Indian Journal of Geo Marine Sciences
Vol. 53 (05), May 2024, pp. 338-352
DOI: 10.56042/ijms.v53i05.21662

Physical parameters-driven models for predicting shrimp growth in aquaculture

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Received 30 March 2024; revised 30 April 2024

As of today, more than half of the world's shrimp production comes from farmed shrimp. Shrimp farming (or shrimp aquaculture) is most common in China and is also practiced in Thailand, Indonesia, India, Vietnam, Brazil, Ecuador, and Bangladesh. Growth models for shrimps in open pond aquaculture systems are being discussed in the paper. The Water quality of the pond and the nature of stocking are proposed as the proxy to determine the growth rates of the cultured organisms. The devised shrimp growth model, when tested on a publicly available dataset obtained from a conducted experiment, with recorded farm parameters like temperature, stocking density, pH and salinity, gave the mean error of 0.1 g and Root Mean Squared Error (RMSE) of 3.76g, in the final weights of the shrimp. This paper demonstrates the first such approach to bring reasonable accuracy growth models for the shrimp without needing any extra ground setup and using data from the various literature sources. Considering the approach to predict shrimp growth through physical parameters and also the feasibility of the framework to be implemented by deploying IoT sensors in the pond water, this study aims to bring the notion of digital transformation in the context of Indian aquaculture systems of open ponds shrimp farms.

[Keywords**:* Aquaculture, Digital transformation, Marine spatial planning, Productivity, Shrimp, Vannamei**]

Introduction

Aquaculture is a rapidly growing sector within the food production industry. Defined as the cultivation of aquatic organisms in freshwater, brackish, or marine environments[1], it encompasses the controlled breeding, rearing, and harvesting of fish, shellfish, seaweed, and other aquatic animals and plants[2]. This practice stands in contrast to traditional capture fisheries, which rely on the extraction of wild populations from the natural ecosystems.

In recent years, the rise of aquaculture has been driven by several factors, including the increasing global demand for seafood coupled with the decline of wild fish stocks due to overfishing and environmental degradation[3]. Aquaculture offers a controlled and sustainable alternative, allowing farmers to optimise growing conditions for target species. Through practices like selective breeding and manipulation of water quality, aquaculture farms can potentially achieve higher yields while minimising environmental impact compared to open-ocean fishing methods[4], where the water quality cannot be altered as and when required and is also prone to natural effects. Aquaculture encompasses a diverse range of techniques, from intensive pond-based systems for finfish like salmon to open pond aquaculture for shrimps and the cultivation of seaweed lines in coastal areas[1].

While there are many aquatic organisms, as mentioned earlier, produced via farming and aquaculture to meet the global demand, shrimps production especially saw an impressive aquaculture production growth in the past decade (as depicted in Fig. 1). The growth is attributed mainly to overfishing and also the declining wild stocks that pushed shrimp capture fisheries to their limits[3]. Aquaculture offered a controllable alternative, allowing intensive production and meeting the rising demand for shrimp. Currently, about fifty-five per cent of shrimps produced worldwide are farmed[5].

India, with its vast coastline, extensive inland water bodies, and rich aquatic biodiversity, presents a significant opportunity for aquaculture. As expected, India is one of the leading countries in aquaculture production, currently holding the second position globally[6].

Here, shrimp farming is traditionally fractionalised; much of it is done on small farms like other Southeast Asian countries. Building shrimp ponds near tidal areas saves farmers from the expense of high-elevation water pumps and long-term pumping costs[5]. Digging deeper into the consequences of its expansion, various case studies have depicted the negative ecological impacts of large-scale expansion of aquaculture farms. Intensive aquaculture practices can lead to pollution through

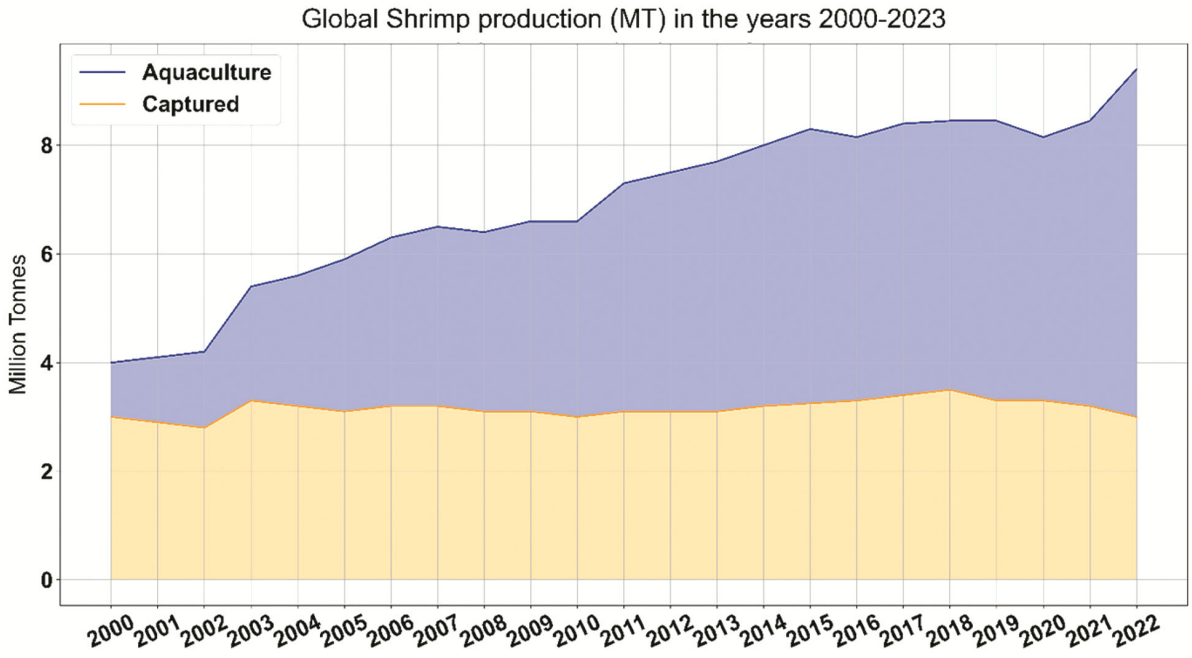

Fig. 1 — Global shrimp production from all sources, fragmented into captured fisheries and aquaculture[19]

excess nutrients like nitrogen and phosphorus released from uneaten feed and fish waste[7]. This nutrient overload can trigger algal blooms, deplete oxygen levels in water bodies, and create dead zones detrimental to marine ecosystems[8]. Additionally, the use of antibiotics and antifoulants to prevent disease outbreaks in aquaculture can potentially harm wild fish populations and contribute to antibiotic resistance in the environment[9]. Mangroves are vital nurseries for fish which provide crucial coastal protection. Their destruction disrupts these vital ecological functions and contributes to biodiversity loss[10]. Aquaculture's dependence on fishmeal and fish oil for certain farmed fish species, like salmon, can exacerbate pressure on already strained wild fish populations[11]. Inadequate containment measures can lead to the escape of farmed fish into the natural environment. These escaped fish can compete with native species for resources and potentially introduce diseases, further disrupting the ecological balance[12]. While these were some of the ecological impacts, aquaculture development can also lead to social conflicts, particularly in coastal communities. Competition for water resources between aquaculture farms and local communities is a growing concern[13]. Additionally, large-scale aquaculture projects can lead to displacement of traditional fishing communities and disruption of local livelihoods.

