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Development of an Adaptive Grid-Based Soil pH Mapping and Lime Recommendation System †

Abdul Rasheed [1,2,*], Thangavel Krishnasamy [1] and Rajesh Moozhiyil Razhikulath [1,3]

[1] Department of Electronics and Communication, Hindusthan College of Arts and Science, Coimbatore 641028, India; thangavel@hicas.ac.in (T.K.); rajeshmr@sngcollegechelannur.edu.in (R.M.R.)
[2] Department of Electronics, WMO Arts and Science College, Muttil 673122, India
[3] Department of Electronics, Sree Narayana Guru College Chelannur, Kozhikode 673616, India
* Correspondence: abdul.rasheed@wmocollege.ac.in
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Abstract

Maintaining optimum soil pH for specific crops is essential for improved nutrient intake and maximum yield. Conventional soil testing methods use composite samples tested in laboratories, which fail to capture the spatial variability within the field. This paper presents an adaptive grid-based soil pH mapping and rule-based, zone-specific lime recommendation system. The system incorporates an ESP32-based pH sensing node and a smart phone for fetching GPS coordinates. Bluetooth communication is established between the microcontroller and smart phone. The pH sensor is calibrated using laboratory results for improved measurement accuracy. Median filtering with averaging is used to eliminate sensor noise. Adaptive grid sampling is implemented, so that a greater number of samples is taken from regions with high pH variability and a reduced number of samples from relatively homogenous areas. pH measurements are then used to generate a spatial map with an interpolation technique. Based on the soil pH and agricultural recommendations, the system estimates zone-specific lime requirements for the field. This approach suggests variable-rate lime application for different zones of the field and reduces unnecessary lime usage. The proposed system aims to provide a cost-effective alternative to the conventional technique, suitable for precision agricultural application.

Keywords: soil pH mapping; adaptive grid; lime recommendation; precision farming

1. Introduction

Soil pH influences nutrient cycling, plant uptake, and the effectiveness of contaminated soil remediation [1]. Maintaining a crop-specific optimal soil pH is essential for plant growth, nutrient availability, biological activity, crop productivity and long-term soil fertility [2–5]. Soil pH can exhibit considerable spatial variability within the agricultural field [6]. Structural factors including parent material, soil type, topography, vegetation, agricultural practice and climate influence the spatial heterogeneity of soil pH [5,7,8]. Accurate soil pH maps are required for zone-specific variable-rate lime application in precision agriculture [9].

The conventional method for measuring soil pH uses samples collected from multiple locations selected across measurement fields and mixed to form a composite representative sample. This composite sampling method provides an overall representation of the field,

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but does not capture the spatial variability of the plot [10]. Grid-based soil sampling better characterizes and maps intra-field spatial variability [11].

Adaptive sampling has been applied to soil spatial characterization using various approaches, including variogram-based sampling-density estimation [12], kriging-based uncertainty and threshold-misclassification criteria [13], model-derived spatial uncertainty for digital soil mapping [14], and prior-based adaptive sampling using auxiliary soil and environmental information [15]. Additional sampling near areas of high spatial variability has also been investigated [16]. These approaches employ statistical models, uncertainty measures, or auxiliary covariates to determine subsequent sampling locations. The proposed method uses a simple measurement-driven grid refinement strategy, where additional sampling is triggered by predefined pH differences and transitions between soil pH management classes within affected grid cells.

This study presents an integrated framework that combines adaptive grid sampling, low-cost soil pH sensing, spatial interpolation, and rule-based lime recommendation for site-specific soil acidity management. The proposed system aims to (i) characterize the spatial variability of soil pH using adaptive grid sampling, (ii) generate a spatial soil pH map from the collected observations, and (iii) estimate the spatially varying lime requirement to support zone-specific soil acidity management.

2. Materials and Methods

2.1. System Overview

Figure 1 shows the architecture of the proposed adaptive grid-based soil pH mapping and lime recommendation system. An ESP32 (Espressif Systems, Shanghai, China)-based sensing node acquires the pH value using a calibrated sensor. A smart phone receives the pH value from the sensing node via Bluetooth and tags it with GPS coordinates. An adaptive gridding technique is implemented to collect additional samples in directions where pH variability exceeds a predefined threshold or crosses a soil classification boundary. The GPS-tagged measurements are then used to generate a continuous soil pH distribution using spatial interpolation. The resulting pH distribution is then classified into management zones, according to predefined pH ranges. Finally, a rule-based lime recommendation system determines the lime requirements based on the Kerala soil health information system [17].

