Validating Satellite Imagery for Remote Monitoring of Water Quality at Fish Farms

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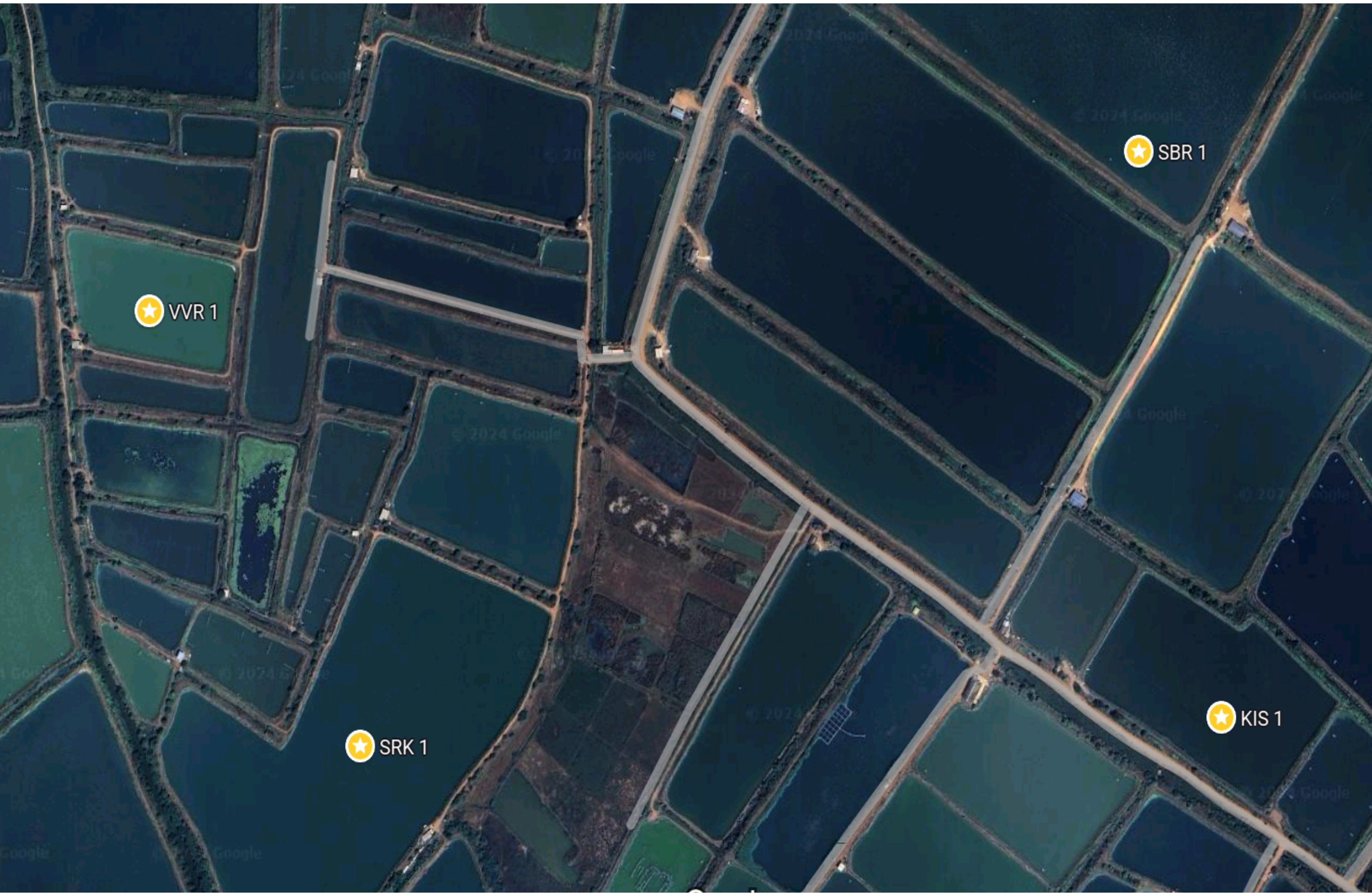

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Acknowledgements

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Acronyms and Abbreviations

ARA	Alliance for Responsible Aquaculture
Chl-a	Chlorophyll-a
DO	Dissolved Oxygen
FWI	Fish Welfare Initiative
MAPE	Mean Absolute Percentage Error
PC	Phycocyanin
PMSE	Root Mean Squared Error

Executive Summary

Fish Welfare Initiative's (FWI) current core program is the Alliance for Responsible Aquaculture (ARA). This program centers on FWI field teams collecting water quality data from aquaculture ponds and providing the farmers with recommendations for corrective actions in the event of key water quality parameters indicating that fish may be exposed to poor conditions. The current ARA model requires FWI data collectors to physically visit fish farms, with the current strategy being to conduct visits approximately once a month to each pond. The requirement to physically visit farms limits scalability, and the once-a-month frequency of visits—which is driven by resource requirements—limits the impact, as farmers may experience water quality issues requiring corrective actions in-between visits. Given these concerns, there is a desire to make improvements to the ARA such that the program is more scalable and impactful.