Varying climatic profile in the Indian subcontinent especially the Indian Ocean region, over the recent years also poses an alarming situation. Rising water temperatures and erratic rainfall patterns can disrupt optimal growth conditions for key farmed species like shrimp and carp[14]. Increased frequency of extreme weather events like floods and cyclones can damage aquaculture infrastructure and lead to stock loss[15]. Additionally, saltwater intrusion due to sea level rise threatens coastal freshwater resources crucial for inland aquaculture[16]. The combined impact of these factors can lead to reduced farm productivity and economic hardship for Indian aquafarmers[17].

Shrimps, also known as prawns, are crustaceans with a hard exoskeleton and segmented body and are the key players in aquatic food webs[18]. The unparalleled rise in the demand of shrimp in the past decade has fuelled a boom in shrimp supply, with global production skyrocketing from 4 million tons in 2000 to over 9.4 million tons in 2022[ref. 19] (Fig. 1).

To make the most of the shrimp farmlands, that is, to improve the productivity of the shrimp aquaculture farms, this study aim to propose a shrimp growth model that links water quality to the growth rate of the shrimp as an indirect measure to predict the growth rates of shrimp being cultivated. The study analyse water quality and suggest adjustments to create ideal conditions for the shrimp growth. This optimised environment will lead to larger and healthier shrimp with fewer chances of diseases and

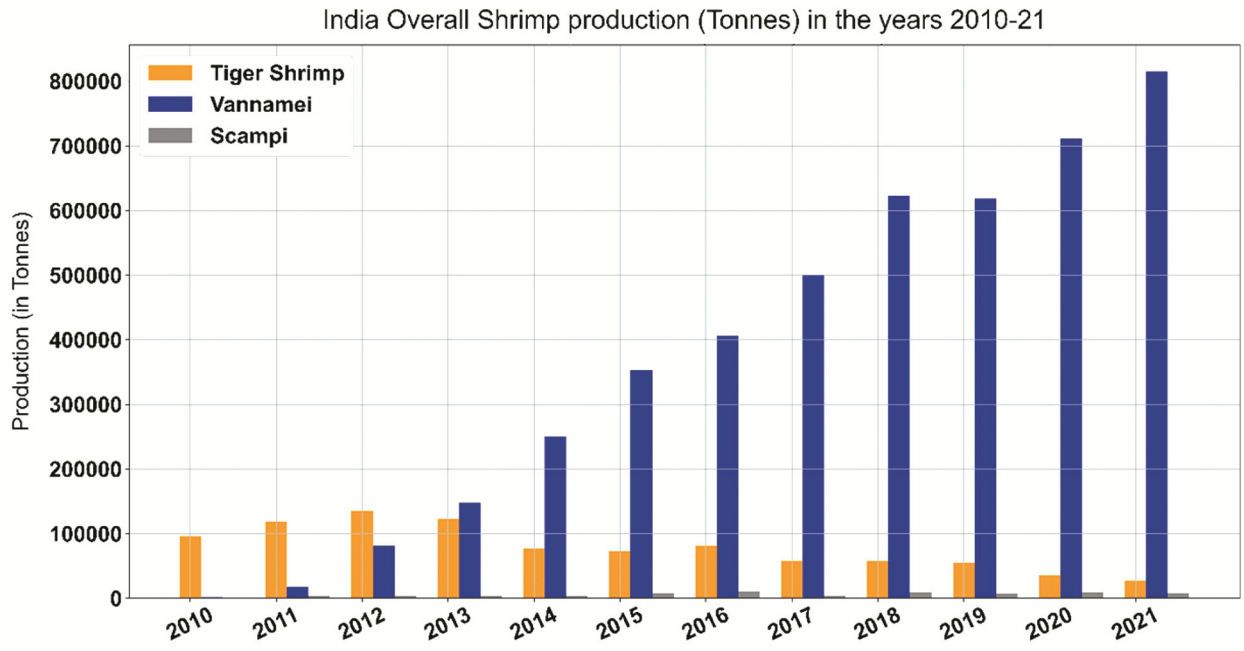

Fig. 2 — Aquaculture production levels of top 3 (ranked in terms of total gross tonnage production) farmed shrimps in India[20]

deaths. Ultimately, this will result in increased production and higher profits for farmers.

The paper centers on developing growth function models using curve fitting and machine learning techniques (regression) for the chosen species of shrimps based on the identified water quality parameters, the ones that affect growth and metabolism and are quantifiable.

Materials and Methods

While there are various species of shrimps grown worldwide, more than half of the grown shrimps are Whiteleg shrimps (*Litopenaeus vannamei* or King prawns, named based on their large sizes)[5]. In the context of India, the production of Whiteleg shrimp is at top and completely overshadows the production of the second most produced species Tiger shrimp (*Penaeus monodon*), by a huge margin[20] (Fig. 2).

Rapid growth rates for Whiteleg shrimp translate to quicker harvest cycles and higher profitability for farmers[21]. The Whiteleg shrimp species exhibit a relatively wider tolerance range for water quality parameters like salinity and temperature (compared to *Penaeus monodon* species), allowing for farming in diverse environments[22] making them less susceptible to environmental fluctuations and climatic variability. Whiteleg shrimps are also relatively resistant to certain diseases compared to other farmed shrimp species[23]. This reduces disease outbreaks and associated economic losses for aquaculture farms. Consumer demand grew based on the preference for the taste and texture of the Whiteleg shrimp, coupled with their affordability[24]. This brings us to the point of selecting the Whiteleg shrimp species for further study of their growth and metabolism.

Understanding of the growth of organisms and modelling it with the use of mathematical equations dates back to one of the famously known von-Bertalanffy growth model, devised by Ludwig Von Bertalanffy[25]. The von Bertalanffy growth model (VBGM) is a mathematical equation that describes how organisms grow, capturing the natural slowdown in growth as they approach their maximum size. Over time, various experiments have been conducted to determine the growth response of organisms under various conditions, the data from these experiments can be used for new age models, which are trained upon the data using techniques like regression (machine learning) and curve fitting.

Literature review

Whiteleg shrimp, scientifically known as the *Litopenaeus vannamei*, was first described and classified by Boone, a marine biologist, in 1931[(ref. 26)]. Boone's work established the *L. vannamei* shrimp as a distinct species with unique characteristics. The growth and metabolism of *L. vannamei* shrimp are highly dependent on the environment in which it is being grown. *Litopenaeus vannamei* growth

variability showed strong dependence on temperature changes[27]. The growth rate of the Whiteleg shrimp is significantly varied when temperature falls from 27 and 23 °C, because of the large temperature coefficient for growth. The optimum temperature is size-specific, and decreases when shrimp size increases (more than 30 °C for small shrimp and about 27 °C for large shrimp)[28]. Further increases in temperature beyond 30 °C will adversely affect the growth. When the temperature is below 23 °C, all sizes of shrimp are negatively affected, and when the temperature exceeds 30 °C, feed consumption and growth of large shrimp decline[29]. The FCR values or Feed Conversion Ratio determines how much proportion of the feed intake by the organism translates to its weight gain, and lower FCR values determine the higher efficiency of farm culture. It is found that large *L. vannamei* had the most efficient growth (lowest FCR) at 27 °C and the least efficient growth (higher FCR) at the higher (30 °C) and lower (23 °C) temperature[27,28]. Based on the experimental results[27,28], it was recommended that farmers should maintain pond (a shrimp aquaculture pond is shown in Fig. 3) temperatures around 27 °C to be able to grow shrimp bigger than 15 g. The growth of the Whiteleg shrimp is shown to be affected by large fluctuations in the temperature even if the average is maintained in the range of 27 – 30 °C[(ref. 30)].

