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Simulation-Based Modeling of Soil Dynamics for Understanding Crop Responses.

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Abstract: Traditional models of crop yield have overlooked the complex relationship between soil properties and plant performance. The proposed simulation-based models in this study used a new approach that considered, comprehensibly the major soil factors such as pH, moisture, temperature, and NPK involved, let alone the complex interactions. These models would then portray how soil-related interactions could modify crop responses in a significant manner without necessarily depending on data from the real world. This is a breakthrough framework that provides a refined comprehension of these elaborate dynamics controlling the yield of crops.

I. Introduction

Since agriculture is the largest industry in the world and it is very important for food security, employment as well as maintaining ecological balance (Food and Agriculture Organization of the United Nations, 2020; Raven & Wagner, 2021). Covering almost half of all inhabitable lands on Earth, agriculture's significant footprint accompanies an equally delicate compromise with the environment. Sustainable methods are a pledge to maintain ecosystems, safeguard water resources, and nurture healthy soils, while the unsustainable ones carry inherent risks.

It then becomes apparent that between agriculture and the environment, there is a close relationship when the knowledge and practice of the farmers are investigated (Hansson, 2019). Farmers act as cultivators and local experts surrounding environmental disturbances and the interventions they make to avert the resulting negative effects. This empirical base, intrinsically linked up with formal scientific approaches, encapsulates the core of agricultural knowledge (Hansson, 2019).

Against this background of those global challenges, this paper homes in on Simulation-Based Modeling of Soil Dynamics for Understanding Crop Responses. It explicitly touches on the incorporation of different critical soil aspects ranging from pH, moisture, temperature and nutrients. Focusing more on simulation and modeling, it attempts to unravel mysteries in the complicated soil-plant continuum. In this way, the synthesis is meant to connect the traditional agricultural wisdom with modern scientific approaches by providing insights into the working of these components and how they affect crop responses

II. Literature review

Review of literature establishes a rich patchwork of research in agricultural modeling and optimization to counter pivotal challenges with respect to crop management and productivity. Zagaria et al. (2021) apply an agent-based model that brings to the forefront the scope of transformative adaptation on Italian crop farming as climatic changes. Its results underscore the impact exerted by the risk of drought on system change, with strategies such as larger farm and irrigation being adopted by farmers. On the other hand, water policies that seek to reduce the incidence of drought may damp transformation affecting the sector's profitability. The paper recommends applying the agent-based models as the means of developing effective adaptation strategies, with account of the complex dynamics.

In an entirely different area of study, Vyska et al. (2016) provide some elucidation on the issue of development of high disease-resistant crops and trade-off that exists with their yield characteristics. They emphasized over the partial resistant varieties and planting them exactly optimally even when then there are uncertain outbreak scenarios, which sheds light accompanying the unique contributions on farms and policy makers too. Shifting the focus in farming awareness impacts, Basir et al. (2019) use the mathematical model to portray the potential brought about by the awareness programs on crop pests towards reduced losses in crops and improved food security through the decreased uses of pesticides.

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Ivanyo et al. (2020) contributed by introducing a mathematical algorithm to optimize agricultural production in high-risk environments. At the backdrop where extreme agro-meteorological events are threatening and causing huge losses in the economy, the validated algorithm showcases the potentiality to make reductions in economic loss in using optimized crop production. Finally, being aware of the tremendous potential for designing complex algorithms allowing to increase farming readiness for different environmental challenges, this paper proposes research directions.

Finally, Sukhova et al. (2021) made a review in mathematical models of photosynthesis and considered their application in studying productivity of plants. The authors observe the capability of these models in predicting plant productivity under varied environmental setups. In general, this brings in the study, making an informed understanding on the integral role played by mathematical modeling in the betterment of agricultural-based practices and results.

Knowledge Gap:

Some useful knowledge of adaptive strategies on crop management can be gleaned from the existing literature on agricultural modeling and optimization. However, an obvious gap in knowledge springs from Zagaria et al.'s (2021) study that deals with transformative adaptive strategies in Italian crop farming under climate change. Not accounted for in the study on the comprehensive soil proper ties and which tremendously influence plant responses and yield include pH, moisture, temperature, and nutrient levels. These key factors have been left out in the developed models and they underscore a critically lacking concept, demanding for the incorporation of soil atmosphere and plant root dynamics to form an integrated framework such as Simulation-Based Modeling of Soil Dynamics (SBMSD). There is hence the need to bridge this gap so as to enhance accuracy in the adaptive strategies and predictions in crop farming under changing climatic conditions.

