**Smart Agriculture with NPK Sensors: A Sustainable Approach to Soil Health and Fertiliser Optimisation in Guava Farming**

**Abstract:**

Soil health is deteriorating due to excessive use of fertilisers. As a part of smart agriculture NPK sensor can improve the soil fertility status. The study was conducted to evaluate the efficacy of NPK sensors for soil health management in smart agriculture. The study was carried out during the winter season (2024) at the Guava (*Psidium guajava* L.) Farm, Baruipur, South 24 Parganas, West Bengal, India. The experiment was laid out in a Randomised Block Design with two treatments and five replications. The treatments consisted of T1: Control, T2: NKP Sensor. During the study, data were recorded and analysed through formulas using Microsoft Excel. The total nitrogen ranged from 215.5 kg ha-1 to 224.3 kg ha-1, which indicated the low nitrogen content in soil (<280 kg ha-1). The available phosphorus status (P2O5) in the plots was high (>90 kg ha-1), whereas the available potassium (K2O) was medium (150-340 kg ha-1). The average total nitrogen for T1 required per plant was 614.04 g, whereas in T2, the average nitrogen requirement was 128.2 g. The application frequency was higher in T2 (5). The N sensor saved 79% of nitrogen. The average amount of phosphorus was 367.28 g per plant in T1, whereas it was 120.32 g. The P sensor saved 67.24% of phosphorus fertiliser. The average potassium fertiliser applied for T1 without NPK sensor was 508.62 g per plant, whereas it was only 122.7g for T2.  It was found that the sensor resisted the excess use of potassic fertilisers and saved 75.87 %. The yield was increased by 99.69 % in T2 (23.012) compared to T1(11.524). Overall total amount of fertilisers decreased (72.37%) when the NPK sensors were utilised for soil health monitoring in smart agriculture. The study concluded that the NPK sensor improved the soil health through smart agriculture.

**Key Words**: Smart Agriculture, NPK Sensor, Soil Health, Guava farming, Crop Production

**Introduction**

Soil health refers to the capacity of soil to function as a living system, sustaining plant and animal productivity, maintaining water and air quality, and promoting plant and animal health (Parameswari et al., 2024). Smart agriculture is being promoted by technology to optimise and improve agricultural practices. It involves the application of sensors, the Internet of Things, data analytics, automation, and other technologies to monitor and manage various aspects of farming, like soil conditions, irrigation, and crop health.  Various intelligent systems based on AI differ in their ability to record and interpret data and assist farmers in making the right decisions at the right time. Data can be recorded using installed IoT nodes (sensors), processed by any deep learning method, and imposed decisions on operational areas through actuators. Other state-of-the-art technologies, such as remote sensing geographic information, global satellite positioning, and automated computer control, augment the AI system in monitoring and managing agriculture in real-time (Altalak et al., 2022). Application of technology in modern agriculture is becoming more essential, especially when it comes to controlling major plant nutrients like nitrogen (N), phosphorus (P), and potassium (K) which directly involve in crop productivity (Al-Mamun et al., 2021; Potdar et al., 2021; Yohannes et al., 2024). Excessive use of fertilisers in conventional farming results in financial inefficiency and environmental pollution (Hafsi et al., 2014; Leghari et al., 2016). Use of NPK sensors strengthens farmers to make accurate, data-driven decisions by giving them real-time information on soil nutrient management (Zhang et al., 2021). NPK sensors can be employed to detect soil nutrient levels, providing valuable data to assess whether the soil is nutrient-rich or deficient (Bachhav et al., 2024). Mapping of macronutrients requires the development of sensors (Ramane et al., 2015). NPK sensors' temporal and spatial study is the most essential part of the temporal and spatial study from crop management (Ramane et al., 2015; Kulkarni et. al., 2014). According to Pooniya et al. (2018) and Eli et al. (2019), sensor helps fertiliser application with crop needs, lowering environmental pollution, including phosphorus runoff and nitrogen leaching. Automated nutrition management is made possible by NPK sensors coupled with Internet of Things (IoT) devices (Ahmed et al., 2021; Sangwan et al., 2022). According to Mohanty et al. (2020) and Park et al. (2017), these sensors also improve fertiliser recommendations by making sure nutrients are only supplied when necessary, increasing agricultural productivity and environmental sustainability. According to Lee et al. (2021), NPK sensors are crucial for smart agriculture in the context of climate change due to their exceptional precision and flexibility in response to changing environmental conditions (Ahmed et al., 2020; Ada˜o et al., 2020). The study was conducted to evaluate the efficacy of NPK sensors for soil health management in smart agriculture.

