultural practices will have to change because of environmental changes (Wang et al., 2022; He et al., 2021). As a result, agricultural practices will need to change to cultivate plants sustainably, ensuring the continued production of food commodities. Therefore, digital agriculture is key to improving cultivation in this new agricultural era, revealing answer to the concept and development of ecological agriculture system that a

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former scholar created almost half a century ago (Kiley-Worthington, 1981). This system attempts to manage the sustainable biological systems but with no practice and no use of the digital technology. Digital agriculture complements this system through technological, economic, and environmental, indicating the ability of biological systems to maintain productive, diverse, and healthy overtime. Many scholars have used digital agriculture in technological term to maintain agricultural abundances, grassland managements, and perfect yields, as well as creating knowledge and skills to maximise the real profits of net production in agriculture and ecosystems (Qiao et al., 2024; Chaichana et al., 2021; Higgins et al., 2019). In economic terms, the use of digital agriculture maximises returns that are limited to the required investments and the increase in employment must be small but appropriate to local conditions (Chaichana et al., 2024; Chaichana et al., 2021). For example, investing in digital technology on farm increases productivities by using less labour but it complies with local content laws. Lastly, many researchers have used digital agriculture in environmental terms to support by-product recycling, wastes reduction, animal ratio control (including humans) to plants, and maximising biomass production. Consequently, the self-reliance and stability characteristics of biological systems suitable for sustainable agriculture have increased (Chaichana, 2020; Jónsson and Davíðsdóttir, 2016). Hence, digital agriculture has greatly advanced the concept and development of ecological agriculture system. Half a century ago it was impossible to implement sustainable agriculture and ecosystem.

Digital agriculture is a system that uses electronic equipment and/or computers for agriculture. This system involves the conversion of information into digitised data, represented as a series of 1 s and 0 s (Chaichana et al., 2017). It digitises, records, and shows agricultural information in the form of digital data and uses it to perform job tasks. This relates to agricultural computing (computing in agriculture), which uses Internet/offline data from machine to machine (Chaichana et al., 2017). We can use data generated from digital agriculture to improve cultivation in three respects: cultivation of plants, green economy, and economic security. Bespoke plant culture refers to the practise of cultivating particular plants with a focus on plant migration, quality control, resource utilisation, resource conservation, and environmental protection (Chaichana and Chakrabandhu, 2021; Chaichana et al., 2021; Chaichana et al., 2017; Chaichana and Sun, 2024). A green economy aims to reduce ecological scarcity and environmental risks (Nandy et al., 2022; Lee et al., 2022). Economic security, in this context, pertains to the concept of food and nutrition security, denoting the capacity of people to fulfil their dietary requirements (Moore et al., 2021; Wang et al., 2021). Consequently, it is evident that the green economy and economic security are completely linked to the bespoke cultivation of plants using digital agriculture.

There are numerous advantages to using digital agriculture (Muangprathub et al., 2019; Lekbangpong et al., 2019a; Pitakphongmetha et al., 2016; Boonnam et al., 2017; Kajornkasirat et al., 2021; Lekbangpong et al., 2019b; Vincent et al., 2019; Abba et al., 2019). In 2019, Muangprathub et al. (2019) described the use of electronic devices to develop smart farming practices. Node sensors (e.g., temperature, humidity, and ultrasonic sensors) were deployed in the crop field to digitise digital data. The web application was designed to display digital data and manipulate electronic devices in the crop field. Muangprathub suggested that digital agriculture is useful. It can be used to monitor a farm and automatically control the water pump to water the plants when they need water (Muangprathub et al., 2019). Consequently, this saves resources, protects the environment, increases agricultural productivity, and reduces production costs. Lekbangpong et al. (2019) proposed that electronic devices could control simulated weather within a greenhouse to grow St. John's Wort, a flower found in Davon, England (Lekbangpong et al., 2019a). Their study demonstrated that digital sensors and systems successfully assisted and supported the growth of St. John's Wort (Lekbangpong et al., 2019a; Lekbangpong et al., 2019b; Pitakphongmetha et al., 2016). In 2016, Pitakphongmetha et al. used an Internet of Things (IoT) planning platform to assist plant growth phases in hydroponics (Boonnam et al., 2017). Their electronic devices primarily include solenoid valves and temperature, humidity, and light controllers. Their research revealed that digital agriculture clearly assists farmers in meeting their needs, such as monitoring plant growth in numerous phases, planning irrigation systems, and supplying water to watering plants per day. Thus, this platform may help reduce water scarcity in the future (Boonnam et al., 2017; Kajornkasirat et al., 2021).