III. Methodology

The paper makes use of a Simulation-Based Modeling approach to expound on soil dynamics and its effect on crop responses, elaborately. Soil properties and environmental components that are relevant to the subject are outlined in a mannered simulation method, to enhance comprehension of the agricultural systems, for enhancing crop management strategies.

Material

Herein, the ongoing research employs the main Simulation-Based Modeling platform through Python, incorporating vital toolkits such as NumPy and SciPy for value creation and carrying out scientific computations. Furthermore, Matplotlib is used in generating graphical plots and it offers a flexible tool set for the informative simulation of soil dynamics and graphical representation of the results of a dynamic simulation for improved understanding hence optimizing crop responses. The considered parameters in the designed soil-atmosphere model include:

Variable	Description
β	Coefficient for the effect of rainfall on temperature
γ	Coefficient for the effect of sunlight intensity on temperature
α	Combined coefficient representing the net effect of rainfall and sunlight intensity on temperature change (°C/day)
T	Soil temperature (°C)
R	Rainfall rate (mm/day)
I	Sunlight intensity (W/m^2)
a	Combined coefficient representing the net effect of rainfall and sunlight intensity
Q_1	Optimal soil temperature for desired crop (°C)
$H+$	Hydrogen ion concentration (representing pH)
L	Lime application rate
P	Insecticide/pesticide use
O	Organic matter content (% of soil weight)

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Q_2	Expected/normal soil pH level
b_0	Effect of added lime on pH
b_1	Effect of insecticide/pesticide use on pH
c	Effect of organic matter decomposition on pH change
M	Soil moisture content (% of soil volume)
R	Rainfall rate
I	Sunlight intensity
E	Evaporation rate (dependent on temperature and humidity)
K	Infiltration rate (dependent on soil properties)
Q_3	Natural moisture rate
N	Soil nutrient concentration (ppm)
I	Sunlight intensity
Q_4	Natural nutrient rate
a_2	Effect of sunlight intensity on nutrient loss
R	Rainfall rate

Table 1: variables used for the simulation

Method adopted

The study adopts Simulation-Based Modeling in Python with NumPy and SciPy for numerical operations alongside Matplotlib that helps to display the graphs. This will assist us to explore soil dynamics over the optimization of crop responses, whereby it details procedures are put forth for analysis and interpretation.

Separate Model for Soil Temperature:

Variables:

T : Soil temperature (°C)

R : Rainfall rate in mm/day

I : Sunlight intensity in W/m²

a : Combined coefficient indicative of the net impact of precipitation and sunlight intensity in terms of temperature changes per day (°C/day)

Q_1 : Optimal soil temparature of crop concerned (°C)

Equation:

$dT/dt = a * (R - b * I) + Q_1$ ……………………………………………………………………….(1)

Assumptions:

The coefficient `a` takes care of the rainfall and sunlight intensity effect combined after taking care of positive impact on the ground of one climatic factor and at the same time it captures the negative impact of another factor.

The coefficient "b" will describe the relative dominance of sunlight intensity cooling effect to rainfall warming effect.

Q_1 will refer a target temperature so that optimum growth of the crop can be observed or for optimal soil function to occur.

Soil pH Sub-Model:

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Variables:

H+: For representing hydrogen ion concentration (pH)

L: Lime application rate

P: Insecticide/pesticide use

E: Content of organic matter (e.g., weight percentage of soil)

Q_2: Level of normal/expected soil pH

b_0: Effect on pH due to lime applied

b_1: Effect on pH by using Insecticide/Pesticide Value

c: The effect from the decomposition of organic matter on change of pH

The equation:

$d(H+)/dt = Q_2 + b_0 * L - b_1 * P + c * dO/dt$ …………………………………………………….(2)

Assumptions:

Upon lime application, use of insecticides/pesticides and decomposition of organic matter, rate of change in H^+ concentration linearly depends.

Expected/normal pH level (Q_2) and coefficients (b_0, b_1, c) are constants.

Hence, there is a separate modeling of organic matter decomposition.

Soil Moisture Sub-Model:

Variables:

M: Soil moisture content (e.g. % of soil volume)

R: Rate of rainfall

I: Intensity of sunlight

E: Evaporation rate (dependent on temperature and humidity)

K: Infiltration rate (dependent on soil properties)

Q_3: Natural moisture rate

Equation:

$dM/dt = R + K * R - E - (M / d) * I$ ……………………………………………………………….(3)

Assumptions:

Rate of change in the soil moistures (dM/dt) is governed by four factors: Rainfall, Infiltration, Evaporation, and intensity of sun rays.