**Materials and Methods**

The study was undertaken during the winter season (2024) at the Guava (*Psidium guajava L*) Farm, Baruipur, South 24 Parganas, West Bengal, India. The experiment was laid out in a Randomised Block Design with two treatments and five replications. The treatments consisted of T1: Control, T2: NKP Sensor. The plot size for each treatment and replication was 5m x 4 m, with plant spacing 2.5m x 2m. Guava thrives well in tropical and sub-tropical climates. The variety of guava was Allahabad Safeda, and four-year-old tree. The study location belongs to a sub-tropical climate and new alluvial soil. The soil is loamy. The total nitrogen content of the soil sample has been estimated by using the alkaline KMnO4 titration method (Subbiah and Asija, 1956). Available phosphorus content of soil samples has been determined either by extracting samples with the Olsen extractant (0.5M NaHCO3 adjusted to pH 8.5) or by the Bray and Kurtz No. 1 extractant (0.3N NH4F in 0.025 N HCl). The Olsen method of extraction has been selected for the soils having a pH of 6.0 and above, while the Bray and Kurtz No. 1 extractant was used for soils having a pH below 6. The colour intensity has been recorded by the stannous chloride reduced molybdophosphoric blue colour method in the hydrochloric acid system using a spectrophotometer. The available phosphorus content has been determined by plotting the reading on the standard curve (Jackson, 1976). The soil sample has been extracted with neutral ammonium acetate for potassium estimation. The filtrate has been ignited by using a flame photometer. The recorded reading has been plotted on the standard curve to get the content of available potassium in the soil sample (Hesse, 1971). During the study, data were recorded and analysed through the formulas by using Microsoft Excel.

**Result and Discussion**

The major nutrient (NPK) content in the soil of the study area for each plot was estimated before the inception of the experiment in the month of October, 2024 (Tables 1- 3). The total nitrogen ranged from 215.5 kg ha-1 to 224.3 kg ha-1, which indicated the low nitrogen content in soil (<280 kg ha-1). The available phosphorus status (P2O5) in the plots was high (>90 kg ha-1), whereas the available potassium (K2O) was medium (150-340 kg ha-1). The sensors were placed in the T2 plots with their five replications. The sensors’ results were not similar to the soil testing report. Therefore, the reading of NPK sensors was calibrated with the establishment of a correlation between soil results and readings of sensors (Fig. 1-3). It showed that N Sensor reading was highly correlated with the soil result (R2= 0.945), but P sensor reading was moderately correlated (R2= 0.8132). The K sensor had good correlation with soil testing results (R2= 0.9499). This helped to find the exact NPK status in real-time and specific location.

Table -1: Calculation of total nitrogen (kg ha-1)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Treatment | R1 | R2 | R3 | R4 | R5 |
| T1 | 224.3 | 219.8 | 218.7 | 221.1 | 217.9 |
| T2 | 223.1 | 218.2 | 220.8 | 215.5 | 219.3 |
| N Sensor | 201.4 | 205.7 | 198.8 | 195.6 | 204.2 |

Fig.1: A regression plot between N sensor reading and soil test report

Table -2: Calculation of Initial soil P2O5 (kg ha-1)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Treatment** | **R1** | **R2** | **R3** | **R4** | **R5** |
| T1 (Lab. tested) | 153.4 | 150.1 | 153.8 | 157.4 | 156.1 |
| T2 (Lab. tested) | 154.2 | 149.8 | 153.4 | 158.6 | 155.7 |
| P Sensor (Recorded) | 148.3 | 147.1 | 150.2 | 154.3 | 153.2 |