Furthermore, Kajornkasirat et al. (2021) developed a web-based application for an information system regarding rubber plantations (Kajornkasirat et al., 2021). The data were digitised from the Thai Rubber Research Institute, and the generic attribute information included latex, rubberwood, price of rubber, rubber research, and specific industries. According to their findings, the digital data system assisted stakeholders, farmers, and the government with rubber plantation administration (Kajornkasirat et al., 2021). Vincent et al. (2019) described the electronic sensors used in agricultural farms to digitise the data for assessing land suitability and making agricultural recommendations (Vincent et al., 2019). Vincent's findings previewed that the farmers would benefit from the proposed digital agriculture in terms of decision-making on land suitability for cultivation. As a result, agricultural recommendations regarding agricultural land have been divided into four tiers: unsuitable, moderately suitable, suitable, and more suitable. Abba et al. (2019) developed a low-cost IoT system for controlling and monitoring irrigation systems (Abba et al., 2019). Abba's digital platform is used to optimise water use for irrigation farming in remote locations while reducing the amount of supervision required. The practical usefulness and versatility of this innovation extended beyond the agricultural sector, benefiting not just farmers but also the local economy. Tsai and Lee (2024) analysed cultivation practices that affect the environmental sustainability of the agriculture system and resource use efficiency. Their findings show that changing cultivation practices significantly contributes to environmental sustainability and land use management. Consequently, adapting new cultivation methods can develop agricultural ecosystems to respond to regional economic and social systems (Tsai and Lee, 2024). Recent studies have shown that changes in agricultural methods improve the efficiency and sustainability of agriculture and land use management. Climate change affects agricultural production can be reduced by changing cultivation practices (Zhang et al., 2024; Fathololoumi et al., 2024; Nsabiyeze et al., 2024; Bouteska et al., 2024; Tsai and Lee, 2024).

In 2020, Ciruela-Lorenzo et al. (2020) proposed a digital diagnosis tool for digitising agricultural operations within the framework of smart agriculture. Their study showed that digital agriculture is transforming the agriculture sector into a more efficient and sustainable economic activity (Ciruela-Lorenzo et al., 2020). For example, the digitisation of activities includes using drones to control and optimise fertiliser application in crop fields, using electronic devices to generate soil mapping and control the quality of the nutrients, and increasing farmers' capacity to manage and control large crop fields. In addition, Jin et al. (2020) digitised and collected weather information using an agricultural IoT system (Jin et al., 2020). They used digital agriculture to study the cultivation of Chinese goji berries in China. Jin's study suggested that weather changes can be predicted and used to control and manage plant cultivation, hence facilitating the production of sustainable agricultural yields. The present research proposes a novel digital agricultural method to investigate a bespoke cultivation of seablite with the aim of understanding their migration possibility. The study demonstrates that machine learning (ML) may be used to anticipate and calculate future growth conditions of seablite. Fig. 1 shows the overall research on cultivating specific plants using digital agriculture, and the relationship among cultivation, digital agriculture, and ML, which management (bespoke cultivation technique) is a core domain. Present research in agricultural and biological sciences and decision sciences areas provides an empirical investigation of new concepts in monitoring, acquisition,

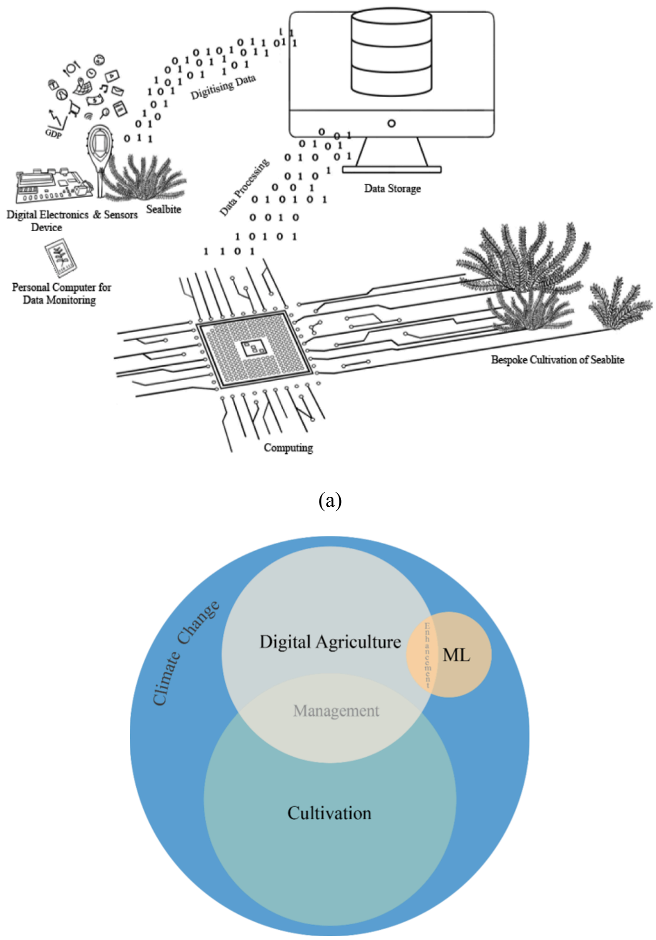

Fig. 1. Digital agriculture concept (a) and relationship (b).

