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Economically optimum N fertiliser decisions for rice cultivation in Sri Lanka: Does soil type matter?

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Abstract: In rice (*Oryza Sativa*) production, appropriate nitrogen (N) management needs to consider the relationship between the rate of N fertiliser application, time of application and crop yield for different soil types. N demand is a crop-specific factor, while N supply is related to soil characteristics and crop management practices such as N fertilisation. Balancing N supply against demand makes N use more efficient by avoiding N losses from the system, which impacts farming profit and the environment. A coupled, biological and economic modelling approach was adopted to identify the economic optimum rate of N (EORN) for rice cultivation in three soil types in Sri Lanka (Figure 1). The three soil types are Low Humic Gley (LHG) poorly drained soil, Reddish Brown Earth (RBE) well imperfectly and well-drained soil.

The APSIM-Oryza model was parameterised for the conditions of the study area. Model validation confirmed that there was good agreement between actual and simulated rice yield. The validated APSIM-Oryza model was used to evaluate the rates of N application between 0 and 300 kg N/ha/season for the last 20 years of weather. Rice yield response to N varied between soils, and yield variability over the years was also observed due to weather. The highest potential yield at the median and lowest yield variability across years was observed in LHG poorly drained soil which is highly suitable for rice cultivation. RBE well-drained soil showed poor response for applied N with lowest yield potential while RBE imperfectly drained soil varied between responses of other soil types.

The simulated rice yields for each N application was considered as the inputs to an economic evaluation of the N decisions. A modified Mitscherlich-Baule yield response function was used to fit the relationship between N rate and grain yield for each soil type since the visual pattern of APSIM-Oryza simulated yield best matched with the functional form. Profit maximising conditions applied to the yield responses developed EORN of 228, 156, and 118 kg N/ha in LHG poorly drained soil, RBE imperfectly drained soil and RBE well-drained soil, respectively. Rice yields at the economic optimum were 6.1, 4.0 and 2.8 t/ha, respectively. The economic optimum was highly price-sensitive; hence the quantitative values could be varied with changing rice selling price and N fertiliser price. However, the results indicated that investment in N fertiliser needs to consider the type of soil due to differences of yield responses in soil types; hence blanket application of N fertiliser over soil types caused to deviate from a maximum profit of rice cultivation in given soil types.

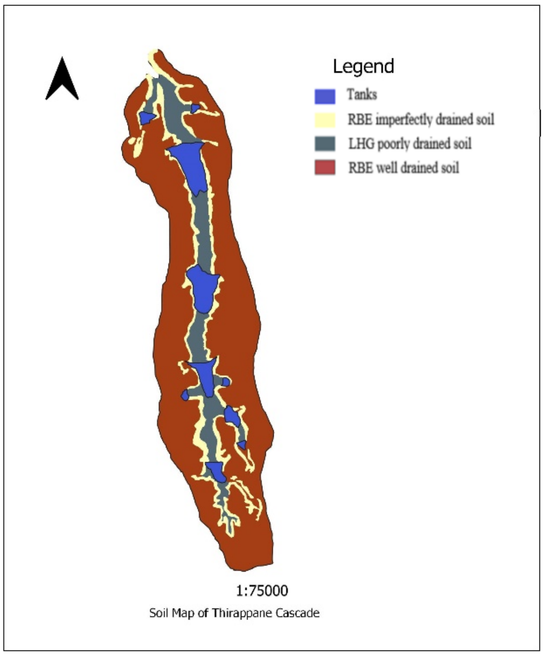

Figure 1. Soil map of study location

***Keywords**: APSIM-Oryza, economic optimum, nitrogen fertiliser*

1. INTRODUCTION

The implications for crop management, such as the effect of water and nutrient management, are generally estimated by using crop system simulation models (McCown *et al.*, 1996). With demonstrated accuracy and reliability, simulation models allow investigation of short and long-term agricultural practices at low cost and time requirements when experimental data are limited and expensive to gather (Ma *et al.*, 2007; Malone *et al.*, 2018). Further, crop simulation models have been shown to provide an excellent approach to explore genotype-environment management interactions and adaptation research for agriculture (Tao *et al.*, 2018). Results from crop simulation models are widely used to answer the research questions for crop management and policy formulation. The results can assist interactions between disciplines and allow the integration of data from the soil, plant, and atmospheric systems into agricultural management decisions. This enables the simulation of a wide range of cropping systems over a broad range of environmental and crop management practices (Mailhol *et al.*, 2001).