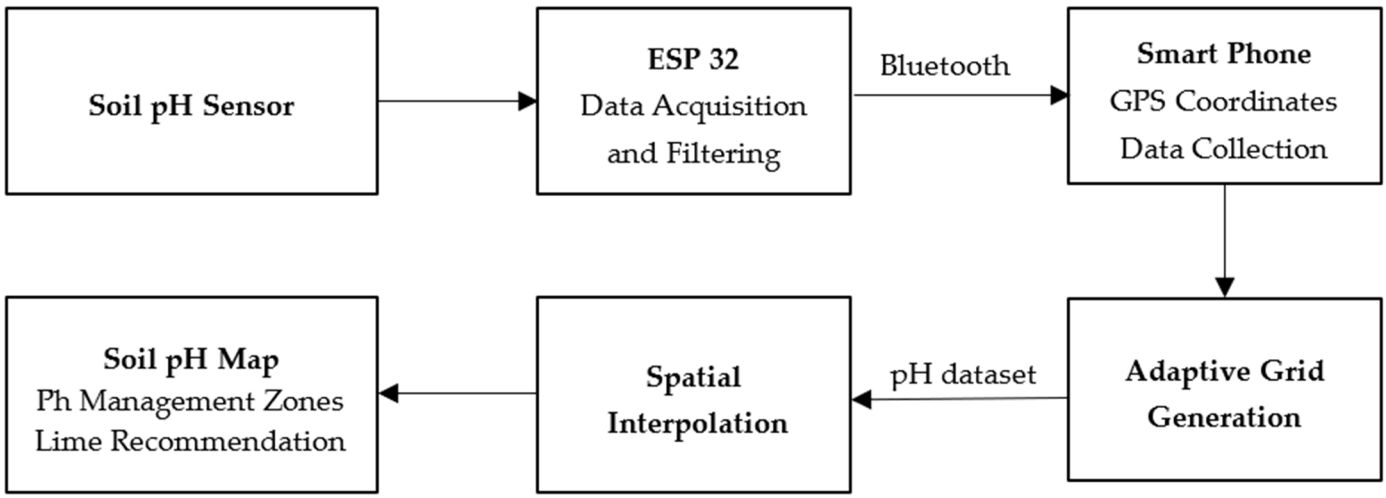


Figure 1. System architecture.

2.2. pH Sensing Node

The pH sensing node comprises a low-cost, low-power, system-on-chip ESP32 microcontroller [18], a soil sensor ZTS-3002-TR-THNPKPH-01 (Zhaotaisheng, Jinan, China) and a smart phone. The technical specifications of the sensor are listed in Table 1. The ESP32 microcontroller reads the pH value from the Modbus register of the soil sensor, processes the measured data and transmits it to the smart phone via Bluetooth. The smart phone is used to record the GPS coordinates of the field boundary and to tag the measured pH data with its sampling location. Figure 2 shows the developed prototype of the proposed system. The sensor was calibrated using a two-point calibration procedure [9] with standard buffer solutions (NICE Chemicals private limited, Kerala, India) of pH 4.0 ± 0.02 and pH 7.0 ± 0.02. Measurements were taken after a 5 min stabilization period following sensor insertion into the soil.

Table 1. Technical specifications of soil sensor ZTS-3002-TR-THNPKPH-01.