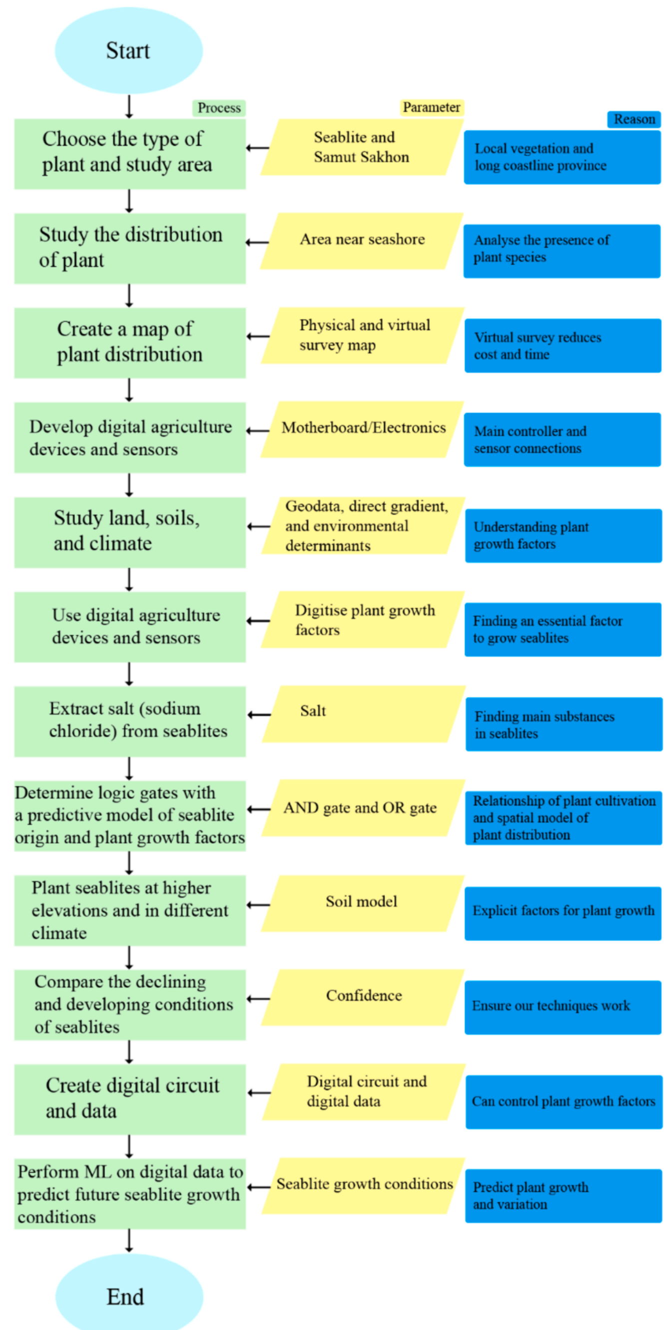

Fig. 2. Generalisability of a methodology for broad applications in agriculture and aquaculture.

management, analysis, and synthesis of ecological data to produce ecological models for specific plant cultivation in driving successful agroecosystems.

2. Materials and methods

This study presents a new technique that is general and can be used more broadly for agricultural and aquaculture applications by following the diagram in Fig. 2 to find factors important to plant needs, fish needs, and water plants and animals' needs. For instance, this new technique can be applied in aquaculture to find an essential factor for fish needs (e.g., dissolved oxygen, turbidity, ammonia, pH, and water temperature). Therefore, the proposed method (Fig. 2) was applied to find important factors in growing seablites for transplantation in different attitudes and weather conditions. Important factors in plant development were discovered using our technique to help plant adaptation processes occur in new areas to which plants migrate.

2.1. Data collection

The data collected were based on three domains: i) specific plant type, ii) study area, and iii) plant growth parameters. The choice of seablite as the specific plant type was made because it is a local vegetable currently consumed by residents in Samut Sakhon, Thailand (Chaichana and Reeve, 2022). It has only been found in coastal regions, indicating its potential for cultivation as a commercially viable vegetable crop in Thailand, Samut Sakhon, as shown in Fig. 3, was chosen as the study area because it has a long coastline that has potential for the growth of plentiful seablites. Finally, the parameters for growing seablites included geospatial data, environmental determinants (soil conditions, wind direction, sunlight, and marine climate), and direct gradients (salinity, pH, moisture, and temperature). Salt (sodium chloride) extraction from seablite was performed on March 4, 2021, using the "AOAC (2019) 937.09" reference method (Central Laboratory (Thailand) Co. Ltd., Samut Sakhon, Thailand).

2.2. Data classification and critical evaluation strategies

Empirical evidence is factual information that represents the important factors in the growth of seablites in Samut Sakhon. These factors were carefully collected using digital agriculture and electronic

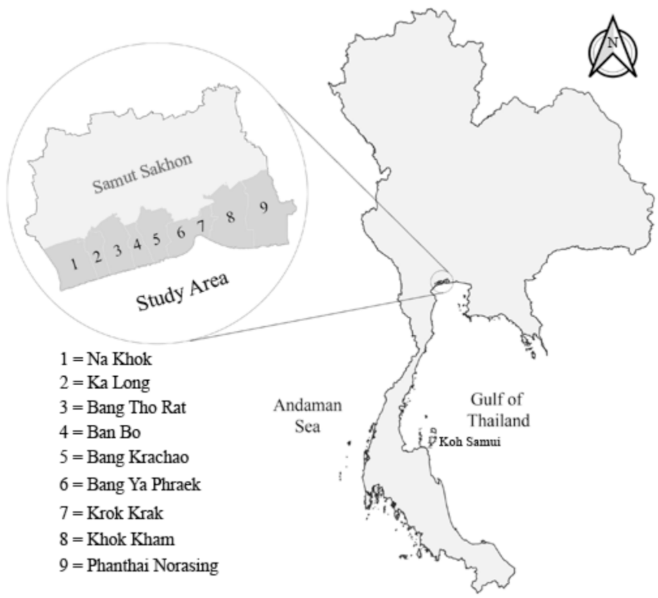

Fig. 3. Study area.

devices that we developed for studying agricultural digitisation. The digitised data are collectively analysed and the digital circuits corresponding to the digital data are designed. Critical evaluation was completed using our technique from previous studies (Chaichana et al., 2011; Chaichana et al., 2021; Sun and Chaichana, 2016a; Sun and Chaichana, 2016b) and assessed in three areas: digital agriculture, plant migration of seablite, and the prediction of future seablite growth states.