Fig.2: A regression plot between P sensor reading and soil test report

Table -3: Calculation of Initial soil K2O (kg ha-1)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Treatment | R1 | R2 | R3 | R4 | R5 |
| T1 (Lab. tested) | 324.5 | 319.8 | 327.6 | 330.2 | 324.5 |
| T2 (Lab. tested) | 325.3 | 321.4 | 328.6 | 320.5 | 317.8 |
| K Sensor (Recorded) | 256.7 | 254.3 | 262.7 | 249.5 | 245.6 |

Fig.3: A regression plot between K sensor reading and soil test report

**Nitrogen fertilizer**

The recommended dose was 1.0:1.0:1.0 NPK kg per year for each four-year-old guava plant. During the winter season (October to March), two split doses @ 250 gm each component for each plant had been recommended. The soil in the study area contained a low level of nitrogen (<280 kg ha-1). The 25% dose was increased for each plot. In T1, the usual application of NPK fertilizers was carried out for two times at an interval of three months (Tab. 4). The average total nitrogen for T1 required per plant was 614.04 g, whereas in T2 the average nitrogen requirement was 128.2 g (Tab. 5). The application frequency was higher in T2 (5). The N sensor saved 79% of nitrogen from wastage and environmental pollution (Fig. 4).

Table -4: Nitrogen Fertiliser Application for T1 (g per plant)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Replication | 1st Dose (2nd October) | 2nd dose (2nd January) | Total Fertilisers (g) | Average amount (g) |
| R1 | 312.5 | 312.5 | 625.0 | 614.04 |
| R2 | 306.2 | 306.2 | 612.5 |
| R3 | 304.7 | 304.7 | 609.4 |
| R4 | 308.0 | 308.0 | 616.1 |
| R5 | 303.6 | 303.6 | 607.2 |

Table -5: Nitrogen Fertiliser Application for T2 (g per plant)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Replication | 1st Dose (2nd October) | 2nd dose (15th November) | 3rd dose (10th December) | 4th dose (14th January) | 5th dose (28th February) | Total amount (g) |
| R1 | 20.5 | 25.3 | 31.6 | 21.4 | 32.5 | 131.3 |
| R2 | 21.5 | 20.8 | 24.8 | 26.3 | 23.9 | 117.3 |
| R3 | 24.3 | 21.7 | 28.5 | 31.4 | 25.3 | 131.2 |
| R4 | 19.8 | 27.1 | 24.5 | 21.7 | 31.8 | 124.9 |
| R5 | 23.4 | 22.6 | 27.4 | 30.2 | 32.7 | 136.3 |
| SEM |  |  |  |  |  | 1.735836 |
| CD 0.05 |  |  |  |  |  | 5.066794 |

Fig.4: Nitrogen application in T1 and T2

**Phosphorus fertilizer**

The soil contained a high level of phosphorus (>90kg ha-1). The 25% recommended dose was decreased for each plot. The average amount of phosphorus was 367.28 g per plant in T1, whereas it was 120.32 g. Two times of applications of fertiliser in T1 added more chemical inputs in the soil, which were not required by the plant. This excess fertiliser was jeopardising the environment. The P sensor saved 67.24% phosphorus fertiliser (Fig. 5) and suggested the efficient use of phosphatic fertilisers for better crop productivity and a healthier nature.

Table -6: Phosphorus Fertilisers Application for Treatment T1 (g per plant)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Replication | 1st Dose (2nd October) | 2nd dose (2nd January) | Total Fertilisers (g) | Average application (g) |
| R1 | 182.7 | 182.7 | 365.5 | 367.28 |
| R2 | 178.8 | 178.8 | 357.6 |
| R3 | 183.2 | 183.2 | 366.4 |
| R4 | 187.5 | 187.5 | 375.0 |
| R5 | 186.0 | 186.0 | 371.9 |

