Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org
© 2024 SCPE. Volume 25, Issues 5, pp. 3766–3777, DOI 10.12694/scpe.v25i5.3132

SMART FERTILIZING USING IOT MULTI-SENSOR AND VARIABLE RATE SPRAYER INTEGRATED UAV

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Abstract. This paper introduces a "Smart Fertilizing Using Internet of Things (IoT) Multi-Sensors" system to enhance fertilizer management in agriculture. The system has four main parts: the Nutro Determining Unit (NDU), the Nutro Sensing Unit (NSU), the Nutro UAV Variable Fertiliser Spray System, and a Variable Rate Unmanned Aerial Vehicle (UAV) Sprayer model. The NDU collects vital data on Soil Moisture (SM) and Environmental Conditions (EnC) using advanced IoT cameras, while the NSU consolidates and normalises the data for advanced analysis using Heuristic Decision Trees (HDT) and Random Forest (RF) algorithms. In India, a data-driven UAV system uses IoT and UAV technologies to determine nutrient needs and create a prescription map for fertilizer application. The approach caused increases in the efficient utilisation of resources, Crop Yield (CY), and ecological footprint when it underwent evaluation in a crop maize field that was 14 hectares in size. A fresh benchmark for Smart Farming (SF) techniques has been set up by this method of operation, which is motivated by data and symbolises an important innovation in modern and ecologically conscious SF methods.

Key words: UAV, IoT, Sprayer Model, Smart Fertilizing, Crop Yield, Smart Farming

1. Introduction. The major developments that have currently taken advantage of the field of agriculture in the past few decades have caused the origin of revolutionary ideas like "Smart Farming" (SF) and "Precision Agriculture" (PA). New technologically focused SF approaches have succeeded conventional farming methods as an impact of these changes. The modern-era SF procedures leverage revolutionary technologies like autonomous devices, statistical analysis of data, and the Global Positioning System (GPS) in order to improve farmer productivity and effectiveness. High crop yields (CY), better consumption of resources, less ecological damage, and maximized use of resources are feasible because PA's data is updated constantly. Precise SF tasks become possible with this method of treatment because it enables selective application on particular areas or crops [7].

The Internet of Things (IoT) generates an evolution in the agricultural sector by implementing an online network of connected devices, including cameras, sensor networks, and Unmanned Aerial Vehicles (UAV) [6]. The main objective of IoT devices is to contribute to making SF more productive by collecting and analyzing data about the crop and the Earth's Soil Moisture (SM). Some examples of inventions that showcase this include autonomous irrigation and precise monitoring systems. By pairing to the World Wide Web in real-time, farm IoT devices provide agriculturalists access to additional valid data, which enables them to make more accurate selections [10].

Ethical practices in ecological awareness finance can now develop owing to this better connectivity, which improves profitability and helps in the effective control of resources. IoT technology plays an integral part in

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monitoring SM and environmental conditions (EnC), namely the levels of nutrients and SM, which is necessary for optimizing fertilizer consumption for successful economic crop development. Periodic data analysis makes it possible to identify the proper proportion of fertiliser to use, which, in consequence, serves to prevent spraying less or excess. Highly accurate and effective fertiliser treatments can be generated by using data pertaining to soil and crop requirements collected by IoT-enabled devices across a period of time frames [5].

A form of application that simplifies the use of pesticides is the Variable Rate Sprayer (VRS), which regulates the volume of fertiliser or pesticide sprayed based on particular regions and data in real-time. Better crop production, better conditions for crops, fewer waste products, and less negative environmental impact are the results of this approach's use.

More and more innovative farmers are employing VRS systems to integrate PA methods into their farming practices. This has the potential to minimize waste and the adverse impact of agricultural products on the natural world [3]. A multi-sensor IoT architecture and a prototype for SF fertilisation using a UAV-based VRS have been recommended in the present investigation on the "Smart Agriculture using IoT Multi-Sensors (SA-IoT-MS)" of the entire system.

The Nutro Sensing Unit (NSU), Nutro Gateway Unit (NGU), Nutro Decision Unit (NDU), and Nutro UAV (NUAV)-Variable Fertiliser Spray System (VFSS) are the 4 portions that make up the entirety of the system. The efficient functioning of the Sustainable Agriculture System (SAS) is enhanced by continually tracking both the soil quality of a crop and outside factors.

An array of parameters are recorded and digested by a unified system. These factors include soil water content, temperature, humidity, and NPK levels. The Decision-Making Process (DMP) revolves around the NDU, which generates a treatment map and forecasts nutrient requirements via a Heuristic Decision Tree (HDT) and Random Forest (RF) method. In order to achieve optimal use of resources while improving CY and good health, this map has been used to guide the accurate placement of fertiliser by the UAV system. By this creative approach, the developers have achieved significant progress towards attaining SAS standards.