However, practical applications of crop simulation models require sets of weather, soil, and management data, together with other information including time-series data of crop development, yield and components of yield, soil moisture and soil nutrients (Holzworth *et al.*, 2014; Keating *et al.*, 2003). Evaluation of a crop simulation model involves establishing confidence in its capability to predict outcomes experienced in the real world (Woodward *et al.*, 2008). Models which simulate nutrient release patterns according to the resource quality (Shaviv & Mikkelsen, 1993), soil conditions (Timilsena *et al.*, 2015), and climate can be used to make nutrient recommendations to optimise the use of different resources, depending upon their availability. The Agriculture Production Simulator (APSIM) is a widely used crop model which includes N dynamics in soil, mostly under tropical and subtropical climatic conditions. SoilWat within the APSIM suite is used for analysing the N dynamics (Huth *et al.*, 2012). SoilWat is a cascading layer model. In SoilWat, simulations include a mixing algorithm and assume that all water and solutes entering into soil layers are thoroughly mixed. Then, by considering an efficiency factor, SoilWat calculates the amount of solute leaving each layer

This study focuses on the N fertiliser applications for rice production in the Thirappane Tank Cascade of Sri Lanka, where eutrophication in water was observed. The current N fertiliser decisions at the Cascade are similar for all three soil types. Possible soil specific fertiliser management options can contribute to reducing wastage of fertiliser and maximizing farmers profit. The main objective of this paper is to develop and adopt a bio-economic modelling framework using predicted effects of N rate applications on rice crop yields on three soil types and identify soil type based EORN. This will be achieved using a parameterised and validated crop model coupled with a production economics framework to identify the soil specific N rates to ensure maximum farm profits.

2. METHOD OF ANALYSIS

2.1. Description of the study area

Data for model parameterisation and calibration were collected from the Thirappane Tank Cascade, located in the Dry Zone of Sri Lanka. The Cascade comprises six tanks. The distance between a most upper tank[1] to lower tank[2] is 8 km, while the Cascade is 2 km wide. The total cultivation area is 207 ha. Three soil types were studied; namely, LHG poorly drained soil, RBE imperfectly drained and well-drained soil. The distribution of soils in the study location is given in Figure 1. RBE well-drained soil is the most common soil type within the study location (around 75% of total land area), but LHG poorly drained soil is prominent in rice cultivation areas (around 80% of the rice cultivation area).

2.2. Biological model: Model parameterisation and validation

APSIM crop simulation model

The Agricultural Production Simulator (APSIM) version 7.10 was parameterised and validated for rice yield at the study locations for the primary rice cultivation season (Maha) in 2018. The validated APSIM-Oryza model was used to develop simulations using historical climate data from 1997 to 2019.

Crop phenology

The main rice variety, "Bg 359", a 3.5-month growing period rice variety, is cultivated during the main cultivation season. The phenological parameters used were obtained from Amarasingha *et al.* (2015) and included (i) the development rate in juvenile phase-DVRJ ($^{\circ}Cd^{-1}$), (ii) the development rate in photoperiod-

[1] Coordinates of upper tank : 8.156604469144911 N, 80.52444518529929 E

[2] Coordinates of lower tank: 8.218808726954416 N , 80.51946332221384 E

sensitive phase -DVRI (°Cd^{-1}), (iii) the development rate in panicle development phase-DVRP (°Cd^{-1}), and (iv) the development rate in reproductive phase-DVRR °Cd^{-1}).

Weather data

Daily weather data (maximum and minimum temperature, rainfall, and sunshine hours) from January 1976 to March 2019 for Mahaillupallama[3] were obtained from the Mahaillupallama Meteorological Station. Daily incoming radiation (MJm^{-2}d^{-1}) was calculated using sunshine hours, latitude and longitude and angstrom coefficient (a=0.29, and b=0.39) (Samuel, 1991).

Soil data

Soil characteristics of the study site were obtained from Mapa and Pathmarajah (1995) and Mapa *et al.* (2010), allowing available layer-wise data to be incorporated in the model.

Crop Management data

The crop management practices data were obtained from a household survey conducted within the study location in 2019. The crop management data was collected for the main crop production season in 2018. The model was configured for soil being puddled and levelled before planting. Inorganic fertiliser application is generalised according to the farmer practice at the Cascade. N fertiliser (Urea) applications (three times) were included as normal farmer practice. Direct seeding was conducted with 90 plants/m^2 density. A seven-day sowing window was used in the simulation. In the absence of rainfall, irrigation was applied until two weeks after flowering to maintain a ponding depth of 7 cm.