Parameter	Specification
Supply Voltage	5 V–30 V
Interface	RS-485 Modbus-RTU
Operating Temperature	−30 °C–70 °C
pH Range	3–9 pH
Accuracy	±0.3 pH
Stabilization Time	≤5 min
Response Time	≤1 s

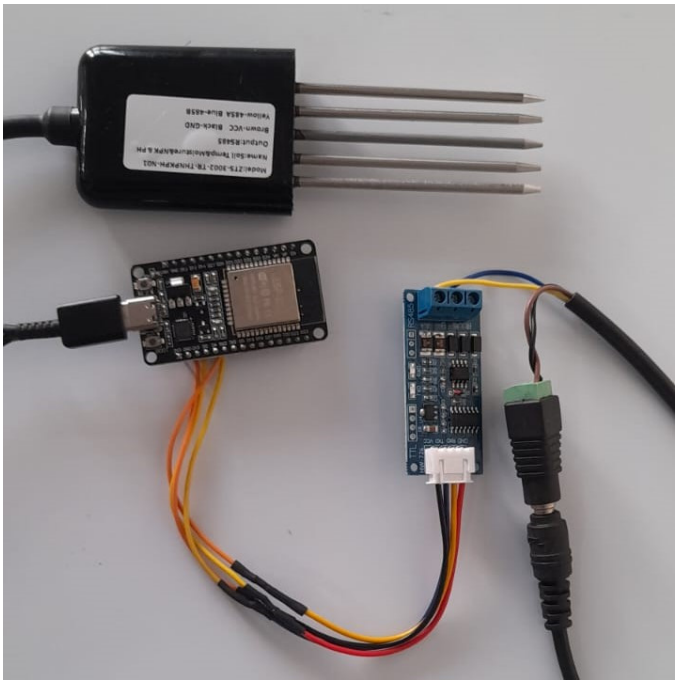


Figure 2. Prototype of the sensing node.

2.3. Adaptive Grid Generation

The field is initially divided into (20 m × 20 m) coarse grids within the field boundary and pH is measured at the center of each cell. For each measured cell, the pH value

is compared with those of its boundary-sharing cells. The pH variability between two neighboring cells is quantified using the absolute pH difference:

$$\Delta pH_{ij} = |pH_i - pH_j| \quad (1)$$

where pH_i and pH_j represent the pH values of two boundary-sharing cells i and j, respectively. If $\Delta pH_{ij} > 0.5$ or if they belong to different soil pH classification classes, then the parent cell is refined by splitting in that direction. The parent cells' pH value is retained and new sampling locations are generated within the refined region. This process is repeated until the minimum cell size (5 m × 5 m) is obtained. The resulting georeferenced pH dataset is subsequently used for spatial analysis and mapping. Figure 3 represents the adaptive grid generation flow.

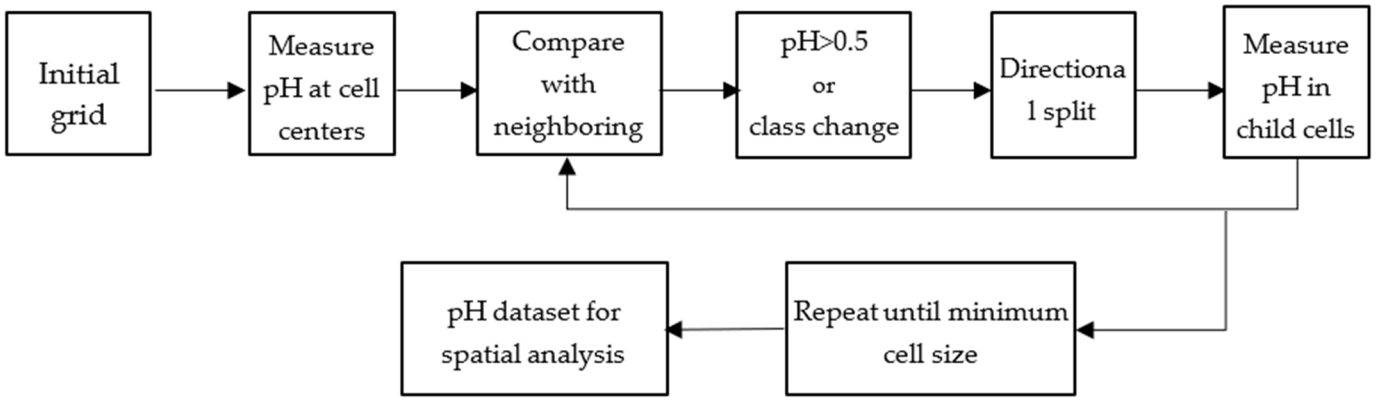


Figure 3. Adaptive grid refinement process.