This study article outlines the following: Chapter 2 starts with the existing literature analysis; Chapter 3 presents the framework hypothesis; Chapter 4 includes experimental research, and Chapter 5 concludes the research.

2. Literature Review. In order to effectively analyze soil nutrients, [1] developed an IoT-based system using a novel Nitrogen (N), phosphorus (P), and potassium (K) (NPK) sensor. Their use of fuzzy logic for data interpretation demonstrates the growing trend of incorporating complex data processing methods into SF technology.

[8] highlighted the importance of IoT in monitoring SM and EnC, specifically indoor plants, by measuring SM and NPK values and providing user feedback through an online data display, showcasing the integration of IoT with user-friendly interfaces in agriculture.

The authors emphasize the significance of precise data collection and analysis in agriculture, as highlighted by [2, 12]. They propose an SF system integrating Artificial Intelligence (AI) and sensor technology, focusing on energy-efficient deployment and sustainable SF. They also discuss the technical aspects of field data attainment systems in PA, emphasizing the need for accurate data in fertilizer and irrigation systems.

UAV technology has gained significant applications in SF [13, 4, 9], particularly precision farming. They have developed a pulse width modulation variable spray system, which an STM32 chip controls, showcasing the innovative integration of precise control mechanisms in UAV systems for spray farming.

3. System Model. The work puts forward the SA-IoT-MS system, an original concept developed with a clear goal to provide optimal fertiliser management in PA farms. The NUAV-Variable Fertiliser Spray System, the NSU, the NGU, and the NDU are the four interrelated elements that make up the basis of this proposed model. The NSU is not simply planned between the trees, but it has been connected with revolutionary IoT sensors [14, 15, 11, 16]. These sensors collect a wealth of data on the SM and EnC. The data obtained include temperature, humidity, pH, SM, and NPK. The primary objective of the distinct GSP-ID assigned to every NSU is to collect and monitor real-time data that is important in comprehending soil properties.

The NGU's function as a computing unit is to obtain the data collected from the NSUs and send it to them. The NGU may obtain data from numerous NSUs, do the initial analysis, and verify for reliability and consistency while sending it on for deeper analysis because of its architecture. It is the task of the NGU to

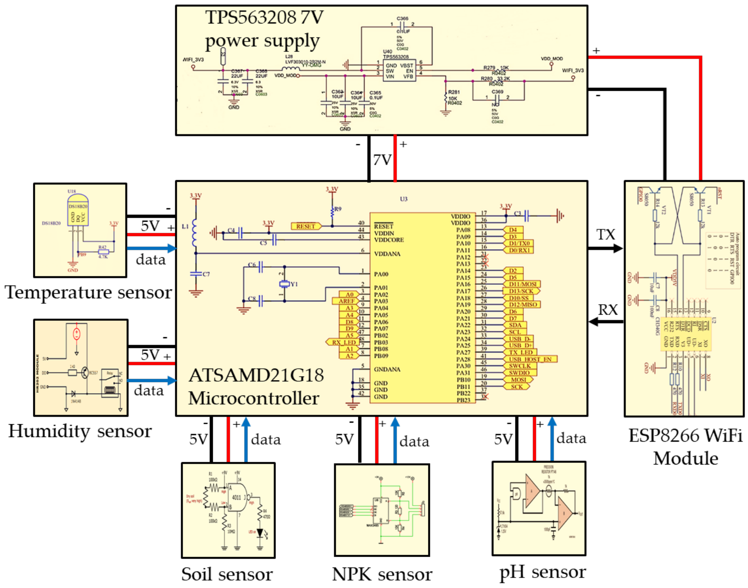

Fig. 3.1: NSU unit structure

ensure that the sensory data have access to the DMP entity uninterrupted any delays. The data is vulnerable to an HDT analysis by the NDU after the NGU stops receiving it. Using methods of empirical research, this elaborate study evaluates the temperature, SM, and NPK levels on an individual basis. In furtherance of analyzing the information that is presented, the NDU is assigned to detecting emerging patterns and trends. This attribute is vital in order to make intelligent DMP about fertiliser services, which will result in improved effectiveness and efficiency of deployments based on real-time and historical information.

In this framework, implementing the NUAV-VFSS is the final phase. This UAV-based system sprays fertilizer precisely where it is required, owing to the extensive instruction presented by the NDU. According to data analysis, the UAV employs VRS innovation to optimize the level of fertilizer sprayed in different regions of the crop. The productivity and efficacy of the fertilization method are significantly improved by this approach, which provides a personalized and efficient use of fertilizer.