It is at a rate R and the same directly adds to the moistures in the soil.

K of infiltration helps multiply rainfall, taking into consideration soil properties that shape water intake.

Finally, some rate E of evaporation is lost from the soil due to temperature and humidity.

Indirectly, sunlight intensity I through increasing evaporation reduces moisture content. The effect is in proportion to M/d, where d represents the depth of soil layer considered.

Q_3 is not appeared in the equation but referred as a reference point by comparing the actual M value with desired or natural moisture content level.

Nutrient Soil Sub-Model:

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Variable:

N: Soil nutrient concentration (e.g., ppm)

I: Intensity of sunlight

Q_4: Natural nutrient rate

a_2: Loss of nutrient in influence of intensity of sunlight

R: Rate of rainfall

Equation:

$dN/dt = Q_4 - a_2 * I + b * R$ ………………………………………………………………….… (4)

Assumptions:

Variation of concentration of nutrient (dN/dt) in the soil is dominant to amplitude of sunlight intensity I and the natural nutrient rate Q_4.

Intensity of sunlight $\alpha_2' \omega$ has a negative influence on the nutrient levels, due to: Some nutrients are degraded photo-chemically.

There is an enhancement of leaching and erosion under certain conditions.

Q_4 indicates optimum nutrient level required for normal growth.

Other nutrient dynamics affecting factors that can be supplemented with other terms:

Rainfall (R) spreads the applied nutrients either through leaching of rainwater or erosion depending on intensity as well as soil properties. Soil Quality Model:

Equation: $dQ/dt = \alpha * (ST / M) + \beta * (M * N) + \gamma * H+$ ………………………………………….(5)

Variables:

α, β, γ: Weighting factors and which express the relative importance of each individual factor in influenc- ing overall soil quality.

IV. Results

iteration	Rainfall (mm/day)	Sun intensity(w/m^2)	Soil Temperature (°C)
1	15	180	53.090
2	20	160	81.231
3	25	140	109.423
4	30	120	137.666
5	35	100	165.960
6	40	80	194.305
7	45	60	222.701
8	50	40	251.148
9	55	20	279.646
10	60	0	308.195

Table 2: Simulated data for soil temperature over time in 10 iteration.

Iteration	Lime rate	Pesticide use	Organic matter	dH/dt
1	0.2	0.10	0.001	0.101001

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2	0.3	0.05	0.003	0.104503
3	0.4	0.00	0.005	0.108005
4	0.5	-0.05	0.007	0.111507
5	0.6	-0.10	0.009	0.115009
6	0.7	-0.15	0.011	0.118511
7	0.8	-0.20	0.013	0.122013
8	0.9	-0.25	0.015	0.125515
9	1.0	-0.30	0.017	0.129017
10	1.1	-0.35	0.019	0.132519

Table 3: Simulated data for soil pH over time in 10 iteration

iteration	M	R	I	E	K
1	-9.366052e+03	8.248437	312.936586	3.725902	0.30583
2	5.852602e+06	8.248437	312.936586	3.725902	0.30583
``	-3.657134e+09	8.248437	312.936586	3.725902	0.30583
4	2.285245e+12	8.248437	312.936586	3.725902	0.30583
5	-1.427988e+15	8.248437	312.936586	3.725902	0.30583
6	8.923115e+17	8.248437	312.936586	3.725902	0.30583
7	-5.575815e+20	8.248437	312.936586	3.725902	0.30583
8	3.484177e+23	8.248437	312.936586	3.725902	0.30583
9	-2.177169e+26	8.248437	312.936586	3.725902	0.30583
10	1.360454e+29	8.248437	312.936586	3.725902	0.30583

Table 4: Simulated soil Moisture data for 10 iteration overtime

Iteration	**α**	**β**	**γ**	S_T	S_M	S_N	S_{H+}	dQ/dt
0	0.548309	0.528029	0.502334	22	45.2	0.34	5.6	9.909493
1	0.475452	0.783354	0.923360	23	45.4	0.39	5.7	17.440824
2	0.262684	0.747075	0.787940	24	45.6	0.44	5.8	17.852053
3	0.257152	0.189612	0.486743	25	45.8	0.49	5.9	6.762834
4	0.583530	0.487780	0.213930	26	46.0	0.54	6.0	12.527457