2.4. Spatial Interpolation and Lime Recommendation

The georeferenced pH dataset obtained after the adaptive grid refinement process is used to generate a continuous spatial representation of pH across the field. Continuous soil pH maps can be obtained from discrete measurements using spatial interpolation techniques such as inverse distance weighting (IDW) and kriging [19]. In this study IDW was employed to estimate pH values at unsampled locations. IDW is a simple and computationally lightweight deterministic spatial interpolation method that calculates values at unsampled locations as a weighted average of neighboring observations, with weights decreasing with increasing distance [20]. The pH value at an unsampled location (x_0) is estimated as a weighted average of all measured pH values using the general formula of IDW [19] with a power parameter (β) of 2.

$$\hat{Z}(x_0) = \frac{\sum_{i=1}^{n} \frac{1}{d_i^{\beta}} Z(x_i)}{\sum_{i=1}^{n} \frac{1}{d_i^{\beta}}} \quad (2)$$

where $\hat{Z}(x_0)$ is the estimated value, n represents the total number of samples, $Z(x_i)$ is the value of ith sample, d_i is the distance between the interpolation point and the sample point and β represents the IDW power.

2.5. Soil pH Classification and Lime Recommendation

The interpolated values were classified into soil pH classes provided by the Kerala Soil Health Information System [17]. The soils of Kerala are generally acidic due to high rainfall and heavy use of fertilizers necessitating regular application of lime to neutralize soil

acidity [3]. A distinct color was assigned to each pH class to generate a visually identifiable, color-coded soil pH map. The application rate of $CaCO_3$ recommended by the Kerala Soil Health Information System portal [17], as presented in Table 2, is used for calculating the lime requirement for each zone. The lime requirement is calculated as follows:

$$Lime\ Requirement\ (kg) = \frac{A \times R_c}{1000} \quad (3)$$

where A is the zone area in m^2 and R_c represents the lime recommendation for the corresponding soil pH class in kg per hectare.

Table 2. Soil pH classes and lime recommendation.

Class	Nomenclature	pH Range	Lime Recommendation (kg $CaCO_3$ ha^{-1})
1	Ultra acidic	<3.5	1000
2	Extremely acidic	3.5–4.4	850
3	Very strongly acidic	4.5–5.0	600
4	Strongly acidic	5.1–5.5	350
5	Moderately acidic	5.6–6.0	250
6	Slightly acidic	6.1–6.5	100
7	Neutral	6.6–7.3	-