3.1. NSU. Figure 3.1 illustrates the elements of the NSU that were developed for the purpose of this research to promote accurate data collection and effective communication in the proposed SF model. The NSU's primary operation is regulated by the ATSAMD21G18 microcontroller, which effectively controls the unit's functions while using less power. The NSU collects an enormous amount of soil-based and environmental information using a number of unique sensors. The DSB18B20 temperature sensor is noted for its accuracy in measuring room temperature; the HR202 moisture sensor performs well at monitoring the level of SM in the atmosphere; and the Jxct soil sensor is great at analyzing the attributes of soil. Measuring SM and EnC in full is required for SF effectiveness. The I2C-SM sensor and the Sen0161 pH sensor have been used in the present study.

Reliable transfer of data for analysis is made possible by the ESP8266 Wi-Fi module, making it possible for simple internet access with the NGU. The NGU depends on the TPS563208 power system for reliable power control. This module provides all sensors and microcontrollers with stable and uninterrupted power, ensuring that they can function and collect data without delay in a number of crop settings.

1. **ATSAMD21G18 Microcontroller:** The NSU powers the ATSAMD21G18 Microcontroller, a low-power, high-performance microchip on the ARM® Cortex®-M0+ platform that is ideal for home automation and industrial applications. Its 256 kb flash and 32KB SRAM provide ample memory for data processing. The ATSAMD21G18 microcontroller is a versatile device with six configurable SERCOM

Table 3.1: Microcontroller Configuration

Feature	**Description**
Microcontroller	ATSAMD21G18, ARM® Cortex®-M0+ based
Memory	256KB Flash, 32KB SRAM
Operating Frequency	Up to 48MHz
PWM Channels	20 channels
Power Supply Range	1.62V to 3.63V

Table 3.2: Wi-Fi Module Configuration

Feature	**Specification**
Processor	L106 32-bit RISC, 80MHz
Memory	32 KiB instruction RAM, 80 KiB user-data RAM, up to 16 MiB QSPI flash
WiFi	IEEE 802.11 b/g/n
GPIOs	16 pins
Interfaces	SPI, I^2C, I^2S, UART, ADC
Power Management	APSD for VoIP, Bluetooth co-existence
RF System	Self-calibrated

modules, three 16-bit timers, a 32-bit real-time clock, and 20 PWM channels, enabling rapid data processing and accurate environmental monitoring. It also features a 14-channel 12-bit analog-to-digital converter and a 10-bit digital-to-analog. The ATSAMD21G18 microcontroller is a high-performance device that supports full-speed USB devices and embedded host functionality, can handle 120 touch channels, and operates within a power range of 1.62V to 3.63V, as detailed in Table 3.1.

2. **ESP8266 WiFi Module:** The ESP8266 Wi-Fi Module, a small and cost-effective System on Chip (SOC) with an integrated TCP/IP protocol stack, enables Arduino controllers to connect to Wi-Fi networks. This module additionally decreases the requirement for a CPU. The module's built-in processing and storage capabilities and high on-chip integration require less additional hardware, reducing the space required for the Printed Circuit Board (PCB). Because of its space-saving design, the ESP8266 is a good option for applications with limited free space for living. It is not essential to use external RF devices because the module's self-calibrated Radio Frequency (RF) system ensures reliable performance in a wide range of temperature and humidity conditions. Table 3.2 displays comprehensive setup details for the installed Wi-Fi module.
3. **Power Module:** The NSU devices are able to run properly because the TPS563208 input module provides them with power through its 3-A synchronous communication step-down inverters. The key objectives of this unit, enclosed in a SOT23 package and small in size, include easy operation, low idle current, and no reliance on external elements. It has a wide input voltage range (4.5V to 17V) and output voltage range (0.76V to 7V). It also has D-CAP2 mode control, which lets it respond quickly to transients, and continuous current mode, which works well with low loads. Additionally, the module ensures safety and dependability by including controls such as the current limit, UVP, and TSD. Furthermore, it performs well across a wide temperature range, ranging from -40° to 125°. Additionally, Table 3.3 contains the configuration information of the electric power module.

The following sensors are integrated into the NSU unit:

- *Temperature:* This investigation uses the DS18B20 sensor to measure the temperature in SF models. The precision, dependability, and ease of integration of this digital sensor led to its selection as the winner. It is a well-liked option in San Francisco because it accurately measures and controls the temperature in the agricultural environment.
- *Humidity:* SF applications, in which energy efficiency is a top priority, are a good fit for the HR202 sensor because of its improved moisture tracking capabilities, wide measurement range, and higher

Table 3.3: TPS563208 description

Feature	**Specification**
Output Current	3A
Control Mode	D-CAP2 Mode
Input Voltage Range	4.5V–17V
Output Voltage Range	0.76V–7V
Operating Mode	Continuous Current
Switching Frequency	580kHz
Shutdown Current	<10mA
Voltage Accuracy	2/cent at 25°
Soft Start	1.0mins
Package	6-pin SOT23 (1.6mm×2.9mm)
Temperature Range	-40° to 125°