2.3. Digital agriculture

Agricultural knowledge and techniques are gained through the farming experience of individuals in plant cultivation. Digital agriculture is a conceptual methodology that transforms personal skills into digital information to facilitate sustainable agriculture and plant migration. A digital agricultural device was developed to digitise plant cultivation data to study a specific plant and was applied to a bespoke cultivation of seablite. Fig. 4 shows the development of the digital agricultural device. The seablites were manually cultivated in lowland areas. Originally, they were migrated from coastal areas. The basic factors of the seablite cultivation data are listed in Table 1.

Boolean algebra is a mathematical logic in which the variable values are either true or false, typically denoted as 1 and 0, respectively. The basic operations of Boolean algebra are conjunction, disjunction, and negation, expressed by the corresponding binary operators AND, OR, and the unary operator NOT, respectively. A predictive model was successfully developed using the data collected in Section A. In addition, the geospatial data of the seablites were studied together with the environmental determinants and direct gradients used to build a predictive model. Fig. 5 clearly shows the relationship between geological and topological embedding with environmental determinants and direct gradients. Thus, a digital circuit was designed using logic AND gates as the primary predictive model, and its output is expressed as follows:

$$Q = (A.B.C.D).(E.F) \quad (1)$$

The Boolean logic was used to define the relationship between basic factors for cultivating seablite, which was then converted into a digital circuit, as shown in Fig. 6a, and the truth table of the proposed logic circuit is shown in Table 2.

Table 1
Seablite cultivation factors.

No	Factors	Measurements
1	Salinity	Saline/Non saline
2	pH	Acidity(3 to < 7)/Neutrality(7)/Alkalinity(>7 to 10)
3	Moisture	Dry/Wet
4	Wind	Kilometre per hour, km/h
5	Temperature	Celsius, °C

2.4. Plant migration of seablite

Rapid climate change has the potential to alter regional bioclimatic agricultural localities. Plant species respond differently through phenotypic plasticity, evolutionary adaptation, migration, and extinction (Chaichana et al., 2022; Vitt et al., 2010; Neilson et al., 2005). Consequently, plant migration has increased because of the potential impacts of global climate change. Plants engage in the natural process of dispersal and expansion of their growing zones as a means of ensuring their survival. Plant migration is of two types: plant migration by nature and plant migration facilitated by humans and animals. For example, dandelion seeds are naturally moved by the wind. Therefore, the workflow diagram of seablite migration by humans from the seashore to lowland areas is shown in Fig. 6a, illustrating a predictive model of seablite origin in the upper part and the digital circuit of seablite cultivation in the lower section.

2.5. Prediction of the future seablite growth conditions

Seablite data were successfully digitised using our developed digital agriculture device, and the essential factors for seablite migration were uncovered. Seablite digital data are the inputs for the ML algorithms to predict the possibility of future seablite growth conditions. Deep neural networks (DNN) and support vector machines (SVM) were selected as automated prediction models to compute the future growth phases of

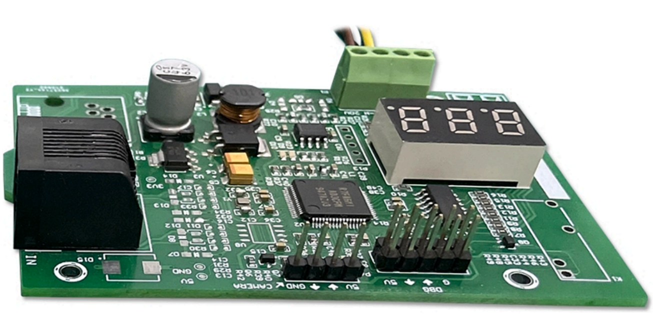

Fig. 4. Digital agriculture devices.

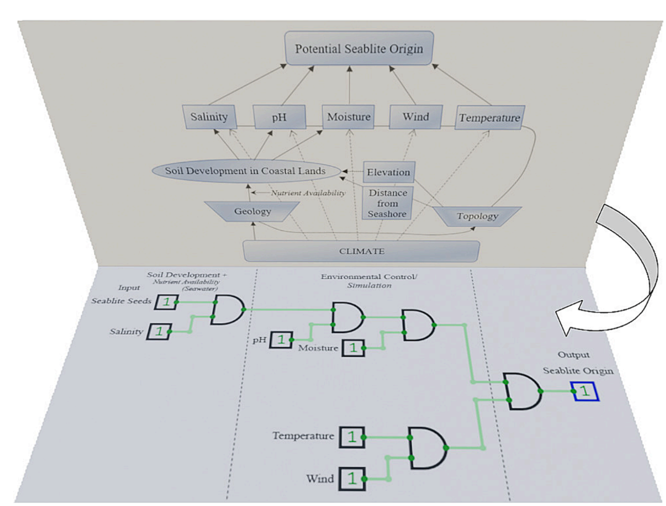

Fig. 5. Digital circuit converted from the predictive model of seablite origin.