FWI is interested in exploring if using satellite imagery to remotely monitor water quality is a viable option to consider incorporating into the ARA. The hypothesis is that if studies reveal that water quality data collected through analysis of satellite imagery are sufficiently accurate and reliable, the ARA model could be modified to exploit remote data collection, allowing for more frequent collection of water quality data at all ponds without the need for additional human resources.

To provide evidence as to whether water quality parameters determined through analysis of satellite imagery are sufficiently accurate and reliable to inform decisions on the ground, FWI collaborated with Captain Fresh, an Indian technology company with experience using satellite imagery within the aquaculture industry in India. A proof-of-concept study was conducted across 20 fish farms—all part of the ARA in the Kolleru region of Andhra Pradesh—in which water quality data obtained from analysis of satellite images (provided by Captain Fresh) were compared with empirical water quality data obtained by direct measurements at the same fish farms (provided by FWI).

Water quality data were collected at the 20 study ponds using both empirical data collection (i.e. data collected directly from ponds) and remote data collection (i.e. data determined through analysis of satellite imagery). Data were collected for six water quality parameters: ammonia, dissolved oxygen (DO), chlorophyll-a (Chl-a), phycocyanin (PC), pH, and temperature. Water quality parameters were collected every five days, corresponding to the flyover schedule for the Sentinel-2 satellite, with five rounds of data collection for each pond (once every five days).

For each of the six water quality parameters, matched data points (i.e. data points collected by both methods—empirically and remotely—at a given pond at a given time point) were split randomly into two groups. One of the two groups was used to train the model to predict the relevant water quality parameter, and the other group was subsequently used to validate the trained model. Validating the models involved assessing how closely the predicted and empirical values matched, and used four statistical measurements: correlation coefficient (r); coefficient of determination (R^2); root mean squared error (RMSE); and mean absolute percentage error (MAPE). Generally, r values close to ±1, R^2 values close to 1, and small RMSE and MAPE values, are associated with the best predictive models.

For four of the six water quality parameters—ammonia, DO, Chl-a, and PC—predicted and empirical data were sufficiently correlated to suggest that remote monitoring may have utility. Most encouragingly, the predicted and empirical data for both PC and Chl-a show high correlations (r values of 0.99 and 0.96, respectively; and R^2 values of 0.98 and 0.92, respectively). Predicted and empirical data for both DO and ammonia were less strongly correlated (r values of 0.90 and 0.92, respectively; and R^2 values of 0.81 and 0.85, respectively), but still at levels that suggest that remote monitoring of these water quality parameters is feasible. For two of the six water quality parameters—pH and temperature—analysis of predicted and empirical data showed no correlation (r values of 0.22 and 0.41, respectively; and R^2 values of 0.05 and 0.17, respectively).

The four water quality parameters with high r and R^2 values—ammonia, DO, Chl-a, and PC—also had low RMSE and MAPE values, implying the models' predictions are close to the actual values. This suggests that the models may have utility for remote monitoring of ammonia, DO, Chl-a, and PC. In contrast, the high MAPE values for pH and temperature—25.03% and 29.06%, respectively—imply significant deviation of the predicted values from the actual values. This, coupled with their low r and R^2 values, suggests that remote monitoring of pH and temperature using these models will not provide sufficiently accurate information.

Overall, the findings from this proof-of-concept study are highly encouraging, indicating real potential to utilize remote monitoring for ammonia, DO, Chl-a, and/or PC via analysis of satellite imagery as part of FWI's flagship ARA program. However, before incorporating remote monitoring of fish farms into the ARA, additional work is needed to improve the models for predicting these water quality parameters to ensure accuracy and reliability, Additionally, consideration needs to be given to understanding how weather—specifically, cloud cover—may impact the ARA if the program shifted to a model based on analysis of satellite imagery. The effect of clouds is a well-recognized limitation of utilizing satellite imagery for remote data collection, and cloud cover did impact data collection during this study. Regardless of how accurate and reliable the models are, understanding how significant a limitation cloud cover would be is an important factor to consider before modifying the ARA program.