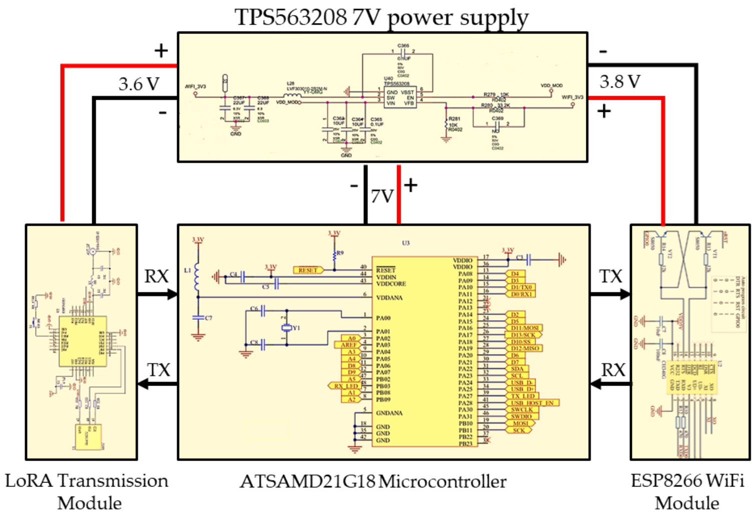

Fig. 3.2: NGU structure

accuracy. As a result, it is an excellent option for SF applications.

- *SM:* The I2C-SM sensor employs the capacitive sensing method, resulting in an accurate and non-corrosive device with consistent long-term reliability, regardless of the predominant soil conditions. It is suitable for SF devices because of its low-voltage functioning, which promotes the use of energy.
- *pH:* Acidity in soils impacts crop growth, fertilizer absorption and soil health; the Sen0161 pH sensor is a significant device for monitoring this factor. Its investigations are vital for making smart choices about soil care along with growth because they are accurate and endure for an extended period of time.
- *NPK:* For precise soil mineral levels of difficulty, fertility tests, and SF use approaches, the LNPK-1 sensor is required. The system delivers accurate fertilizer data employing modern chemical tools for measurement.

3.2. NGU. Collecting and analysing data from NSU distributed around the trees is the task of the NGU, which is a vital part of the SF system. Its core is the ATSAMD21G18 microcontroller, which has been designed for practical use. According to Figure 3.2, the NGU includes the ESP8266 Wi-Fi Module, which enables the creation of reliable wireless connections and the sending of data to a primary server or a cloud-based system.

The NGU has a LoRA transmission module that enables transmission over long distances. This technology

Table 3.4: LoRA Module Description

Specification	**Description**
Frequency Range	433MHz
Modulation Techniques	FSK/GFSK/MSK/LoRa
Sensitivity	-136 dBm
Output Power	+20 dBm
Data Rate	<300 kbps
Operating Temperature	-40° to +80°
Standby Current	$\leq$ 1mA
Supply Voltage	1.8V to 3.6V

is intended for use in low-power, wide-area network (LP-WAN) applications, making it especially useful for SF fields in which NSUs are spread across numerous land areas. While using minimal power, the module can send and receive data over enormous distances most efficiently. When it comes to ensuring that DMPs in remote or difficult locations have a link to an uninterrupted supply of data, the ability of this device to manage large distances without impacting battery efficiency or signal quality is paramount.

The capacity of the TPS563208 power module to provide support for the NGU, which comprises the LoRA module, implies that the operation will be stable and uninterrupted. The microcontroller and communication modules, such as Wi-Fi and LoRA, can function at their highest possible efficiency due to this power module, which provides an uninterrupted and reliable energy supply. This significantly enhances the overall reliability and performance of the NGU, as previously mentioned. As an outcome of the synergistic combination of cutting-edge microcontroller technology, numerous communication options, and a reliable electrical system, the NGU has been determined to be a vital and practical element within the overall structure of the SF.

1. **LoRa Transmission Module:** LoRa Transmission Modules, more specifically for use in SF, make it possible for IoT applications to participate in long-range wireless communication. These modules operate on the LoRaWAN network and use wavelengths that typically fall within the frequency spectrum of 864MHz to 915MHz, following the regulations of the different regions. LoRa modules can send data over ranges of up to 15 kilometres, even in areas that are susceptible to noise. LoRa modules are renowned for their low power consumption and high receiver sensitivity. These modules stand out for their autonomous power supply, typically powered by batteries and capable of lasting up to 10 years without needing a new battery.