Model validation

Actual field and simulated data can be compared graphically and analysed statistically (Loague & Green, 1991). Experimental data was not available for the validation of the model. The model was parameterised with soil, weather and phenological data. The N rate was adapted from district averages for the last 20 years, and then simulated rice yield was compared with the district average of rice yield. The model performance was evaluated via the root mean square error (RMSE) (Pham, 2019). In this process, mean differences were compared between the values simulated by the model and actual values.

$$Root\ Mean\ Square\ Error\ (RMSE) = \sqrt{\frac{\sum_{i=1}^{i=n} (P_i - O_i)^2}{n}} \qquad (1)$$

Where, P_i is the simulated value for ith observation, O_i is the actual value ith observation, and n is the number of observations. For best model performance, values of RMSE should be close to 0; high values of RMSE indicate poor model performance. The unit of the RMSE is the same as the variable being evaluated. The minimum value of RMSE is zero, and there is no maximum.

Scenario analysis

The validated APSIM-Oryza model was used to simulate rice yield responses to rates of N application in the main rice cultivating season (Maha) from zero N to 300 kg N/ha/season for the three soil types.

2.3. Economic framework

A visual examination of the patterns of crop yield response (see below) indicated a response pattern of yield to N increasing at a decreasing rate up to a maximum, or asymptotic, level. Therefore a modified Mitscherlich-Baule (Brorsen & Richter, 2012) yield response function was used to fit the relationship between N rate (x) and grain yield (Y) for each soil type. EORN is determined at the profit maximisation point (assuming farmers aim for profit); the rate of N application where extra returns from the associated increased yield just cover expenditure on an extra unit of N fertiliser. This relationship is based on the assumption that fertiliser N was the only variable cost and that all other costs do not vary with the N rate (Anderson *et al.*, 1977; Anderson & Dillon, 1992). The first partial derivative of the yield response function is set equal to the price ratio between fertiliser and rice. The yield response (or production) function with a modified Mitscherlich-Baule form is (Harmsen, 2000),

$$Y = a + b(1 - e^{-kx}). \qquad (2)$$

[3] Mahailluppalama is the nearest weather station to the study location, which is 10 km from the study location.

In equation (2), x is the rate of N application (kg/ha), Y is rice yield (t/ha), a is the yield at zero fertiliser application (t/ha), b is the parameter above a where yield increases to the asymptote, and k is a coefficient of gain. The level of asymptotic yield is given by $a + b$.

The first derivative of the response function with respect to x is calculated, and from the profit function, it is set equal to the price ratio to determine the level of EORN,

$$\frac{dY}{dx} = kbe^{-kx} = \frac{P_x}{P_y}. \quad (3)$$

In equation (3), P_x is the price of N fertiliser (LKR/kg), and P_Y is the price of rice (LKR/kg). N fertiliser in Sri Lanka is provided under subsidy policy (maximum 188 kg N/ha at the rate of LKR 22/kg of N), and farmers can buy commercial fertiliser at the rate of LKR 109 /kg of N (Weerahewa *et al.*, 2010). The farm-gate price of rice used was 40 LKR/kg. A weighted average price for N fertiliser of LKR 84/ kg of N was used for this study. The survey results indicate that the maximum N application is 300 kg N/ha.

Equation (3) is solved for x to find EORN:

$$EORN\ (x) = \frac{1}{-k}\ ln(\frac{P_x/P_Y}{kb}). \quad (4)$$

The economic framework can be adapted to account for risk aversion by the farmer. If farmers are risk-averse or cautious about using higher amounts of N because of uncertainty about crop outcomes and because they generally need to borrow money to buy fertiliser, then they may decide to apply less fertiliser (Hardaker, 2004; Jáuregui & Sain, 1992).

Statistical analysis

Data were analysed using RStudio software. The nlreg package was used to estimate the production function coefficients (equation 2). Graphics were designed in RStudio using the ggplot2 package.

3. RESULTS AND DISCUSSION

3.1. APSIM-Oryza validation

There was good agreement of the field observed and model-simulated data for the Maha season (see Figure 2). RSME in Maha (Bg 359) was 0.9 t/ha (perfect match, RSME=0). This result indicates that the parameterised APSIM-Oryza could explain most of the yield variability. Further, actual irrigation (in m^3/ha/season) at the field level was compared with simulated irrigation as a validation of the model. There was a good match between actual irrigation and modelled amount of irrigation in APSIM-Oryza.