Salinity, plays a critical role in the life cycle of the Whiteleg shrimp[31]. Whiteleg shrimps are said to be euryhaline species, where they can grow in a wide range of salinities from 0.5 – 40 ppt. A higher incidence of moulting (the process of shedding the old exoskeleton) problems and mortality at salinities below 10 ppt in *L. vannamei* have also been observed[32]. Whiteleg shrimp have a preferred salinity range for optimal growth, typically between 15 – 25 ppt[33], which mainly translates to brackish water and seawater-based aquaculture. Conversely, high salinity can also hinder growth, where *L. vannamei* post-larvae exhibited reduced growth at salinities exceeding 35 ppt[34]. This is crucial from the point of efficiency because higher growth rates again tend to be more efficient in terms of FCR (higher efficiency means lower FCR).

Stocking density describes the number of cultured organisms per unit area or per unit volume. For example, a stocking of 1000 post-larvae in 25 sq. m pond will translate to 40 post-larvae per sq. m, which is the same as the stocking density. Stocking density is one of the key parameters affecting the shrimp's growth as well as their survival and mortality rate. High stocking densities can lead to several challenges that hinder growth[35]. Competition for resources like oxygen and food intensifies[36]. Increased waste production can deteriorate water quality, further

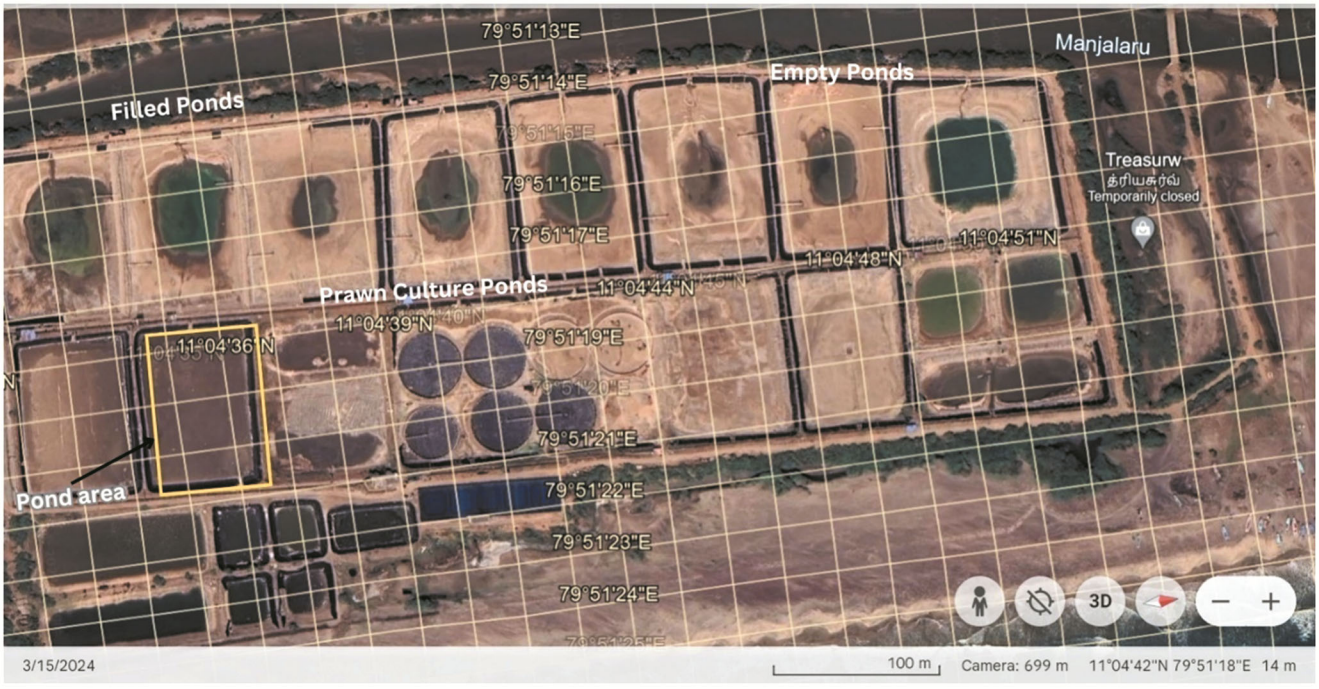

Fig. 3 — Open pond shrimp aquaculture along the coastal region, near the port of Thirukadaiyur (India). Image taken from satellite imagery available on Google Earth[43]

stressing the shrimp. With limited space for movement, shrimp may become more susceptible to diseases due to increased contact. Studies have observed a clear decrease in the growth rate of *L. vannamei* with increasing stocking density[37,38].

The water's pH, a measure of $[H^+]$ ion concentration or acidity, also plays a vital role in the growth rate of *L. vannamei* shrimp. Optimal growth typically occurs within a narrow, near-neutral alkaline pH range that allows for the efficient functioning of their physiological processes. Highly acidic (low pH) or alkaline (high pH) environments can create challenges for shrimps. Various studies have demonstrated that between 7.2 and 8.5 pH favours the shrimp growth[39], and a significant decrease in the growth rate of the Whiteleg shrimp at low pH (below 6.5) and high pH (above 8.5) is observed. Exposure of shrimps to very high acidic conditions, just for a few hours, can not only hinder their growth but can potentially kill the whole culture too. Dissolved Oxygen (DO) level, is another crucial factor that drives the growth of the shrimps. Oxygen is absorbed through their gills, similar to fish, and plays a vital role in various physiological functions[40]. Studies also reported higher susceptibility of Whiteleg shrimp to White Spot Syndrome Virus (WSSV) at low salinities, which can often coincide with reduced DO levels. When oxygen becomes limited, shrimp exhibit behavioural changes in an attempt to conserve energy. They become less active, reducing swimming and feeding behaviour. This further limits their growth potential and can negatively impact the overall health of the shrimp population. The ideal requirement of efficient shrimp aquaculture is to have a dissolved oxygen content of 5 ppm or more at all times. The required DO levels in the aquaculture pond water are maintained via the use of aerators that constantly rotate through the pond water and help dissolve the atmospheric oxygen into the water column.

This brings us to the set of parameters, namely temperature, stocking density, salinity, pH, and DO level (as tabulated in Table 1), which have crucial and notable impacts on the growth rates and metabolism (including impacts on survival) of the Whiteleg shrimp, as proven by the decades of experimentation in the open-source literature.

Data and Methodology

To model the growth of the shrimp and variations occurring due to changes in the water quality and stocking parameters, a function that maps the changes in the water quality parameters to the changes in the growth rates is required.

Table 1 — Farm parameters having significant effect on the growth rates of shrimp

Sr. No.	Parameter	Range
1	Temperature	*K or °C*
2	Stocking density	per sq. m
3	Salinity	ppt/ppm/PSU
4	Water pH	0 – 14 on pH scale
5	Dissolved oxygen level	ppm

Mathematically, it translates to

$$g = f(T, SD, S, pH, DO) \quad \ldots (1)$$

Where, T is the temperature, SD denotes the stocking density of the Whiteleg in a particular pond, S is the salinity of the culture water, pH is the Hydrogen ion concentration of the water, DO is the dissolved oxygen level in the water, and g is the growth rate of shrimp in grams/day or grams/week.