Table 5: simulated data for the soil quality for five iteration over time

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V. Discussion

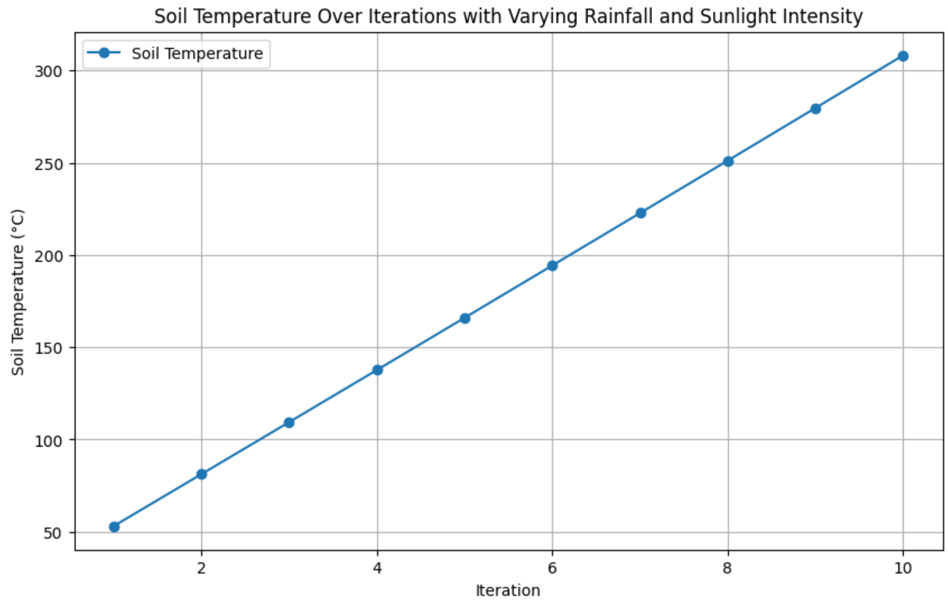

Figure 1: result of change in soil temperature over iteration value

The dynamic response of the parameter with variable rainfall and sunlight intensity is presented in Figure 1 for a soil temperature simulation of the 10th iteration. The plot is presented with respect to iterations on the x-axis and resultant soil temperature (°C) on the y-axis. The model represents the influences of rainfall and sunlight upon temperature as opposing factors that lead to easy observation of variations. The parameters necessary for describing this model are coefficients representing these influences which define the pattern of temperature. Through the influence of Q_1, therefore, the system is directed towards desired conditions for growth of crops, which is the optimal soil temperature. The figure offers model sensitivity insights help agricultural practice optimization regarding the environmental alterations.