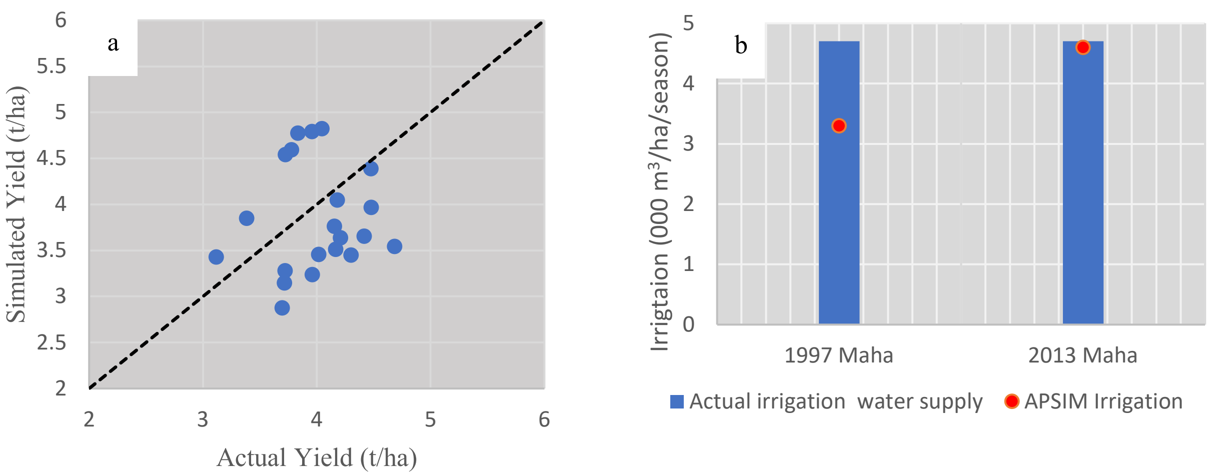

Figure 2. APSIM model validation (a: yield, b: irrigation)

3.2. Crop simulation results

Simulated rice yields for increased N rates show general increases at a decreasing rate up to a plateau in all soil types. The highest yield response/potential for applied N was observed in LHG poorly drained soil, while the lowest was in RBE well-drained soil at the median (see Figure 3). As expected, there was variation in yield at each level of N input due to the stochastic nature of weather. In general, there was a lower variation in simulated rice yield in LHG than in other soils. The poor drainage condition (lower saturated hydraulic conductivity of soil) has limited the loss of water and N, hence making them available for plant growth. As a result, the variation of yield over the years is lower than other soils. Over the simulation period, the mean yield at zero fertiliser was 3.1, 2.2, and 1.6 t/ha for the median in LHG poorly drained soil, RBE imperfectly and well-drained soil, respectively. The rate of yield increases for N applications varied between soil types.