The NGU employs the LoRA 433MHz SX1278 module. It is a cost-effective RF front-end transceiver that excels in long-range and low-data-rate applications. Its exceptional sensitivity (-136dB/m in LoRa modulation) and 20dB/m power output ensure reliable connectivity over long distances. The module operates on a 433MHz frequency, supports multiple modulation formats, and can function in extreme temperature ranges from -40° to +80°, making it versatile for varied environmental conditions. Additionally, it includes features such as a built-in temperature sensor with ultra-low standby current that operates within a 1.8 to 3.6V supply voltage range. The following table describes the LoRA module.

3.3. NDU. The NDU is fitted with a vital device called the Heuristic Random Forest (HRF), which is mainly deployed to determine whether or not different agricultural areas require fertilizer replenishment. This DMP is supported by a series of HAs that evaluate various agricultural factors. The following lists contain detailed descriptions and equations for each technique:

1. **Estimation of Evapotranspiration (ET):** For the goal of measuring the amount of water that evaporates as a result of evaporation and crop water loss, the estimated amount of ET is an important metric. Conducting a review of the water level is particularly significant in the SF sector because it has an indirect impact on the rate at which plants absorb fertilizers.

$$ET = ET_o \times K_c \tag{3.1}$$

Here, ET_o represents the reference ET, calculated based on climate data, including temperature, humidity, and solar radiation. K_c is the crop coefficient that varies according to different growth stages, signifying the crop's ET under specific conditions as compared to the reference.

2. **Water Retention Ratio (WRR):** The WRR is the most crucial measure of the soil's capacity to store water. If the WRR is higher, it means the soil can store additional moisture, which in turn impacts its capacity to maintain nutrient solutions and determine how to apply fertilizer plans. EQU (3.2) for WRR is:

$$WRR = \frac{FC - PWP}{AWC} \tag{3.2}$$

The field capacity (FC), the permanent wilting point (PWP), and the available water content (AWC) of the soil are represented in this equation.

3. **Nutritional Deficiency Predictor (NDP):** This study compares the required nutrient levels for a particular crop cycle with the readily accessible nutrient levels in the soil. The goal of this heuristic is to make a prediction about the possibility of nutritional deficiencies. Obtaining this data is essential for determining the necessity of supplemental nutrition. The NDP's EQU (3.3) stands for:

$$NDP = \sum \left(N_{\text{req}} - N_{\text{avail}}\right) \times F_{\text{factor}} \tag{3.3}$$

Where N_{req} is the nutrient requirement for a specific crop stage, N_{avail} represents the available nutrient level in the soil and F_{factor} is a crop-specific adjustment factor.

4. **Soil pH Influence (SPI):** Using the SPI heuristic, one can identify how the pH of the soil affects the availability of nutrients. This heuristic assists with changing the pH of the soil in order to enhance the absorption of nutrients, which is essential because numerous crops have distinct optimal pH levels for production. The is calculated as EQU (3.4).

$$SPI = pH_{\text{opt}} - pH_{\text{soil}} \tag{3.4}$$

where pH_{opt} is the optimal pH level for the crop, and pH_{soil} is the current soil pH level.

This experiment set up an HRF model using advanced algorithms and machine learning (ML) methods to determine the nutrient requirements of SF regions. Factors such as ET, WRR, NDP, and SPI ensure that an inclusive and accurate method for adding nutrients across multiple SF zones is provided.

This work begins by computing the RF model using equations 1 through 4. Next, this study will collect and normalize past and present information based on the heuristics EE, WRR, NDP, and SPI. This helps to guarantee that the input is reliable and scalable. Subsequently, we fine-tune the model's set-up, including the number of trees, feature splitting method, and DMP at each node. Every tree in the RF conducts a separate independent evaluation based on the heuristics, which contributes to the final decision about the value of added nutrients across multiple SF areas.

When training the model, it is crucial to use labelled data, which shows if additional nutrition would have been needed under scenarios that were similar in the past. The model can collect information from these data points, allowing it to make intelligent decisions about adding nutrients. After the training phase, we verify the model's precision and reliability using a distinct data set. After verification, we set up the HRF model for practical application. The HRF model uses real-time data associated with ET, WRR, NDP, and SPI to predict the need for additional nutrients in various zones of the SF field. We use the predictions to produce a complete prescription map, making them highly significant. Figure 3.3 below displays the sequence of the NDU module's functions.

After the testing and installation of the HRF model, its essential task will be to analyse real-time data points, such as ET, WRR, NDP, and SPI. This will allow it to calculate nutritional supplementation needs across all SF field zones. The creation of a complex prescription map, which is a vital tool for the NUAV-VFSS, is an effective end to this process. The nutritional map is a digital data file that houses a vast amount of information about the GPS coordinates of the SF field and the determined rates of fertilizer application. A meticulously coded program in MATLAB®is responsible for the development of this map (Fig. 3.4), which combines the data on the range of vital nutrients with the geographical coordinates in order to provide an in-depth representation of the supply of nutrients.