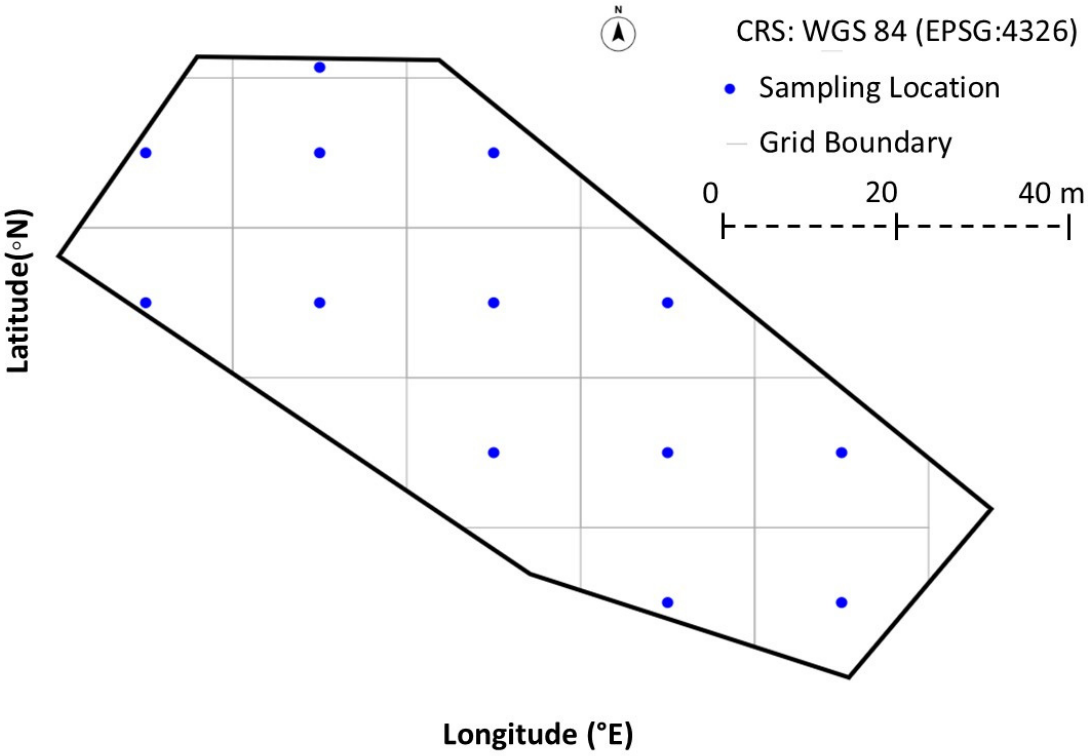
3. Results and Discussions

The study was conducted in a one-acre field located in Chulliode, Wayanad, Kerala, India. Figure 4 illustrate the effect of the proposed algorithm on the spatial distribution of sampling locations. The field was initially divided into uniform grid cells as shown in Figure 4a. Following the initial soil pH measurements, the proposed adaptive sampling approach resulted in the refined grid shown in Figure 4b. The initial grid consisted of 13 sampling locations, whereas the refinement process generated 18 additional sampling locations, resulting in a total of 31. Additional sampling locations were created in regions with greater spatial variability, and relatively homogeneous regions retained the original grid resolution.

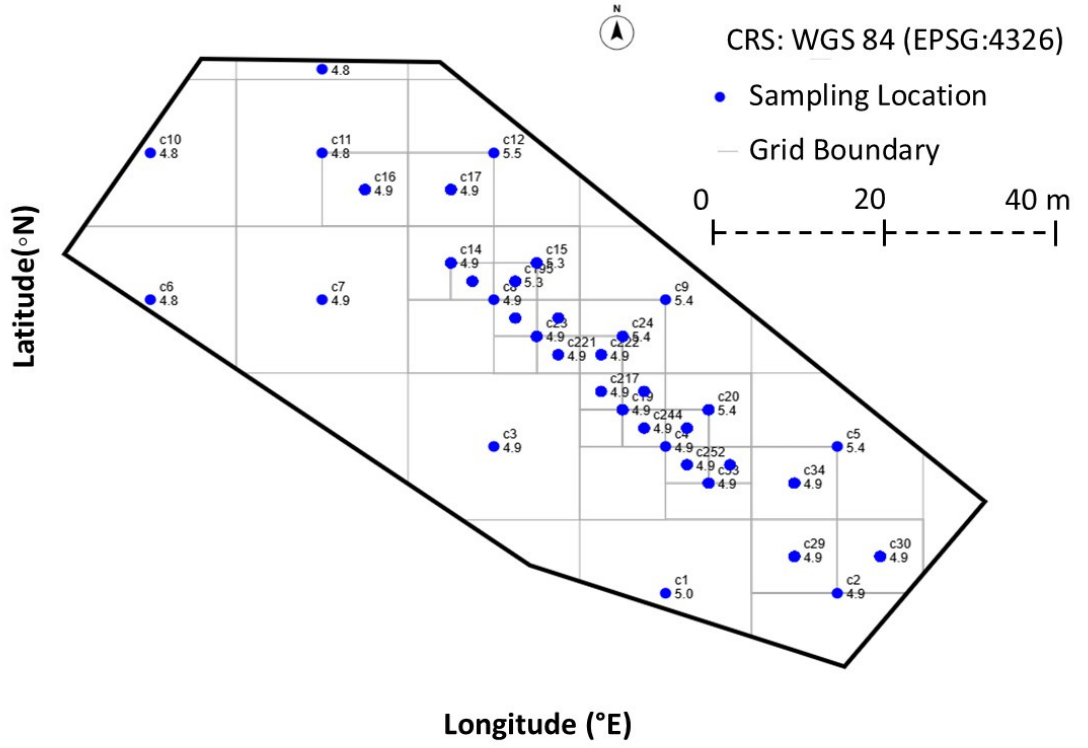
The resulting measurements were used for spatial interpolation using IDW, as shown in Figure 4c. The measured values are acidic in nature with pH values ranging from 4.8 to 5.4. The map shows that the field has two distinct soil pH management zones: very strongly acidic and strongly acidic. The lime recommendation for the study field is presented in Table 3. In total, 72.5% of the field belongs to the very strongly acidic zone (zone 1) and 27.5% belongs to the strongly acidic zone (zone 2). The estimated lime requirement for zone 1 is 191.34 kg $CaCO_3$ and zone 2 is 42.28 kg $CaCO_3$.