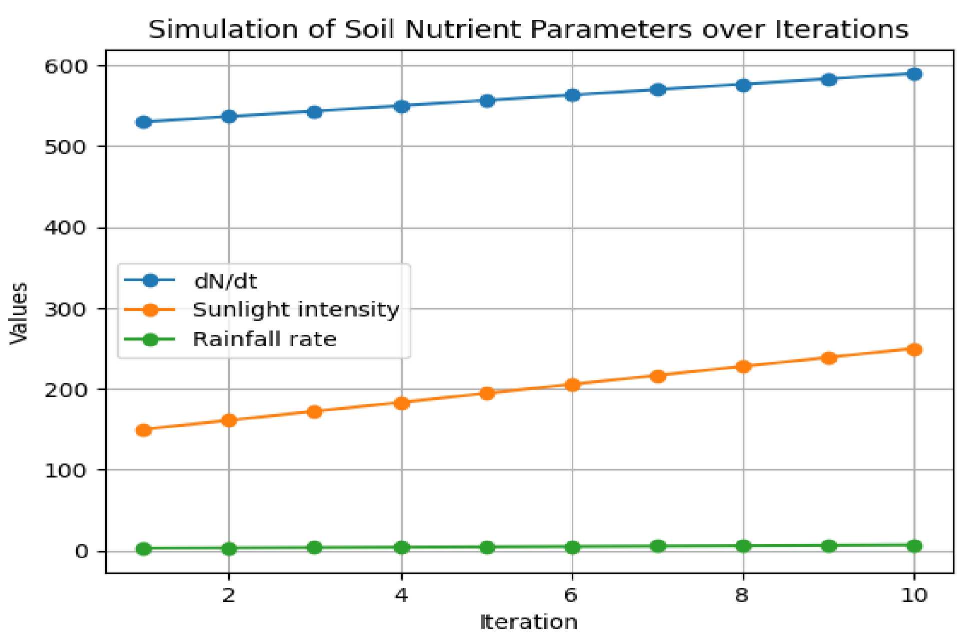

Figure 2: result of change in soil nutrient over iteration value

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Figure 2 shows the progress of dynamics of soil nutrient concentration (dN/dt), intensity of sunlight, and rate of rainfall relative to ten simulations. Fluctuations of dN/dt relate with fluctuations in concentration levels of nutrients as a consequence of variations in rainfalls and intensities of sunlight patterns of conditions. Positive spikes will outline the accumulation of nutrients while negative spikes may indicate possible loss or leaching of the nutrients. The chart successfully demonstrates the intricate interplay of sunlight intensity and rainfall in the variations of nutrients. Peaks in nutrient concentration may correspond to the points of optimal conditions for retention while the little concentrations indicates at times of increased nutrient loss.

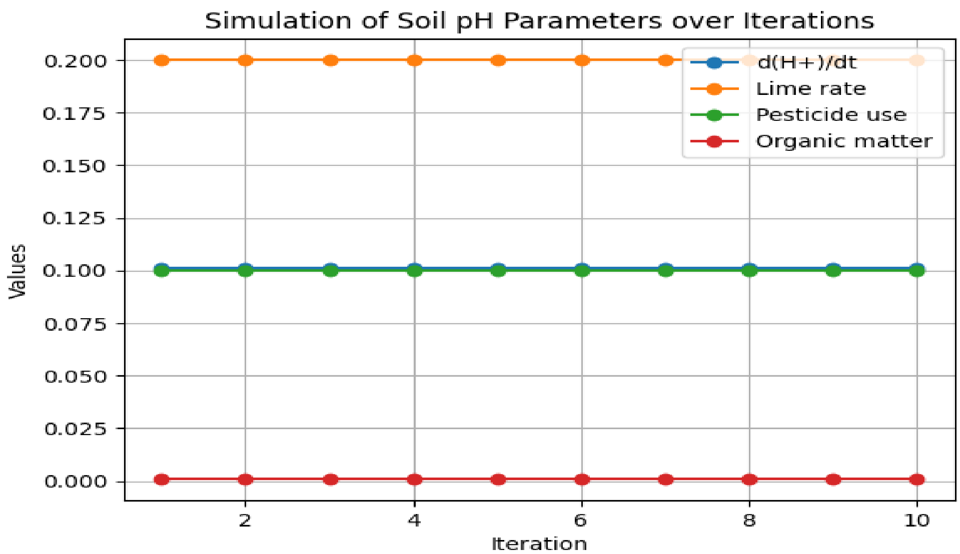

Figure 3: the result of change in pH over iteration value

The following code simulates a sub-model for soil pH over 10 iterations, whereby it depicts d(H+)/dt or the rate of change in pH along with lime rate, pesticide use and organic matter content. In this case, the first line represents the dynamic change in soil pH on a trend of coefficient nature with respect to the selected initial conditions. The second trend represents the lime rate variation with respect to the pH changes. Similarly, the third line represents the pesticide application rate, providing a visual correlation with pH dynamics. The fourth line is the organic matter decomposition rate and finally, it serves to show how this factor leads to soil pH. In so doing, therefore, this graph is able to elucidate how the factors on the graph come together to give a greater picture of the interactions between these parameters in giving an overall view or insight into soil quality in respect to the interaction with agricultural practices. A nice way to explore the effect of different scenarios on soil pH is just by adjusting the coefficients and initial conditions.