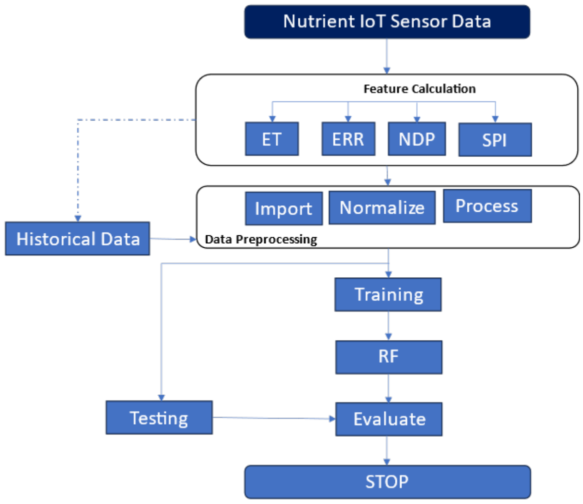

Fig. 3.3: Flowchart of the fertilizer DMP.

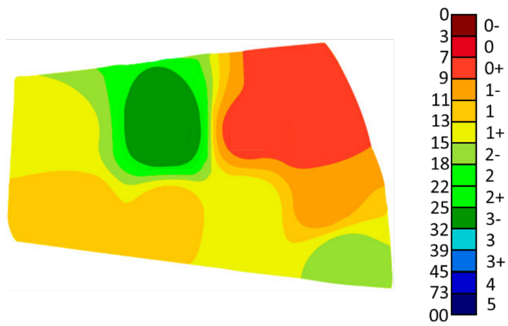

Fig. 3.4: Prescription Map.

This study edges a nutrient map onto a 10 × 10-meter fishnet grid, enabling a more precise approach to nutrient management. This grid divides the map into manageable segments, extracting centroid coordinates and nutrient data. This work uses these data to calculate fertilizer application rates for each grid cell, ensuring they align with the target nutrient requirements. This investigation transmits the resulting digital nutrient application map, complete with precise latitude and longitude coordinates, to the NUAV-VFSS. This data equips the UAV to experiment with targeted fertilizer applications and guarantees a customized nutrient measure for each field zone.

3.4. NUAV-VFSS. The goal of NUAV-VFSS is to deliver focused fertilizer applications with unprecedented precision. The system aims to deliver these applications. Figure 3.6 provides a conceptual model of the UAV-VFSS system, showcasing its complex design and functionality. This assignment utilized the DJI Agras T30 drone, a product of SZ DJI Technology (Shenzhen) Co., Ltd. SZ DJI Technology (Shenzhen) Co., Ltd. developed this specific UAV by integrating specific modules for prescription map conversion and spray control. The HRF model generates a prescription map, which the UAV uses to follow. This guarantees the precise placement of fertilizers where they are required.

A micro diaphragm pump (KLP02-E KA, Kamoer Fluid Technology (Shanghai) Co., Ltd.) is critical to the performance of the VFSS because it ensures that the fertilizer flow is adequately controlled within the system

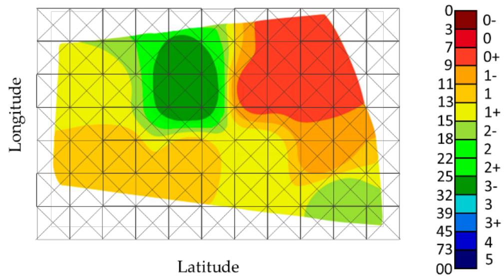

Fig. 3.5: Gridded Prescription Map.

Table 3.5: UAV-VFSS Description

Component	Description	Manufacturer/Supplier
DJI Agras T30	UAV for the VFSS	SZ DJI Technology (Shenzhen) Co., Ltd.
KLP02-E KA	Micro diaphragm Pump to Control the flow of fertilizer.	Kamoer Fluid Technology (Shanghai) Co., Ltd.
F110-015	Spray the Nozzle to ensure the fertilizer is evenly distributed.	Mid-South Ag. Equipment, USA
ATSAMD21G18	Microcontroller for the spray control subsystem.	—
YF-S201	The magnetic hall flow sensor measures the system's flow rate, which ranges from 1–30l/min.	DATAQ Instruments, Inc, Ohio, USA

framework. This pump, when used with a spray nozzle (F110-015 FanTip Nozzle 110, produced by Mid-South Ag. Equipment in the United States), makes it possible to promote the even distribution of fertilizer across the zones that were previously specified. The ATSAMD21G18 microcontroller is the most significant element of the spray control subsystem. It is responsible for regulating the spraying system's performance. Therefore, we require the accuracy and dependability of this microcontroller to ensure accurate fertilizer distribution. The VFSS incorporates a magnetic hall flow sensor (YF-S201, DATAQ Instruments, Inc., Ohio, USA) with a measuring range of 1–30l/min. This sensor plays a crucial role in monitoring and adjusting the fertilizer flow rate, ensuring it aligns with the prescribed demands on the prescription map. Table 3.5 breaks down each element of the UAV-VFSS into smaller sections and provides more detailed information.