Now, to build a function that encompasses all these five parameters together will require a huge amount of data to train a Machine Learning (ML) model like regression or Random Forest/Decision Trees. The unavailability of such a large number of sampled data is a big challenge in the complete modelling of shrimp growth, and only subtle approximations can be made. Since all the data from the experiments are taken in a very precise range of values, the variation is insignificant in those specific ranges. For example, there is a crucial relation between salinity and temperature. Still, the region of interest is just between 22 °C – 33 °C for aquaculture, where it can be assumed that the salinity variations equally affect any temperature in this range, and there is a very mild correlation between the two.

Similarly, the preliminary data analysis of the dataset (from Abdelrahman *et. al.*[28]) in the heat map (as depicted in Fig. 4) suggest that stocking density and temperature are also very weakly correlated (r = 0.17), *i.e.* it is not necessary that any particular stocking density strongly influences the water temperature and vice versa. The temperature of the water is an independent parameter dependent only on the surroundings and is not influenced heavily by how the farm is stocked.

The DO level parameter is a highly variable parameter with strong correlations with salinity, water pH and temperature values. Without a large dataset, the exact relation between DO and these three parameters is tough to quantify. Therefore, in the

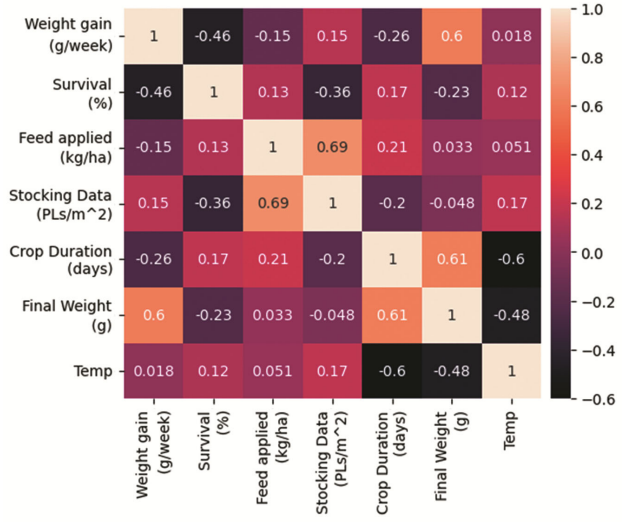

Fig. 4 — Correlation heat map between the input variables for the open pond experimentation carried out by Abdelrehman *et al*.[28]

scaling factor model which is aimed to develop in this study, the DO parameter will be dealt separately. Thus, from the growth model, the DO parameter can be excluded as follows:

$$g = \begin{cases} f(T, SD, S, pH) & DO > DOT \\ 0 & DO < DOT \end{cases} \quad \ldots (2)$$

and,

$$DOT = f(T, S, pH) \quad \ldots (3)$$

Where, the notations hold the same meaning, and *DOT* denotes the Dissolved Oxygen Threshold, which is the minimum oxygen level to be maintained in the water that supports the shrimp's life for given values of *T*, *S*, and *pH*. If DO content is less than the DOT, the metabolic processes are hindered, hampering the growth of the shrimp.

Studies have experimentally shown how the DOT varies with the changing parameters of *T*, *S*, and *pH*. The DOT can be estimated using the following equations[43].

$$DOT_T = 2.43 * 10^{-5} T^3 - 8 * 10^{-4} T^2 + 0.61 \quad \ldots (4)$$

$$DOT_S = -7.82 * 10^{-5} S^3 - 5.8 * 10^{-3} S^2 - 0.13S + 1.24 \quad \ldots (5)$$

$$DOT_{pH} = 0.15(pH)^2 - 2.25(pH) + 8.88 \quad \ldots (6)$$

Where, *DOT* is measured in PPM or PPT.
Building the scaled factor model

$$g = f(T, SD, S, pH) \quad \ldots (7)$$

$$g = f(T, SD, S, pH) = A \cdot \alpha(SD) \cdot \beta(S) \cdot \gamma(pH) \cdot k(T) \quad \ldots (8)$$

Where, the functions α, β, γ are normalised functions, that is, their values lie only between 0 and 1. Here, the idea is that the multivariate function $f(\cdot)$ can be decomposed considering the independence (very weak, close to zero correlation) between its variables. The growth rate g in grams/week is now dependent on the temperature function $k(T)$. At the same time, the variations in the stocking density (*SD*), salinity (*S*), and water pH (*pH*) will scale the function *k(T)* appropriately. The leading factor '*A*' is a constant multiplier to account for any constant scaling needed, mainly because sometimes the normalisation done on the functions might not be accurate according to conditions. To explain its significance in the model, consider the following example. Since stocking density inversely affects the growth of the shrimp in an open pond aquaculture[35,36], therefore, with increasing stocking density, the growth rate of individual shrimp will decrease. Therefore, the theoretical maximum growth rate will be achieved when stocking density is minimum possible, *i.e.* 1. While this function in theory will suggest that as stocking density increases further from 1 (to let's assume 20), the growth rate will significantly decrease. It may turn out that even a stocking density of 20 may allow the maximum theoretical growth rate because the growth was not hindered due to any scarcity of resources. This suggests that while an inversely proportional function can capture the effect of stocking density on the growth rate, it may sometimes over-estimate the effect due to theoretical limits. Therefore, a multiplier '*A*' is added to scale the factor and correct such over-estimations.

Since, all the normalised functions $\alpha, \beta \; and \; \gamma$ are unitless, therefore, the units of the function $g = f(T, SD, S, pH) = A \cdot \alpha(SD) \cdot \beta(S) \cdot \gamma(pH) \cdot k(T)$ g will be same as the function $k(T)$ (as defined in eq. (8)) because multiplication with unitless quantities doesn't affect the unit of a value.

Function for growth rate with respect to temperature

To build/develop the function $k(T)$ based on the curve fitting, the temperature range is considered between 22 °C – 33 °C as mentioned in the literature. As expected from the curve fitting, once extrapolated beyond 22 °C towards the left or 33 °C towards the right, it is a declining trend, showing that the life cycle and growth start to cease outside these

boundaries. It can also be observed that the favourable temperature for optimal growth shift over time as the shrimp grows. The growth rates are highest in the initial stages of the life cycle, and rates start to diminish as the organism grows. This observation is in line with Von Bertalanffy Growth model.

Based on the data points collected from Wyban *et al.*[27] as mentioned in Table 2, the curve fit for a second-order polynomial (quadratic) provides the following results for the growth function $k(T)$ in g/day. One can keep in mind that the growth rates in g/week can be directly converted to g/day by dividing the value by 7 (1 Week = 7 days).

$$k_s(T) = (-0.02T^2 + 1.23T - 17.11)/7 \quad \text{... (9)}$$

$$k_m(T) = (-0.02T^2 + 1.03T - 14.14)/7 \quad \text{... (10)}$$

$$k_s(T) = (-0.01T^2 + 0.79T - 10.16)/7 \quad \text{... (11)}$$

Where, $k_x(T); x = s\ or\ m\ or\ l$ denotes the growth rate for small, medium and large shrimps, respectively. The study demonstrated that the temperature profile changes with the weight and age of the shrimp in the culture, and hence, separate functions for different categories of weight need to be developed (the plot of the equations is shown in Fig. 5).