Table 3. Lime recommendation.

Zone	Soil pH Class	Area (m^2)	Lime Requirement (kg $CaCO_3$)
Zone 1	Very strongly acid	3188.99	191.34
Zone 2	Strongly acid	1208.02	42.28

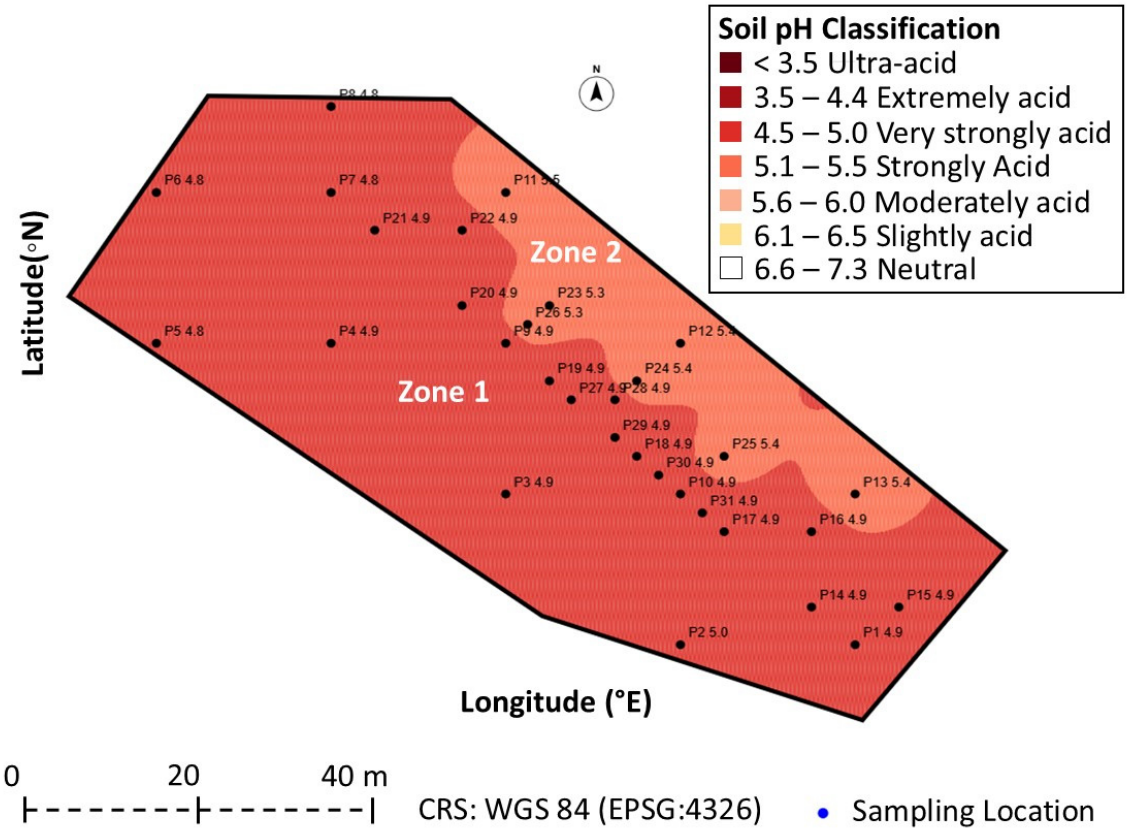


(**a**)



(**b**)

Figure 4. *Cont.*



(**c**)

Figure 4. Adaptive grid refinement for soil pH sampling: (**a**) initial uniform grid; (**b**) adaptively refined grid; (**c**) interpolated soil pH map using IDW.