The NDU unit transmits the prescription MAP, received through the Wi-Fi module and uploaded into the ATSAMD21G18 microcontroller.

The built-in GPS of the UAV-VFSS continuously transmits real-time positional data to the microcontroller on the UAV as it traverses the landscape. The microcontroller initiates a key-matching function as soon as it receives the current coordinates of the UAV. The microcontroller accomplishes this by comparing the UAV's position with the encrypted GPS data in the preloaded prescription map. This map divides the fertilizer application process into distinct areas across the field, providing complete guidance on successful application.

The UAV moves across the field, aligning with a prescription map. A microcontroller identifies the current unit area and retrieves the corresponding prescription value, which is the specific quantity of fertilizer for that area. A variable spray controller then receives this information and adjusts the UAV's spray mechanism to apply the prescribed amount of fertilizer, ensuring the exact amount matches the prescription map for that specific area.

4. Experimental Study. This work tested the "SA-IoT-MS" system in a practical field experiment on a 14-hectare maize field in Maharashtra, India. This method divided the 35,000-square-foot area into smaller

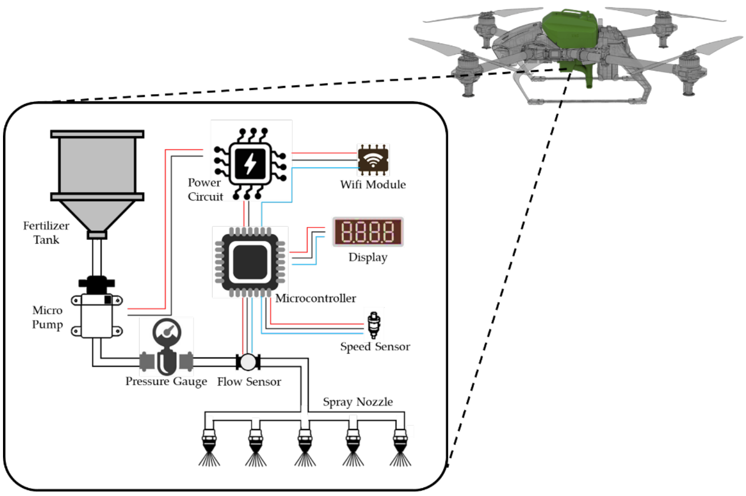

Fig. 3.6: UAV-VFSS Structure.

Table 4.1: Data from three sites showing the results of the Nutrient sensor data

Variable	Unit	Site	Mean	Min	Max	Median	S.D	Variance	Skewness	Kurtosis
Nitrogen	Kg/ha	12	80	70	95	82	7.5	56.25	0.2	-0.5
		42	120	110	135	122	8.0	64	0.1	-0.4
		63	100	90	110	102	6.5	42.25	-0.2	-0.3
Phosphorus	Kg/ha	12	40	35	50	41	4.8	23.04	-0.1	0.2
		42	55	50	65	56	5.0	25	0.3	-0.1
		63	48	43	55	49	4.0	16	-0.4	0.5
Potassium	Kg/ha	12	85	80	95	87	5.0	25	0.2	-0.2
		42	75	70	85	76	4.5	20.25	-0.3	0.3
		63	90	85	100	91	4.8	23.04	0.1	-0.4

zones for detailed analysis and precise intervention, ensuring the system's controlled and measurable application in the region's agronomic conditions.

This simulation advantageously placed the NSUs to collect vital SF data such as SM, temperature, pH, and nutrient content from three sites. The data collection spanned four months (15^{th} March 2022 to 30^{th} July 2022), covering the entire maize growing season and capturing agronomic variables and changes throughout different stages of crop development. The results are crucial in assessing the effectiveness of the "SA-IoT-MS" system in a practical SF setting, as shown in 4.1 and 4.2.

- Kg/ha: Kilograms per hectare.
- Mean: The average value of nutrient content.
- Min: The minimum recorded value of nutrient content.
- Max: The maximum recorded value of nutrient content.
- Median: The middle value in the range of nutrient content.
- S.D (Standard Deviation): Measures the variation in the nutrient content.
- Variance: The square of the standard deviation.
- Skewness: A measure of the asymmetry of the distribution of nutrient content.
- Kurtosis: A measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution.
- °: Degrees Celsius.