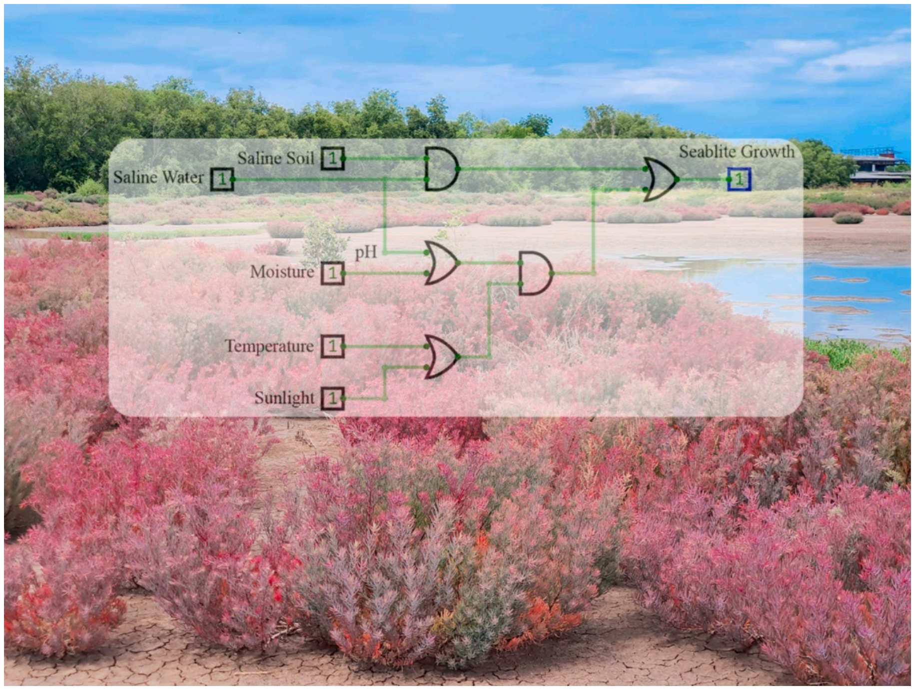

Fig. 6a. Example of single seablite source.

Table 2
Truth table for basic seablite cultivation.

Inputs						Output
A Seablite Seeds	B Salinity	C pH	D Moisture	E Wind	F Temperature	Q Seablite Origin
1	1	1	1	1	1	1
0	1	1	1	1	1	0
0	0	1	1	1	1	0
0	0	0	1	1	1	0
0	0	0	0	1	1	0
0	0	0	0	0	1	0
0	0	0	0	0	0	0

seablites.

ML involves the use of machines to execute tasks. DNNs and SVMs are algorithmic tools in the AI domain. In general, statistical learning theory is an ML framework that includes SVM (Basha and Rajput, 2019) and fuzzy clustering systems (Chaichana et al., 2007). However, our previous study showed that the three most popular classifier algorithms in ML are Naïve Bayes, decision trees, and SVM. SVM is the most effective algorithm, with 88.85 % accuracy, compared with the decision tree (80.25 % accuracy) and Naïve Bayes (71.34 % accuracy) (Boonnam et al., 2022). Deep learning is an ML method based on artificial neural networks. Deep-learning architectures include DNNs, deep belief networks, deep reinforcement learning, recurrent neural networks, and convolutional neural networks (Goodfellow et al., 2016). Recently, DNNs have demonstrated interpretation and discriminative learning capabilities over a wide range of applications (Mahmood et al., 2017). Therefore, the SVM and DNNs were selected and implemented in MATLAB R2017b (MathWorks, Inc., Natick, Massachusetts, USA) in the present study.

There are four types of learning models that depend on data input into ML algorithms: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning (Salian, 2018). Supervised learning is a task under supervision with input data that can be labelled as a training dataset and compared with the test dataset prior to generating the prediction results. Unsupervised learning is a task involving input data that cannot be easily labelled, and researchers cannot presume prediction results such as clustering, anomaly detection, and association. Semi-supervised learning involves both labelled and unlabelled input data commonly used in medical imaging research, such as generative adversarial networks (Goodfellow et al., 2016). Reinforcement learning is an iterative task with intelligent agents attempting to accomplish a particular goal or improve performance on a specific task, and it is normally employed in video game research. Hence, in this study, an unsupervised learning technique was used to analyse unstructured seablite digital data.

In addition, future seablite growth conditions were considered after successfully migrating seablites for cultivation in the lowland regions. They have been cultivated far from coastal areas. However, the follow-up of seablite development can be predicted using AI, with the two subsets of ML (DNNs and SVM) being used. Thus, the accuracy can be expressed as follows:

$$Accuracy = (AIprediction)/(actualmeasurement) \times 100 \quad (2)$$

where the AI prediction results are obtained from the outputs of both the DNNs and SVM. The actual measurement results were collected from the implementation of the developed digital agriculture method.

3. Results

Specific plant cultivation of seablite was performed in Samut Sakhon. The analysis of seablite cultivation was studied, and electronic information was digitised using our digital agriculture concept and device. A digital circuit for a bespoke cultivation of seablite was used to produce unstructured seablite digital data. These digital data were used as inputs for the ML models to predict future seablite growth conditions.