Figure 5 shows the potential impact of sensor measurement uncertainty on soil pH classification. It is conducted based on the sensor accuracy of ±0.3 specified by the manufacturer. The error bars represent the accuracy range associated with the measured pH value. The results indicate that measurements located near classification thresholds may potentially be assigned to adjacent soil pH classes within the specified accuracy range. The lime recommendations are directly linked to soil pH classes. So, boundary-crossing measurements may consequently result in different recommended lime application rates. The estimated lime requirement is a sensor-measured, rule-based recommendation. The proposed system provides a spatially explicit assessment of field pH variability and enables zone-specific lime estimation rather than applying a uniform rate based on a composite soil sample. So, validation using laboratory pH measurements and independent lime requirement assessments across multiple fields would be required to establish the accuracy of the proposed sensing and decision-support framework.

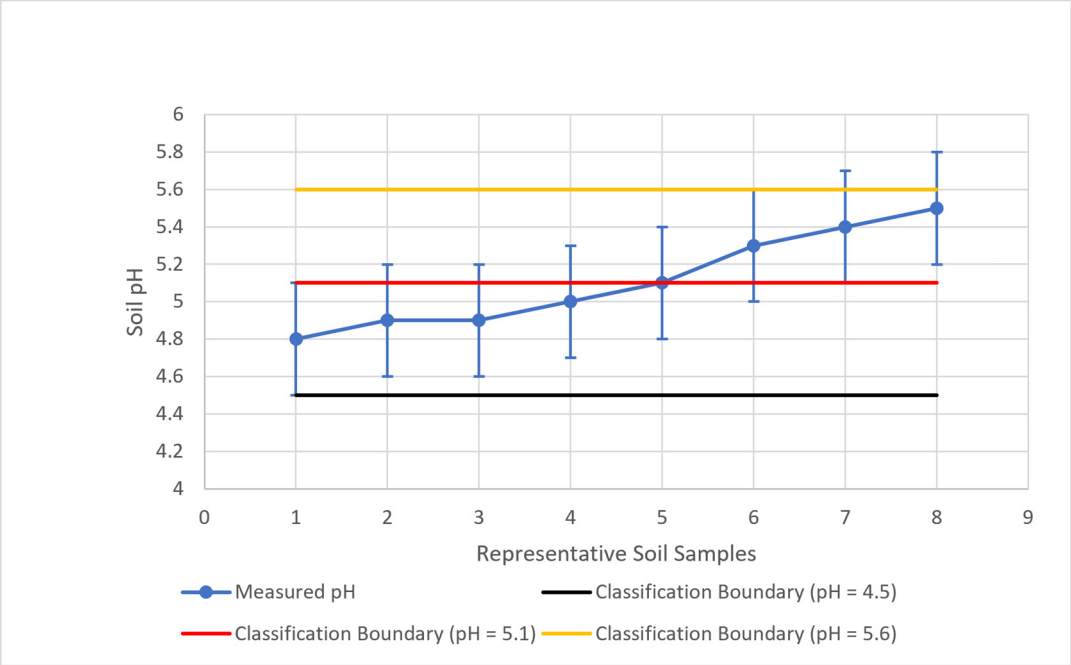


Figure 5. Sensitivity of soil pH classification to the specified sensor accuracy (±0.3 pH units).

4. Conclusions

This study presented an adaptive grid-based soil pH sampling and mapping approach and the lime rate for each zone is recommended based on the information provided by the Kerala Soil Health Information portal. The proposed adaptive sampling technique increased sampling density in areas with higher pH variability and generated a soil pH map using IDW interpolation. The study field was classified into two management zones, very strongly acidic and strongly acidic, with an estimated total lime requirement of 233.62 kg $CaCO_3$ for the one-acre field. The sensitivity analysis shows that measurements near the boundaries of soil pH classifications may cause changes in class assignment and the corresponding lime recommendation. The proposed adaptive sampling, spatial interpolation, and lime recommendation methods are helpful for zone-specific soil acidity management.

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