This categorisation of shrimps based on their weights during their life cycle is adopted from Wyban *et al.*[27], who carried out experiments for three different weights of the shrimps. As the categorisation of the shrimps is done based on their sizes, the rough boundaries for quantifying the shrimps are 0 – 8 g, 8 – 14 g and more than 14 g, respectively, as mentioned in Table 2.

Based on the days of cultivation (commonly abbreviated as DOC), shrimp generally take approximately 30 – 31 days to grow from the post-larval stage to around 8 g. Subsequently, it requires an additional 42 days (approx.) to reach a size of ~14 g, resulting in a total cultivation period of around 72 – 73 days. While the cultivation cycle for the Whiteleg shrimp is 100 – 120 days, farmers tend to stop their crops after 90 days as the growth is highly diminished thereafter, and they prefer harvesting the crop early rather than waiting for further growth. Thus, to build the model, used

$$g = f(T, SD, S, pH) = A \cdot \alpha(SD) \cdot \beta(S) \cdot \gamma(pH) \cdot k_x(T) \quad \text{... (12)}$$

Where, $k_x(T)$ holds the same meaning as earlier.

Hence, the growth rate during the complete life cycle of the shrimp at any instant will be dependent on what is its current weight (either it is small,

Table 2 — Shrimp size categorisation

Sr. No.	Category (size) for particular life cycle	Weight range	Usual number of days for the cycle (approx.)
1	Small	0 – 8	31 days (4 – 5 weeks)
2	Medium	8 – 14	42 days (6 weeks)
3	Large	14 and above	Rest number of days till completion of crop (usually 100 – 140 days of crop duration)

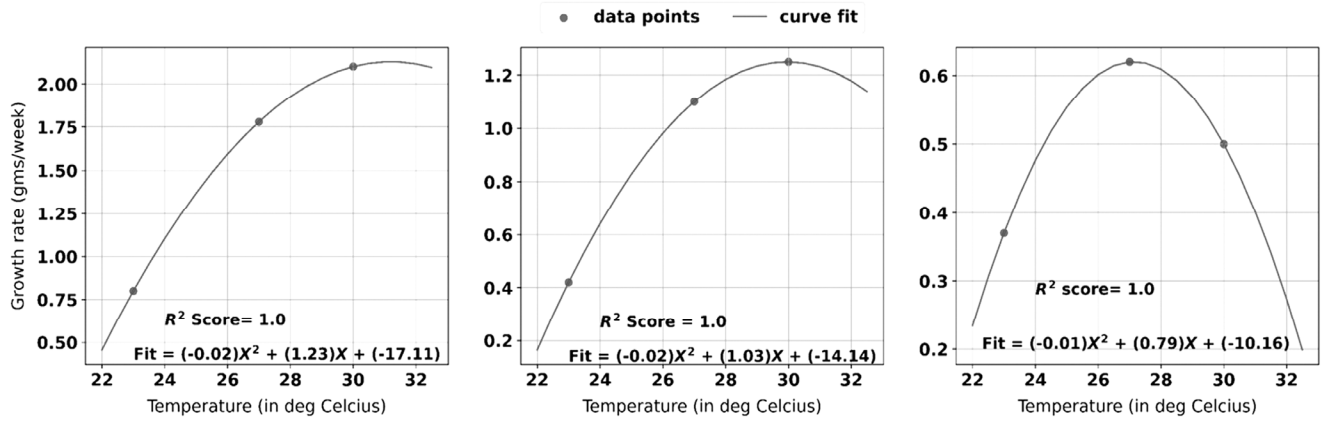

Fig. 5 — The variation of the Whiteleg shrimp weight with temperature, in three different stages (small, medium and large), categorised by its size. The plots are for these three sizes in order (small to large from left to right). Second order polynomial is used for fitting between the temperatures 22 and 33 °C. 'X' here denotes the parameter temperature

medium-sized or large-sized), and thus, the growth rate function will be as follows:

$$g = f(T, SD, S, pH) = \begin{cases} A \cdot \alpha(SD) \cdot \beta(S) \cdot \gamma(pH) \cdot k_s(T) \; if \; W < 8g \\ A \cdot \alpha(SD) \cdot \beta(S) \cdot \gamma(pH) \cdot k_m(T) \; if \; 8g < W < 14g \\ A \cdot \alpha(SD) \cdot \beta(S) \cdot \gamma(pH) \cdot k_l(T) \; if \; W > 14g \end{cases} \quad \text{... (13)}$$

Where, W is the current weight of the shrimp, which itself is dependent on the growth rate.

Normalised function for growth rate with respect to stocking density, salinity and pH

Based on the data points collected (as shown in Table 3) from the effect of stocking density on the growth rates of the culture, the curve fitting is applied to obtain the polynomial variation/relation between the growth and stocking density. Here, a degree 2 polynomial (quadratic polynomial) is used, which provides the curve fit equation as follows:

$$B(SD) = 2.07 * 10^{-6} SD^2 - 1.1 * 10^{-3} SD + 0.295 \quad \text{... (14)}$$

Table 3 — Results of the predictive analysis of built models with the experimental results obtained by Abdelrahman *et. al.*[28]

Weight gain (g/week)	*Survival (%)*	Stocking data (PLs/m^2)	Crop duration (days)	Actual final weight (g)	Temp (°C)	Predicted final weight	Error prediction (g)	Error prediction squared
1.39	67.10	31.00	132.00	26.20	29.71	23.95	2.25	5.08
1.44	58.70	29.00	145.00	29.80	29.60	25.69	4.11	16.91
1.33	76.10	25.00	155.00	29.50	29.03	27.84	1.66	2.76
1.22	74.50	26.00	159.00	27.70	29.15	28.1	-0.40	0.16
1.05	83.90	26.00	166.00	25.00	28.52	29.56	-4.56	20.84
0.95	84.50	26.00	171.00	23.30	28.69	30.07	-6.77	45.84
1.25	51.30	21.00	150.00	26.80	29.00	27.53	-0.73	0.53
1.45	52.44	28.37	139.61	28.29	29.15	25.51	2.78	7.73
1.45	52.44	28.37	139.61	28.29	29.15	25.51	2.78	7.73
1.07	66.10	29.00	167.00	25.50	28.71	29.27	-3.77	14.19
1.17	54.90	32.00	146.00	24.40	28.85	26.48	-2.08	4.33
1.45	40.10	26.00	148.00	30.60	28.52	27.31	3.29	10.81
0.89	87.60	30.00	160.00	20.30	28.60	28.49	-8.19	67.09
1.46	50.50	29.00	139.00	28.90	29.03	25.53	3.37	11.35
1.22	69.70	28.00	151.00	26.30	29.15	26.95	-0.65	0.43
1.02	89.00	28.00	165.00	24.10	28.80	29.04	-4.94	24.45
1.54	50.40	26.00	134.00	29.40	29.89	24.23	5.17	26.73
1.90	45.50	25.00	127.00	34.40	29.08	24.44	9.96	99.17
1.39	90.70	25.00	135.00	26.90	29.69	24.69	2.21	4.89
1.39	82.40	25.00	149.00	29.50	29.13	26.89	2.61	6.80
1.28	103.60	25.00	140.00	25.50	29.49	25.48	0.02	0.00
1.11	74.70	25.00	153.00	24.30	28.85	27.73	-3.43	11.75
1.84	48.70	23.00	118.00	31.00	29.15	23.36	7.64	58.38
1.15	79.90	24.00	155.00	25.40	28.97	27.99	-2.59	6.71
1.54	51.40	23.00	125.00	27.50	29.15	24.2	3.30	10.90
1.28	81.00	22.00	129.00	23.50	29.27	24.69	-1.19	1.41
1.22	86.10	22.00	147.00	25.70	28.76	27.34	-1.64	2.70
1.45	52.44	28.37	139.61	28.29	29.15	25.51	2.78	7.73
1.45	52.44	28.37	139.61	28.29	29.15	25.51	2.78	7.73
1.42	67.90	25.00	115.00	23.40	30.02	21.94	1.46	2.12
1.12	81.80	30.00	148.00	23.70	28.59	27.02	-3.32	11.04
1.15	104.00	26.00	147.00	24.20	29.15	26.68	-2.48	6.15
1.16	98.60	25.00	142.00	23.50	29.00	26.29	-2.79	7.81
0.98	101.00	26.00	168.00	23.50	29.15	29.17	-5.67	32.14
1.01	93.00	29.00	158.00	22.90	28.75	28.15	-5.25	27.54
1.35	93.10	25.00	132.00	25.40	29.82	24.2	1.20	1.45
1.50	47.90	34.00	131.00	28.00	29.15	24.37	3.63	13.21
1.18	41.50	32.00	158.00	26.70	29.15	27.51	-0.81	0.65
1.17	55.00	28.00	148.00	24.70	29.15	26.6	-1.90	3.61
1.12	51.00	30.00	137.00	22.00	29.15	25.12	-3.12	9.74