3.1. Data visualisation and interpretation

Qualitative data were obtained from a study on seablite distribution in Samut, Sakhon. The empirical evidence is shown in Fig. 6b. A maximum number of 1,365 seablite sources were found in the Ban Bo sub-district. The Krak Krok sub-district has a lot of residential buildings; therefore, the seablite sources could not be identified.

Fig. 6b. Seablite distribution map.

3.2. Soil modelling for seablite

Generally, the soil responds to climate change. The plant growth parameters of seablite cultivation were studied in Samut Sakhon and then captured, as shown in Fig. 7, and paired with those in Fig. 6. The amount of salt extracted from the seablite sample can be used to characterise the current soil condition.

3.3. Bespoke cultivation of seablite

Bespoke cultivation of seablite has been studied, and seablite migration has been successfully completed. Seablites were migrated from seashore areas for cultivation in lowland regions. Current study has modelled the essential seablite growth factors and temperature changes required for plant migration. The bespoke seablite cultivation experiment was conducted for two consecutive periods, each lasting 14 days/2 weeks. The experimental results indicated that watering seablite with seawater is the key to keeping seablite alive and growing. In contrast, watering the seablite with still water/tap water (not drinking water) caused the seablite to die within seven days/week. The theory in Section C, digital agriculture, was applied to capture the bespoke cultivation practises of seablite. Consequently, the actual factors for growing seablite were measured using a digital agricultural device and are listed in

Table 3
Factors affecting bespoke cultivation of seablite.

No	Factors	Values	Digital Bit
1	Soil	Saline	1
2	Water	Saline	1
3	pH	≈7	1
4	Moisture	Wet	1
5	Temperature	≈30 °C	1
6	Sunlight	≈10 hrs/day	1

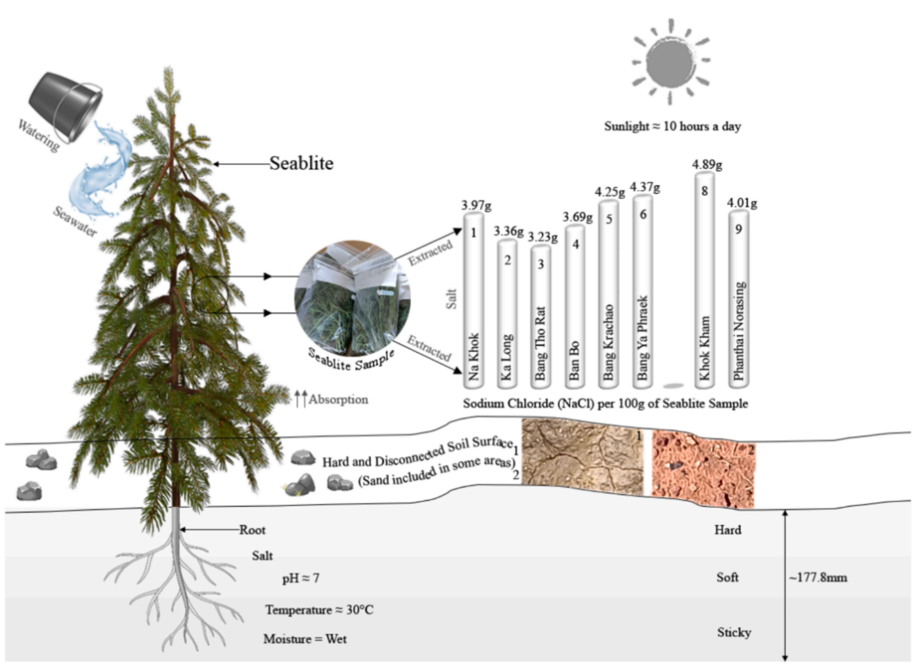

Fig. 7. Soil model of the bespoke seablite cultivation.

Table 3. The cultivation factors of seablite were converted into digital form, with a value of 1 assigned if the measurement values met the conditions shown in Fig. 7.

3.4. Digital circuit of bespoke cultivation of seablite

The current digital circuit was built based on primary data obtained from the experimental results of a bespoke seablite cultivation. Fig. 8 shows the digital circuit built using the data provided in Table 3 and Figs. 6 and 7, based on the digital agriculture theory in Section 2.3.

The digital bits were collected in two distinct time periods (morning and afternoon) per day. These measurements were taken at regular intervals of half an hour throughout the day, and the average value was calculated. Table 4 lists the factors resulting in decline in seablite growth. Saline water and soil are important inputs to the digital circuit shown in Fig. 8. Table 5 lists the growth conditions of seablite development. Saline water is a key controller for growing seablite and is considered a vital input for the digital circuit of bespoke seablite cultivation (see Fig. 8).

3.5. Prediction of the future seablite growth conditions

The digital data phases of seablite development in Table 5 are the input data for automatic predictions of seablite growth using the DNNs and SVM methods. Tables 6 and 7 list the prediction results obtained using the DNNs and SVM methods, respectively. These predictions were assumed to be the digital phases from day 8 to 14. These predictions served as the inputs for the digital circuit shown in Fig. 8, with the purpose of generating the output corresponding to the seablite growth conditions.

3.6. Accuracy of ML prediction results

The outputs of the seablite growth phases were successfully computed using the digital circuit of a bespoke cultivation of seablite, as shown in Fig. 8. The DNNs and SVM outputs obtained from the AI prediction were compared with the actual seablite growth phases. The accuracy parameters are listed in Table 8 and were computed using Equation (2).