Table 4.2: Data from three sites showing the results of the environmental sensor data

Variable	Unit	Site	Mean	Min	Max	Median	S.D	Variance	Skewness	Kurtosis
Temperature	°	12	26	22	30	26.5	2.5	6.25	0.1	-0.2
		42	27	24	31	28.5	2.2	4.84	-0.1	0.3
		63	27	24	31	27.2	2.1	4.41	0.2	-0.3
Humidity	%	12	65	60	70	65.5	3.2	10.24	-0.2	0.1
		42	68	65	72	68.4	2.8	7.84	0.0	-0.1
		63	70	68	73	70.3	1.6	2.56	-0.1	0.2
SM	%	12	30	25	35	30.5	3.1	9.61	0.1	-0.3
		42	28	26	31	28.7	1.5	2.25	-0.2	0.4
		63	32	28	36	32.2	2.5	6.25	0.0	-0.2
pH		12	6.5	6.2	6.8	6.5	0.2	0.04	0.0	0.0
		42	6.7	6.5	6.9	6.7	0.1	0.01	-0.1	0.1
		63	6.6	6.4	6.8	6.6	0.1	0.01	0.1	-0.1

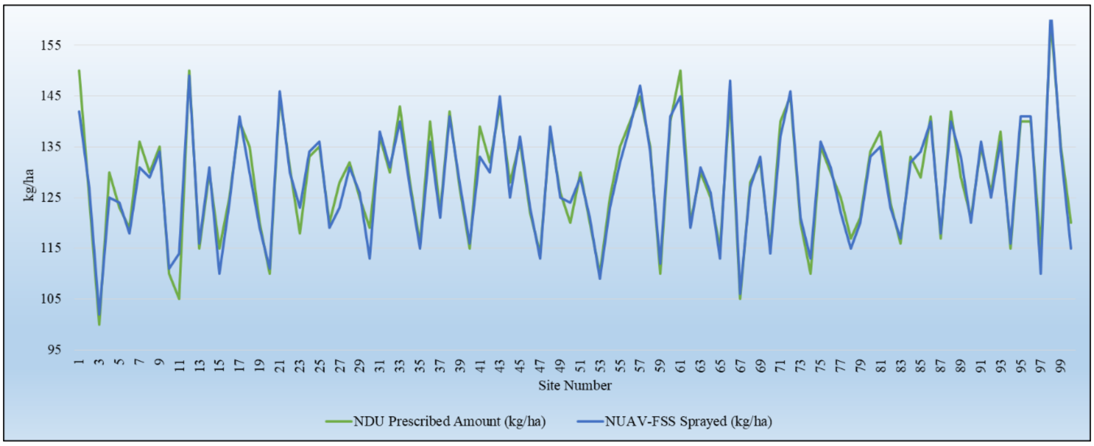

Fig. 4.1: NDU prescribed fertilizer amount vs NUAV-VFSS Sprayed amount.

The NDU uses sensor data to determine the precise amount of fertilizer (measured in kilograms per hectare, kg/ha) needed at each site in the field. This system uses the heuristic RF algorithm to determine nutrient needs based on unique conditions. The NDU calculates the required levels and relays them to the NUAV-VFSS, which uses a control module to apply the prescribed fertilizer levels. This method is more efficient and environmentally sustainable, minimizing waste and runoff while making fertilizer application more efficient and effective. Figure 4.1 showcases the effectiveness of the integrated system, comparing the prescribed fertilizer levels with the actual quantities applied by the NUAV-FSS. The data demonstrates the system's high efficiency and precision, closely mirroring the NDU's prescriptions and proving its value as an integral part of SF practices.

Figure 4.1 highlights that the NUAV-VFSS is a fast system, which is an accomplishment worthy of recognition. This demonstrates the system's ability to precisely adhere to the NDU's rules and adapt to the unique standards imposed by various field regions. SM places a significant value on precision and adaptability, significantly contributing to higher CY, reduced resource waste, and environmentally friendly SF practices.

5. Conclusion. The "SA-IoT-MS" system, combined with a variable-rate UAV sprayer, significantly advances precision agriculture. It improves fertilizer management efficiency and effectiveness by combining IoT technology and UAV capabilities. The deployment of NSUs collects environmental and soil parameters data, enabling data-driven agriculture. The NGU and NDU process this data to make precise fertilizer requirement decisions. The NUAV-VFSS executes these decisions, catering to different agricultural zones. A field experiment in Maharashtra, India, validated the system's functionality and highlighted its potential for revolutionizing SF practices. The results demonstrated crop yields and resource optimization improvements, promoting sustainable agriculture.

This model sets a precedent for future developments in SF, showcasing the benefits of integrating advanced technologies like IoT and UAVs into agricultural operations.

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Edited by: Vadivel Ayyasamy
Special issue on: Internet of Things and Autonomous Unmanned Aerial Vehicle Technologies for Smart Agriculture Research and Practice
Received: Jan 3, 2024
Accepted: Jun 20, 2024