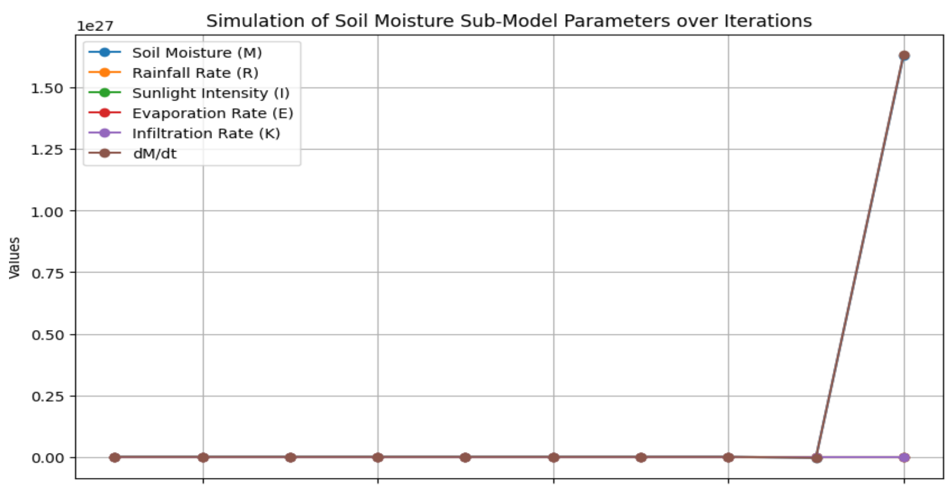

Figure 4: the result of change in soil moisture over interaction value

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As such, the simulation also presents dynamic responsiveness of the soil moisture sub-model to the incidences of rainfall and exposures to sunlight, rates of evaporation and infiltration. Peaks in dM/dt indicate a positive change in soil moisture, which is probably due to intense rainfall or good sunlight while troughs indicate lower values of soil moisture as a result of relatively higher evaporation or lower infiltration. Randomized parameters expose the sensitivity of the model against an extremely diversified environmental condition on the other hand, the plot helps to visualize complex interactions and provide reasoning for the fact that by considering a number of variables, it is possible to predict soil moisture. This information needs to be taken into consideration in agriculture or specifically land management for making decisions.

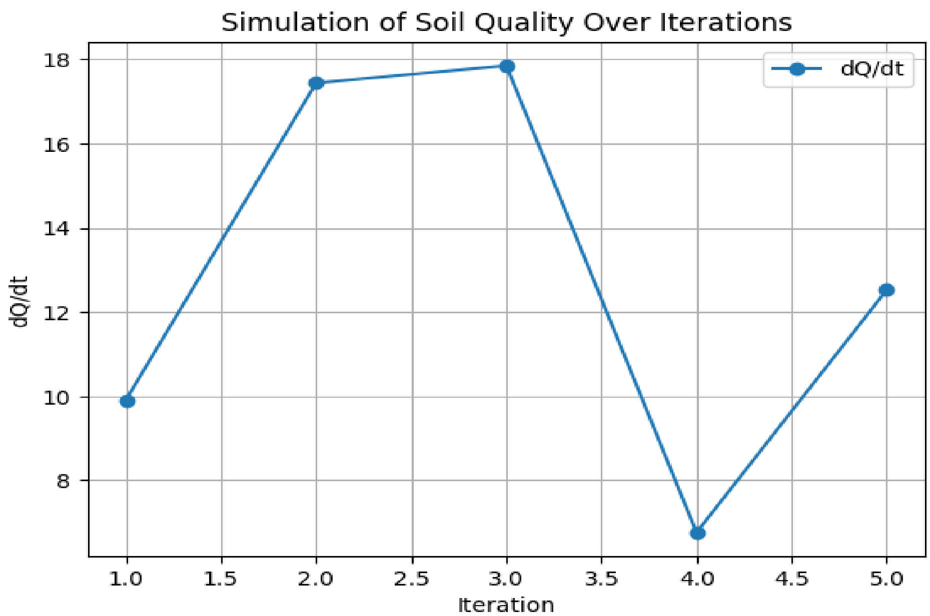

Figure 5: the result of the change is soil quality over iteration value

From the data provided in table5 the result of the dQ/dt were plotted against iteration, the result reveals a dynamic trend in soil quality over the simulated iterations. The plot showcases fluctuations in the rate of change, indicating varying impacts on soil quality. Notably, there is a significant increase in dQ/dt from Iteration 0 to Iteration 2, reaching peaks at 17.440824 and 17.852053, respectively. Subsequently, Iteration 3 shows a notable decrease in the rate of change (6.762834), followed by a moderate increase in Iteration 4 (12.527457). This suggests that specific combinations of coefficients and input parameter variations influence the system's response. Peaks in the plot might correspond to iterations where positive impacts on soil quality are more pronounced, while troughs represent periods of slower change or potential negative effects. The wide variability in

dQ/dt values underscores the system's sensitivity to the dynamic interplay of coefficients and parameter adjustments.

VI. Conclusion

The study by the authors highlights the importance of considering the interactions between soil temperature, soil moisture, soil nutrients, and soil pH when developing crop yield models. The model developed by the authors can be used to improve decision-making in challenging agricultural conditions, such as those with drought or nutrient stress.

VII. Future Work

The authors suggest that future work should focus on validating the model using real-world data and developing more advanced models that consider other factors that can affect crop yields, such as pests and diseases.

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