(*Contd*...)

Table 3 — Results of the predictive analysis of built models with the experimental results obtained by Abdelrahman *et. al.*[28] *(Contd...)*

Weight gain (g/week)	*Survival (%)*	Stocking data (PLs/m^2)	Crop duration (days)	Actual final weight (g)	Temp (°C)	Predicted final weight	Error prediction (g)	Error prediction squared
1.00	63.40	32.00	157.00	22.40	29.15	27.39	-4.99	24.93
1.32	45.20	29.00	151.00	28.50	29.15	26.85	1.65	2.71
1.23	58.30	31.00	146.00	25.70	29.15	26.22	-0.52	0.27
1.35	59.80	18.00	127.00	24.50	29.15	24.72	-0.22	0.05
1.07	61.50	26.00	153.00	23.30	29.15	27.39	-4.09	16.74
1.66	61.00	20.00	146.00	34.60	29.15	26.87	7.73	59.78
1.29	55.70	31.00	144.00	26.50	29.15	25.98	0.52	0.27
1.70	60.80	30.00	112.00	27.20	29.15	22.2	5.00	24.99
1.31	65.40	33.00	126.00	23.50	29.15	23.71	-0.21	0.05
1.41	52.40	27.00	153.00	30.90	28.64	27.79	3.11	9.65
1.45	52.44	28.37	139.61	28.29	29.15	25.51	2.78	7.73
1.16	49.80	27.00	153.00	25.40	29.36	26.93	-1.53	2.34
1.30	45.20	28.00	161.00	29.90	28.98	28.29	1.61	2.60
1.50	40.50	27.00	156.00	33.40	28.93	27.83	5.57	31.01
1.26	64.00	31.00	142.00	25.60	28.77	26.13	-0.53	0.28
1.12	77.80	29.00	162.00	25.90	29.15	28.14	-2.24	5.03
1.05	74.90	32.00	135.00	20.20	29.15	24.84	-4.64	21.56

$$B(SD) = 2.07 * 10^{-6}SD^2 - 1.1 * 10^{-3}SD + 0.295 \quad \text{... (14)}$$

This equation is applicable only in the range of $0 < SD < 200$ and is maximum when *SD* is lowest (as expected that lower stocking density implies higher resources), that is *SD = 0*.

$$B(SD)\max = B(SD = 0) = 0.295 \quad \text{... (15)}$$

Hence, the obtained equation for the best fit normalised relation between growth rate and stocking density is:

$$\alpha(SB) = \frac{B(SD)}{B(SD)max} = 7.014 * 10^{-6}SD^2 - 3.73 * 10^{-3}SD + 1 \quad \text{... (16)}$$

Since this is normalised, the $\alpha(SB)$ is unitless.
For salinity,

$$\beta(S) = \frac{C(S)}{C(S)max} = 5 * 10^{-4}S^2 + 2.6 * 10^{-2}S + 0.66 \quad \text{... (17)}$$

For pH,

$$\gamma(pH) = \frac{Z(pH)}{Z(pH)max} = -0.01(pH)^2 + 0.23(pH) - 0.15 \quad \text{... (18)}$$

Relating the current weight of the shrimp and growth rate

The final weight of the shrimp at the end of the crop cycle can be determined from its daily growth rate, which establishes a mathematical relationship between the initial and final weight, based on days of cultivation:

$$\Delta W = \sum_{t=a}^{b} g(t) \quad \text{... (19)}$$

Where, $g(t)$ denotes the growth rate (weight gained per day) on t^{th} day of observation, with $a < t < b$; ΔW denotes the change in weight from the a^{th}day to the b^{th} day with $b > a$.

If the observation on change in weight is made from the day 0, or the beginning of the cultivation, and ends till the completion of the crop cycle, that is, days of cultivation (abbreviated as *doc*), then the equation modifies into

$$\Delta W = \sum_{t=0}^{doc} g(t) \quad \text{... (20)}$$

This will translate to

$$\Delta W = W_f - W_i = \sum_{t=0}^{doc} g(t) \quad \text{... (21)}$$

Where, W_f denotes the final weight after doc days of cultivation or completion of crop cycle, and W_i denotes the weight at the initial stage of the crop (usually the larvae stage where the weight is < 0.3 g).

For modelling purpose, the data with such fine granularity of observations on the variations of $g(t)$ throughout the lifecycle of the shrimp is unavailable in the literature. The most plausible workaround in this scenario is to work with averages.

Consider, over the complete duration of the growth of the shrimp; there are mean water parameters *T*, *S*, *pH*, *DO* and *SD*

$$\Delta W = W_f - W_i = \sum_{t=0}^{doc} g(t) = \sum_{t=0}^{ts} g_s(t) + \sum_{t=ts}^{tm} g_m(t) + \sum_{t=tm}^{doc} g_l(t) \quad \text{... (22)}$$

Where, g_s, g_m, g_l denotes the growth rates in three categories: small, medium and large and the limits of the summations t_s, t_m denotes the time when shrimp reaches 8 g (the lower-end threshold for medium-size category) and 14 g (lower-end threshold for large-size category). Considering the initial weight of close to zero, the final weight of a shrimp after a duration of cultivation is

$$W_f = \sum_{t=0}^{doc} g(t) = \sum_{t=0}^{ts} g_s(t) + \sum_{t=ts}^{tm} g_m(t) + \sum_{t=tm}^{doc} g_l(t) \quad \ldots (24)$$

Results

Using the derived equations and water quality parameters as input, one can determine the growth rate and, subsequently, the final weight based on the number of days of cultivation.

Accordingly, in the experimental study by Abdelrahman *et al*.[28] recorded the physical parameters like temperature, stocking density and salinity. At the same time, they have adequately maintained the pH and dissolved oxygen content of the water during the culture to favour shrimp growth.