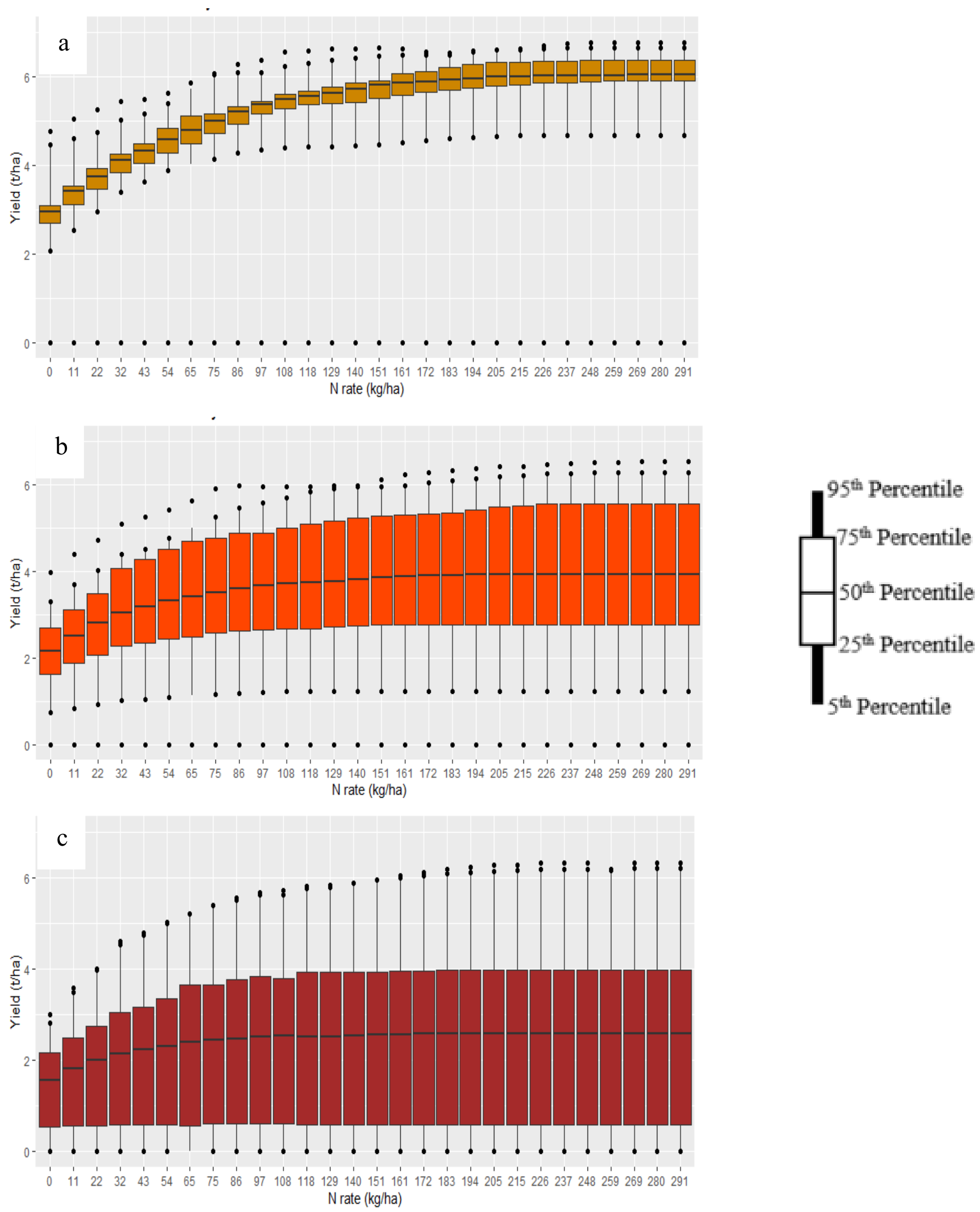

Figure 3. Yield response for the rate of N application in (a) LHG poorly drained soil, (b) RBE imperfectly drained soil and (c) RBE well-drained soil

3.3. Economics of N fertiliser decisions

The Mitscherlich-Baule model was used to fit the relationship between rice yield response and applied N, and the EORN was determined for three soil types. The regression coefficients, EORN and economic optimum rice yield are given in Table 1. The rate of N application has a significant effect on rice yield in both LHG poorly drained soil and RBE imperfectly drained soil at $P < 0.05$. The EORN calculated via modified Mitscherlich model varied among soil types. EORN was 228,156 and 118 kg N/ha for LHG poorly drained, RBE imperfectly drained and RBE well-drained, respectively. The economic optimum yields in the three soils were 6.1, 4.0 and 2.8 t/ha at the median yield level. As indicated in equation 3, EORN is highly sensitive to the price ratio of rice and N fertiliser. Accordingly, the quantitative values of EORN are valid for given price levels. Change of price affects all three soil types simultaneously; hence the differences of EORN between soil types is certain. If the economic analysis includes the social cost of N fertiliser by having environmental damages, the rate of N application may be further reduced.

Table 1. Estimated coefficients, EORN, and economic optimum yield predicted from the modified Mitscherlich model

Soil type	**Coefficients for the model**			**EORN (kg N/ha)**	**Economic optimum yield (t/ha)**
	a	***b***	***k***		
LHG poorly drained soil	3.05***	3.12***	0.014***	228	6.1
RBE Imperfectly drained soil	2.22***	1.92***	0.018**	156	4.0
RBE well-drained soil	1.62***	1.20***	0.021	118	2.8

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

It was evident that soil type-based N management practices, especially altering the rate of N based on the soil type, can reduce the cost of N via avoiding application beyond the economically optimum level. As shown in Figure 1, soils in the study location are presented in a specific pattern with clearly identified area boundaries (soil types are not mixed); hence practical use of the results at the field level is also easier. If the farm has multiple cultivation fields at different soil types, then farming income can be maximised by adopting heterogeneous N rates for fields with various soil types.

4. CONCLUSIONS

The results show that the best economic N rate varies with soil type. Potential yield is higher in LHG soil, and yield variability appears to be lower. Poor drainage conditions explained the higher yield potential of rice. The EORN varied from 138 to 261 kg N /ha. This study shows that the recommended N fertiliser rates can be adjusted for soil type and drainage status, and blanket N recommendations need to be avoided.

5. LIMITATION AND FUTURE STUDY

The study has considered only the most commonly grown rice variety, and more varieties can be included with actual field experiments for other decisions. Further price volatility of rice and fertiliser is not considered here. Environmental impacts are not included in these N decisions. Further study can combine all these aspects to develop better N management policy decisions.

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