4. Discussion

Recent research is the first to describe a new approach in monitoring, acquisition, management, analysis, and synthesis of ecological data for growing specific plants and sustainable agriculture using digital circuits, Boolean logic, and truth tables. This digital circuit clearly explains the new concept of digital agriculture, which captures the environmental determinants and direct gradients suited to a particular requirement for specific plant cultivation. In addition, the digitisation technique proposed in the present study helps maintain and support plant growth phases (see Figs. 7 and 8 and Tables 3 and 5). The digital agriculture concept (Fig. 1) shows that if sufficient plant growth data is collected, a specific plant cultivation/migration might be able to overcome climate change. These data can be beneficial to several research fields, such as economics, logistics, engineering, agriculture, ecosystems, and the environment. Specific plant cultivation data are typically collected by farmers with many years of experience, and these experiences and knowledge are difficult to pass on to the next generation. Thus, digital agriculture can be applied to transform farmers' experiences and knowledge into digital data. We can then develop a digital database and manage the environmental determinants and direct gradients suitable for specific plant growths.

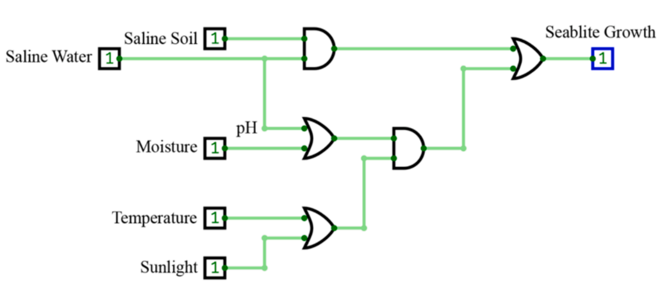

Fig. 8. Digital circuit of a bespoke cultivation of seablite.

In this study, a bespoke seablite cultivation system using digital agriculture and ML was used to build AI models for predicting future seablite growth conditions. We have developed a novel digital agricultural technique that can be applied to digitised seablite cultivation systems. We observed that seablite growth/migration mainly depended on saline water (see Figs. 6 and 7); this was proved by the digital circuit of the bespoke seablite cultivator (see Fig. 8). Additionally, the digital output of the Boolean circuit clearly indicated that seablite growth depended on saline water (see Table 4); otherwise, seablite growth conditions declined. This was proven by our cultivation experiment of seablite migration, which showed that watering seablite with seawater maintained the salinity levels of soil and its pH but moisture and temperature were dependent on sunlight. Sunlight was used as an uncontrollable variable in our study that depends on geographical factors.

In addition, we used the unsupervised ML of both DNNs and SVM to study unstructured seablite digital data (input section in Table 5). The outputs of the DNNs and SVM are the input sections listed in Tables 6 and 7, respectively. These data were the inputs of the digital circuit of the bespoke cultivation of seablite in Fig. 8 to achieve the output of the seablite growth conditions (output section in Tables 6 and 7). Consequently, the computation of accuracy parameters indicated that DNNs outperformed SVM and achieved 86 % accuracy in the prediction of the output of seablite growth conditions (Table 8). Our results obtained from DNNs are in line with those of recent studies, which confirmed that DNNs are preferred in an unsupervised manner and with unstructured data (Usama et al., 2019; Jain et al., 2021). Hence, our preliminary results accurately describe the relationship between the digital agriculture model and seablite cultivation system. The results obtained from these ML models demonstrate the possibility of predicting future seablite growth conditions.

Technological advancements in electronics can challenge agriculture, ecosystems, and the environment (Furber, 2017). Recently, smart and precise farming has received considerable attention in agriculture [10,11]. However, the use of electronic devices in agriculture has been limited. Many studies have reported the use of electronic devices to support agricultural production and yields (Muangprathub et al., 2019; Lekbangpong et al., 2019a; Pitakphongmetha et al., 2016; Boonnam et al., 2017; Kajornkasirat et al., 2021; Lekbangpong et al., 2019b; Vincent et al., 2019; Abba et al., 2019; Ciruela-Lorenzo, et al., 2020; Jin et al., 2020). Nevertheless, only our studies have proposed a digital agriculture concept to promote the use of electronic devices in agriculture, particularly in plant cultivation and migration (Chaichana and Chakrabandhu, 2021; Chaichana and Reeve, 2022; Chaichana et al., 2022). Moreover, we focused on the present and future policies in decarbonising agriculture, forestry, and land use sectors (Thompson, 2022; Ekins, 2022). These efforts underscore the growing significance of digital agriculture practices in addressing environmental concerns (e.g., modelling greenhouse gas (GHG) and carbon dioxide (CO2) in agriculture or land use, the study of plant growth parameters, and GHG and/or CO2 impacts plant biology or migration of plants).

Our feasibility study showed promising results for a bespoke seablite cultivation system using digital agriculture and ML. However, there were some limitations in this study. First, only a single plant type was studied. We only analysed the seablite distribution, modelling the seablite soil using digital circuits. However, this limitation is complementary to the digital agriculture concept. Second, only Samut Sakhon was chosen as the study area because it has a long coastline and the locals

Table 4
Digital data showing declining growth of seablites.