Therefore, during the measurements of predictive analysis, a truncated model was used. This was in accordance with the fact that the $\gamma(pH)$ was considered 1 (since it is already said to be maintained at the optimal levels). The residual equation was used for predicting the final weight of the shrimp for each sample point by substituting the value of the three parameters $T, SD \text{ and } S$ accordingly in the scaled factor model equation.

In all the sample points, the value of DOT (the dissolved oxygen threshold) was calculated for the given value of $T, SD \text{ and } S$ and only in the cases where DO > DOT, the growth equation was used; otherwise, the final weight should be virtually *Zero* (shrimp survival is affected when oxygen is below threshold) (Note: The term *Zero* here is to signify a much hampered growth due to very low survival rate because of the scarce oxygen supply, while the shrimp growth may have some positive value but for the purpose of simplification, the weight is considered zero in an environment below minimum oxygen threshold). However, in the current study, the dissolved oxygen threshold model worked well, as no sample points predicted so low survival that the growth rate will be zero, which is also seen in the actual recorded results.

It is worth highlighting the point here that the Whiteleg shrimp is a euryhaline species. While some of the models suggest low salinity to be more preferable, other suggests the high salinity model. Hence, this study introduced a multiplier '*A*' in the equation to appropriately scale the model so as to accommodate these discrepancies. Abdelrahman *et al*.[28] used the Whiteleg stock that is suitable for low salinity culture, but the model is trained such that under the normalisation, the low salinity values are considered as the suppressed growth (as shown in Fig. 6), and thus, here, the multiplier '*A*' in the growth equation comes handy. A high value of '*A*' was chosen to compensate for such discrepancy since the quality of the Whiteleg seeds used in Abdelrahman *et al*.[28] experiment were more suited towards the low salinity culture.

Results of the prediction from the current study (the *prediction*, see column named Predicted Final weight) were compared with the observed samples of Abdelrahman *et al*.[28] (actual ground truth, see column named Actual Final weight) and are tabulated in Table 3. The modelled shrimp's growth equation has been plotted in a 3D chart (variation of final weight with temperature and stocking density, at A = 1, and salinity and pH at their optimal levels) (Fig. 7).

Based on the absolute difference between the actual $\hat{y}$ and the predicted results y, the mean error and root mean squared error are calculated as follows:

$$y = W_f = \sum_{t=0}^{doc} g(t) = \sum_{t=0}^{ts} g_s(t) + \sum_{t=ts}^{tm} g_m(t) + \sum_{t=tm}^{doc} g_l(t) \quad \ldots (24)$$

$$Mean\ error = \frac{\sum_n (\hat{y} - y)}{n} \quad \ldots (25)$$

$$Root\ mean\ squared\ error = \sqrt{\frac{\sum_n (\hat{y} - y)^2}{n}} \quad \ldots (26)$$

Where, n denotes the number of sample points from the dataset. The comparison results gave the mean error of 0.1 g in the final weight of the shrimp (where days of cultivation (doc) ranged from 100 to 140 days).

Discussion

The final weight of the shrimp, when predicted through models of the present study and verified with the experimental results of Abdelrahman *et al.*[28] showcased a mean error of just 0.1 g, which is roughly 0.5 % error considering the average weight of 20 g, and RMSE of 3.76 g (which is roughly 19 % error rate on average) in the complete sampled dataset. This showcased that for a general pond with 1500 – 2000 sq. m, which are common for open-pond

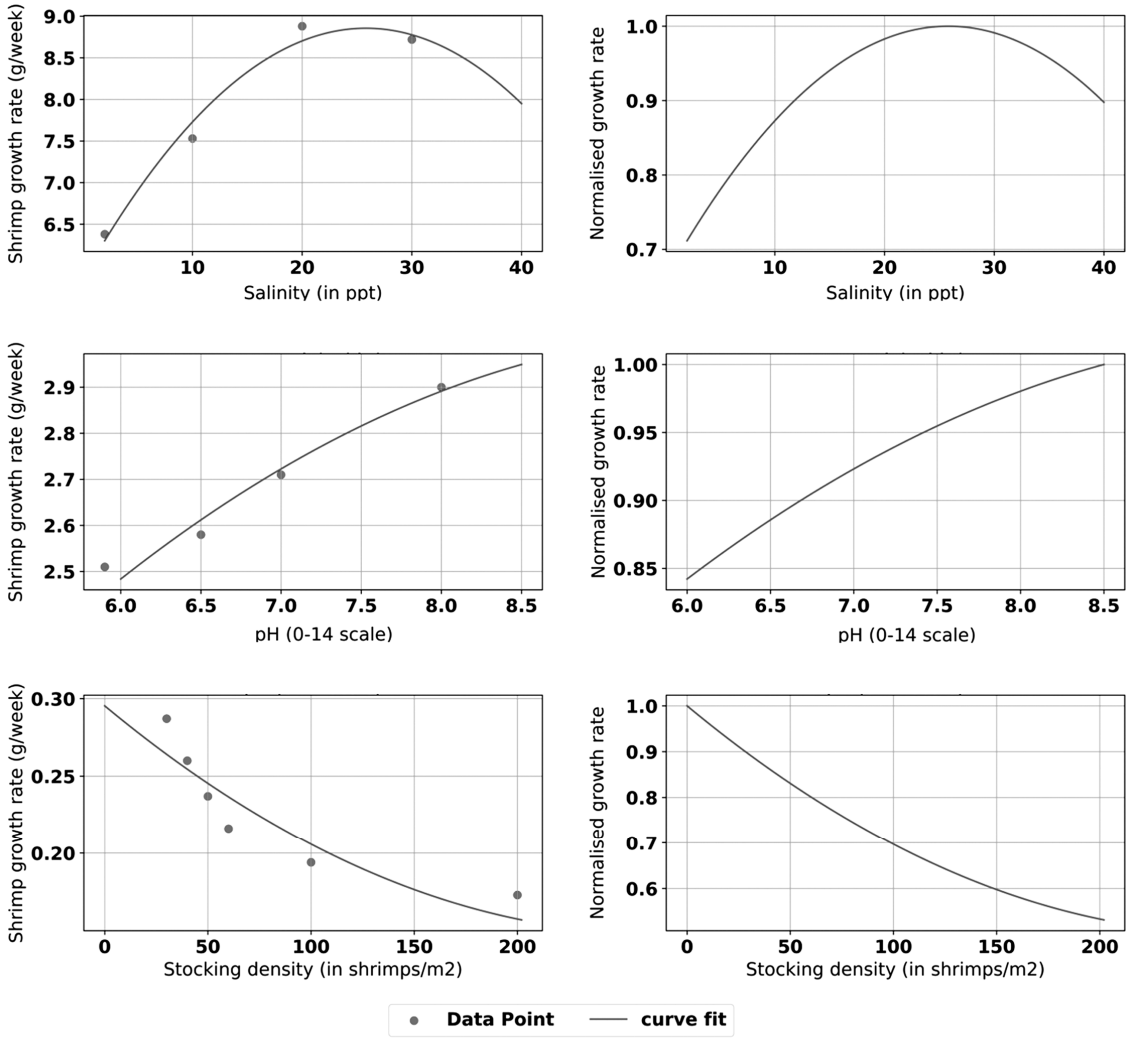

Fig. 6 — Effect of salinity (in parts per tonne (ppt)), pH and stocking density (from top to bottom) on the growth rates of the Whiteleg shrimp. Negative correlation is observed. The normalised graph (by dividing the graph on left by its maximum value) is shown on the right

aquaculture at a small scale, with a stocking density of 30 shrimps/sq. m, implying the total stock of 4500 shrimps, this can accumulate to 90 kg of biomass (considering 20 g per shrimp), and thus the model can predict the expected biomass with 0.5 % error or 450 g (roughly 0.5 kg) of error on average.