Table -7: Phosphorus Fertilisers Application for Treatment T2 (g per plant)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Replication | 1st Dose (2nd October) | 2nd dose (15th November) | 3rd dose (10th December) | 4th dose (14th January) | 5th dose (28th February) | Total amount (g) |
| R1 | 28.1 | 24.3 | 27.5 | 20.5 | 21.7 | 122.1 |
| R2 | 20.4 | 28.5 | 26.2 | 21.8 | 23.9 | 120.8 |
| R3 | 23.8 | 22.6 | 29.1 | 21.5 | 23.8 | 120.8 |
| R4 | 21.4 | 21.8 | 25.7 | 22.3 | 28.4 | 119.6 |
| R5 | 24.1 | 19.2 | 28.2 | 18.5 | 28.3 | 118.3 |
| SEM |  |  |  |  |  | 1.448072 |
| CD 0.05 |  |  |  |  |  | 4.226831 |

Fig.5: Phosphorus application in T1 and T2

**Potassium fertilizer**

The soil contained a medium level of potassium (150-340 kg ha-1). The recommended dose @ 250g was applied for the plot having higher potassic content in soil, and proportionately, the doses were decreased with nutrient status (Tables 8, 9). The average potassium fertiliser applied for T1 without NPK sensor was 508.62 g per plant, whereas it was only 122.7g for T2, where NPK sensors were used to detect nutrient content in real time. It was found that the sensor resisted the excess use of potassic fertilisers and saved 75.87 % (Fig.6).

Table -8: Potassium Fertilisers Application for T1 (g per plant)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Replication | 1st Dose (2nd October) | 2nd dose  (2nd January) | Total Fertilisers (g) | Average fertiliser (g) |
| R1 | 253.7 | 253.7 | 507.3 | 508.62 |
| R2 | 250.0 | 250.0 | 500.0 |
| R3 | 256.1 | 256.1 | 512.2 |
| R4 | 258.1 | 258.1 | 516.3 |
| R5 | 253.7 | 253.7 | 507.3 |

Table -9: Potassium Fertilisers Application for T2 (g per plant)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Replication | 1st Dose (2nd October) | 2nd dose (15th November) | 3rd dose (10th December) | 4th dose (14th January) | 5th dose (28th February) | Total amount (g) |
| R1 | 27.3 | 25.4 | 28.1 | 22.9 | 20.8 | 124.5 |
| R2 | 21.8 | 27.9 | 25.4 | 26.1 | 27.2 | 128.4 |
| R3 | 22.5 | 21.7 | 27.3 | 20.8 | 26.8 | 119.1 |
| R4 | 22.9 | 28.1 | 22.5 | 19.9 | 27.8 | 121.2 |
| R5 | 22.7 | 21.4 | 24.5 | 26.1 | 25.6 | 120.3 |
| SEM |  |  |  |  |  | 1.454347 |
| CD 0.05 |  |  |  |  |  | 4.245147 |

Fig.6: Potassium application in T1 and T2

**Yield and cost estimation**

The yield was increased by 99.69 % in T2 (23.012) compared to T1(11.524) because of the overdose fertiliser applied for a very short time, and the plant absorbed more luxury nutrients, which induced vegetative growth and indulged pest infestation (Table 10). After the exhaustion of fertilisers plant started to starve and yield declined to a great level. T2 was enjoying the balanced nutrients while fertiliser sensors depicted the real-time nutrient status in soil, which guided the application schedule and quantity of fertilisers for the concerned plant nutrient. Overall total of fertilisers decreased (72.37%) when it utilized the NPK sensors were utilised for soil health monitoring.

Table -10**: yield of guava in** T1 andT2

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Treatment | Yield  (kg / plant) | Cost of N Fertilisers | Cost of P Fertilisers | Cost of K Fertilisers | Total Cost |
| T1 | 11.524 | 14.00 | 32.00 | 30.00 | 76.00 |
| T2 | 23.012 | 3.00 | 11.00 | 7.00 | 21.00 |
| Increase / Decrease (%) | 99.69 | -78.57 | -65.625 | -76.67 | -72.37 |

**Conclusion**

Fertilisers are essential for crop production. Soil also has a different nutrient-holding capacity. NPK sensors helped to detect the exact point of nutrient deficiency, which was crucial for better crop production. These sensors reduced the quantity of fertilizers which are polluting the environment and crippling the human health. The cost of fertilisers as well as the cost of total cultivation decreased. This NPK sensor improved the soil health through smart agriculture.

Disclaimer (Artificial intelligence)

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Details of the AI usage are given below:

1.

2.

3.

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