Parameters		Digital States													
		Day 1		Day 2		Day 3		Day 4		Day 5		Day 6		Day 7	
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
Inputs	Saline Water	1	1	1	0	0	0	0	0	0	0	0	0	0	0
	Saline Soil	1	1	0	0	0	0	0	0	0	0	0	0	0	0
	pH	1	1	1	0	0	0	0	0	0	0	0	0	0	0
	Moisture	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	Temperature	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	Sunlight	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Output	Seablite Growth	1	1	1	0	0	0	0	0	0	0	0	0	0	0

Table 5
Digital data for seablite growth development.

Parameters		Digital States													
		Day 1		Day 2		Day 3		Day 4		Day 5		Day 6		Day 7	
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
Inputs	Saline Water	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	Saline Soil	0	0	0	1	1	1	1	1	1	1	1	1	1	1
	pH	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	Moisture	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	Temperature	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	Sunlight	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Output	Seablite Growth	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Table 6
AI-predicted results obtained from DNNs algorithm.

Parameters		Digital States													
		Day 8		Day 9		Day 10		Day 11		Day 12		Day 13		Day 14	
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
Inputs	Saline Water	1	0	1	1	1	1	1	1	1	1	1	1	1	1
	Saline Soil	0	0	0	1	1	1	1	0	1	1	1	1	1	1
	pH	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	Moisture	1	1	0	1	1	1	1	1	1	0	1	1	1	1
	Temperature	1	1	1	0	1	1	1	1	1	1	1	1	1	1
	Sunlight	1	1	1	1	1	1	0	0	1	1	1	1	1	1
Output	Seablite Growth	1	0	1	1	1	1	1	1	1	1	1	1	1	1

Table 7
AI-predicted results obtained from SVM algorithm.

Parameters		Digital States													
		Day 8		Day 9		Day 10		Day 11		Day 12		Day 13		Day 14	
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
Inputs	Saline Water	1	1	1	0	1	1	1	0	1	1	1	1	1	1
	Saline Soil	1	0	1	1	1	1	1	1	0	1	1	1	1	1
	pH	1	1	1	1	1	0	1	1	1	1	1	1	1	1
	Moisture	1	1	1	0	1	1	1	1	0	0	1	1	1	1
	Temperature	1	0	1	1	0	0	0	1	1	1	1	0	1	1
	Sunlight	1	1	1	1	1	0	0	0	1	1	1	1	1	1
Output	Seablite Growth	1	1	1	0	1	0	1	0	0	1	1	1	1	1

consume seablite as their main food source. This reveals the possibility of cultivating seablites in other regions. Thus, we successfully analysed the spatial modelling of the seablite distribution. Third, we used only our digital agricultural device to measure the environmental determinants and direct gradients of the seablite. Thus, our digitised seablite cultivation system created unstructured digital data, which may be difficult for ML. Finally, only two ML models were selected to predict the seablite growth conditions in our study. Notably, we selected DNNs and SVM based on our experience with data analysis (Chaichana et al., 2007; Boonnam et al., 2022; Chaichana and Reeve, 2022; Supot et al., 2007).

5. Conclusions

This finding indicates a positive outcome to represent novel agricultural systems capable of effectively managing and monitoring environmental data of targeted plant cultivation and migration. The soil model has also conducted experiments to explain soil indicators that indicate the origin of environmental determinants. The essential factors for seablite development are saline soil, saline water, pH, moisture, temperature, and sunlight. Digital circuits of seablite cultivation characterise the relationship between the essential factors for seablite

Table 8
Accuracy of AI prediction using DNNs and SVM.

Actual Results		AI Predicted Results				Accuracy	
		DNNs Algorithm		SVM Algorithm		DNNs	SVM
	OUTPUT		OUTPUT		OUTPUT	86 %	50 %
Day	Seablite Growth	Day	Seablite Growth	Day	Seablite Growth		
1	0	8	1	8	1	×	×
	0		0		1	✓	×
2	0	9	1	9	1	×	×
	1		1		0	✓	×
3	1	10	1	10	1	✓	✓
	1		1		0	✓	×
4	1	11	1	11	1	✓	✓
	1		1		0	✓	×
5	1	12	1	12	0	✓	×
	1		1		1	✓	✓
6	1	13	1	13	1	✓	✓
	1		1		1	✓	✓
7	1	14	1	14	1	✓	✓
	1		1		1	✓	✓

growth and seablite growth phases. ML results revealed that DNN performed better than SVM with an accuracy of 86 % when predicting the growth conditions of seablite. This research suggests that the digitisation of specific plant cultivation practises, which assist in farming under changing climatic conditions and facilitate plant migration, together with the adoption of digital agriculture, are important strategies for ensuring future food supply and promoting sustainable agriculture. Therefore, our digitisation methodology for the cultivation of a particular plant can be considered as digital agricultural knowledge and management. As an effective method for cultivating specific plants, other types of plants shall be studied to support future policies for reducing carbon emissions, agriculture, forestry, and land use.

CRediT authorship contribution statement

Thanapong Chaichana: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Graham Reeve:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision. **Brett Drury:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision. **Yasinee Chakrabandhu:** Supervision. **Sutee Wangtueai:** Visualization, Validation, Software, Resources, Formal analysis. **Sarat Yoowattana:** Visualization, Software, Formal analysis. **Supot Sookpotharom:** Supervision. **Nathaphon Boonnam:** Supervision. **Charles S. Brennan:** Supervision. **Jirapond Muangprathub:** Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

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