The study attempts to bring four parameters, the temperature, the stocking density, the pH of the water and the salinity into one single equation that can justify the variations in shrimp growth under varying environmental, water quality and stocking conditions.

While the study makes use of datasets from various sources of literature and makes certain assumptions that simplify the model complexity. There are a few limitations of the study and the most significant one is the range of applicability of the model. Since, the model is derived from very few data points, its applicability can be questioned in the regions where one needs to extrapolate the curve because the existing data does not cover the accurate trend outside of the training data. Another important challenge of such a type of modelling is that it is not even ubiquitous to all the shrimp species. Since, every sub-species also exhibits varying responses to any environmental stress/stimuli, the same curves/ equations cannot be applied to all organisms blindly. For example, two shrimps *Penaeus monodon* and *L. vannamei* don't have significant differences in their feeding patterns, growth rates and final weights. Variations between various seed qualities also pose a key concern because earlier shrimp farms, which mainly derived seeds from wild & natural habitats,

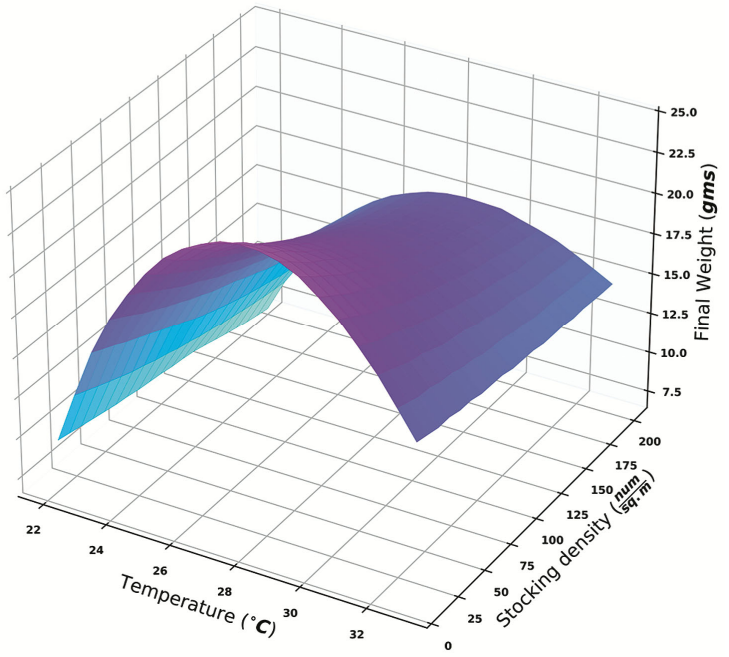

Fig. 7 — Variation of the final weight of the Whiteleg shrimp with temperature and stocking density for 120 days

were better assimilated to higher salinities, and thus, higher salinities between 15 – 30 ppt were traditionally considered optimal for growth. But now, recent advancements have enabled freshwater aquaculture of Whiteleg shrimp. As an euryhaline species, Whiteleg can adapt to low-salinity environments, and these developments have demonstrated the feasibility of producing efficient stocks in freshwater or less saline aquaculture systems. Therefore, despite a traditional study showing a *'false'* suppressed effect of low salinity on the Whiteleg growth (considering the seeds/larvae used in Abdelrahman *et al.*[28] were accustomed to that salinity range) in the present study added a multiplier parameter to account for such discrepancy.

Despite the fact that the scaled growth model depends on a statistical independence between the parameters, there is a relationship (though it is weak and can be considered constant over some reasonable range of temperature) governing the effect of temperature and salinity on the dissolved oxygen level of the water. Warmer water holds less DO compared to colder water. This is because oxygen molecules have more kinetic energy at higher temperatures, making them less likely to be absorbed by water molecules. Also, as the temperature increases, the metabolic rate of shrimp rises. This leads to a higher demand for oxygen, further depleting DO levels. Saltier water (higher salinity) is denser than freshwater. Denser water can hold slightly less dissolved oxygen compared to less dense water at the same temperature. High salinity can create a barrier to oxygen diffusion from the atmosphere into the water column, impacting DO saturation levels. In terms of the effect of the pH level of the water, at extreme pH levels, shrimp expend extra energy regulating internal pH, diverting resources away from growth[41]. Additionally, highly acidic water can impair nutrient uptake and hinder moulting, a crucial stage for shrimp development[42].

While the modelling was restricted to the above-mentioned five parameters, three other key factors to consider are redox potential (or Oxidation Reduction Potential, commonly abbreviated as ORP), feed quality, and Total Ammonium Nitrate (TAN) content. An ideal ORP range (around 650 – 750 mV) promotes beneficial bacterial activity that breaks down organic matter, maintaining good water quality. Low ORP signifies an oxygen-depleted environment, potentially stressing the shrimp. Feed quality directly impacts shrimp health and waste production. High-quality feeds formulated for shrimp need to be ensured for optimal nutrition and minimise waste. Elevated TAN (the sum of ammonia (toxic) and ammonium) levels can cause ammonia toxicity, harming shrimp growth, survival, and immune function. Proper aeration and

biofiltration systems help maintain adequate ORP and remove excess nutrients. While these factors are also significant in orchestrating the shrimp life cycle, as these pose challenges in terms of either quantifiability (the quality of the feed) or feasibility issues. For example, the sensors for TAN content measurement are very specialised and costly. The water quality judged suitable for growth only based on temperature, salinity, pH and dissolved oxygen level will also not abruptly fall outside the suitable limits for ORP parameter (in general) and therefore, measuring ORP explicitly may pose redundancy for many scenarios and will also increase deployment costs, making the complete solution more infeasible for implementation considering the economic demography of the aquaculture farmers in India.

Conclusion

Study bypassed traditional, labour-intensive water quality monitoring for shrimp farms by building a machine-learning model using existing data to identify optimal water conditions for shrimp growth. This innovative approach achieved positive results, demonstrating its feasibility. This is the first such model of its kind, and its potential impact is significant. In India, a major player in aquaculture, this model can revolutionise the industry. The predictive analysis can help farmers optimise the farm conditions, boosting yields, reducing disease, and improving overall farm management. The developed model can be shared as a smart phone application where farmers can provide their farm status and the predictive models can predict the amount of production from the farm based on growth rates of the culture. This will help farmers in planning early for the future crops as well as getting maximum returns from the current crop. A higher productivity and optimal farm management translates to a stronger and resilient local economy and increased profits for Indian shrimp farmers.

Acknowledgement

This research was made possible by the generous support of Maritime Research Center (MRC), Pune. The research fellowship grant and expert support from researchers and staff provided essential resources that enabled us to conduct this research and contribute to the field of aquaculture. We are grateful for Maritime Research Center's continued commitment to supporting innovative research in aquaculture and Underwater Domain Awareness (UDA).

Conflict of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

Author Contributions

SN: Literature review, conceptualisation and devising the methodology. SP: Lead in whole work, programming and software, and supervision of the writing of paper. SN & SP: Writing original draft. AD: Writing, Review and editing.

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