Introduction

Fish Welfare Initiative's (FWI) current core program is the Alliance for Responsible Aquaculture (ARA). This program centers on FWI field teams collecting water quality data—including, ammonia, dissolved oxygen (DO), pH, and phytoplankton indicators (chlorophyll-A [Chl-a] and phycocyanin [PC])—from aquaculture ponds in Andhra Pradesh and providing the farmers with recommendations for corrective actions in the event of key water quality parameters indicating that fish may be exposed to poor welfare conditions.

The ARA currently supports approximately 100 fish farms, primarily in the Kolleru and Nellore regions of Andhra Pradesh. The current ARA model requires FWI data collectors to physically visit fish farms, with the current strategy being to conduct visits approximately once a month to each pond. The requirement to physically visit farms limits scalability, as increasing the number of farms participating in the ARA requires a linear increase in the number of data collectors. Similarly, the approximate once-a-month frequency of visits—which is driven by resource requirements—limits the impact, as farmers may experience water quality issues in between visits, meaning fishes could be exposed to welfare issues which FWI can't identify or respond to. Given these concerns, there is a desire to make improvements to the ARA such that it is more scalable and impactful.

FWI is interested in exploring if using satellite imagery to remotely assess water quality is a viable option to incorporate into the ARA. The hypothesis is that if studies reveal that water quality data collected through analysis of satellite imagery are sufficiently accurate and reliable, the ARA model could be modified to exploit remote data collection, allowing for more frequent collection of water quality data at all ponds (accounting for the frequency of satellite fly-overs, ponds could be monitored five-to-six times a month compared to the current once-a-month strategy) without the need for additional human resources.

FWI has no prior experience using satellite imagery. Instead of setting up its own in-house systems and recruiting experienced personnel to test the validity of using satellite imagery for remotely detecting water quality parameters—which would require considerable time and resources, and is considered a risk given that studies may reveal that the concept is not suitable for FWI to take forward—FWI partnered with Captain Fresh on a short-term proof-of-concept study.

Captain Fresh is an Indian technology company that connects seafood suppliers with retailers using a proprietary farm-to-retail digital platform. Their platform facilitates the streamlining of sourcing, strives to ensure consistent quality through standardization, and offers digital traceability systems. A key player in the Indian seafood and aquaculture industry, Captain Fresh coordinates a vast network of retailers and individual sellers, supporting global trade in fresh and frozen seafood products through the use of advanced technology to maintain quality and operational efficiency across global markets.

While Captain Fresh has considerable experience using satellite imagery for the aquaculture industry in India, they do not use it in the way FWI hopes to use it. Although Captain Fresh does not use satellite imagery for remotely detecting water quality parameters, leveraging their experience with accessing satellite imagery, analyzing images, and developing and refining algorithms allowed FWI to validate the concept of remote water quality monitoring, with a view to informing whether the concept was worthwhile to take forward, either into additional studies or into a fully-fledged program. Figure 1 shows how the study was conceived to inform FWI's programmatic decision-making.

To provide evidence as to whether water quality parameters determined through analysis of satellite imagery are sufficiently accurate and reliable to inform decisions on the ground, FWI collaborated with Captain Fresh to compare water quality data obtained from analysis of satellite images (provided by Captain Fresh) with empirical water quality data obtained by direct measurements at the same fish farms (provided by FWI). This small-scale proof-of-concept study focused on 20 fish farms (earthen ponds)—all part of the ARA—in the Kolleru region of Andhra Pradesh.

Justification for conducting this study

If using satellite imagery is a viable method to detect ponds with water quality issues that are a concern for fish welfare, FWI could:

- scale-up the ARA with less reliance on "on site" water quality monitoring by data collectors
- collect data more frequently than currently practiced as part of the ARA
- offer more targeted support to at-risk farmers (i.e. farmers who exhibit consistent water quality problems)
- identify non-ARA farmers who may benefit from FWI's support, helping FWI to conduct a more targeted farmer engagement/sign-up process (i.e. prioritize signing up farmers with known and consistent water quality problems).
- Improve the ARA program's impact and cost-effectiveness, prioritizing resources towards fish farms with known and consistent water quality issues.

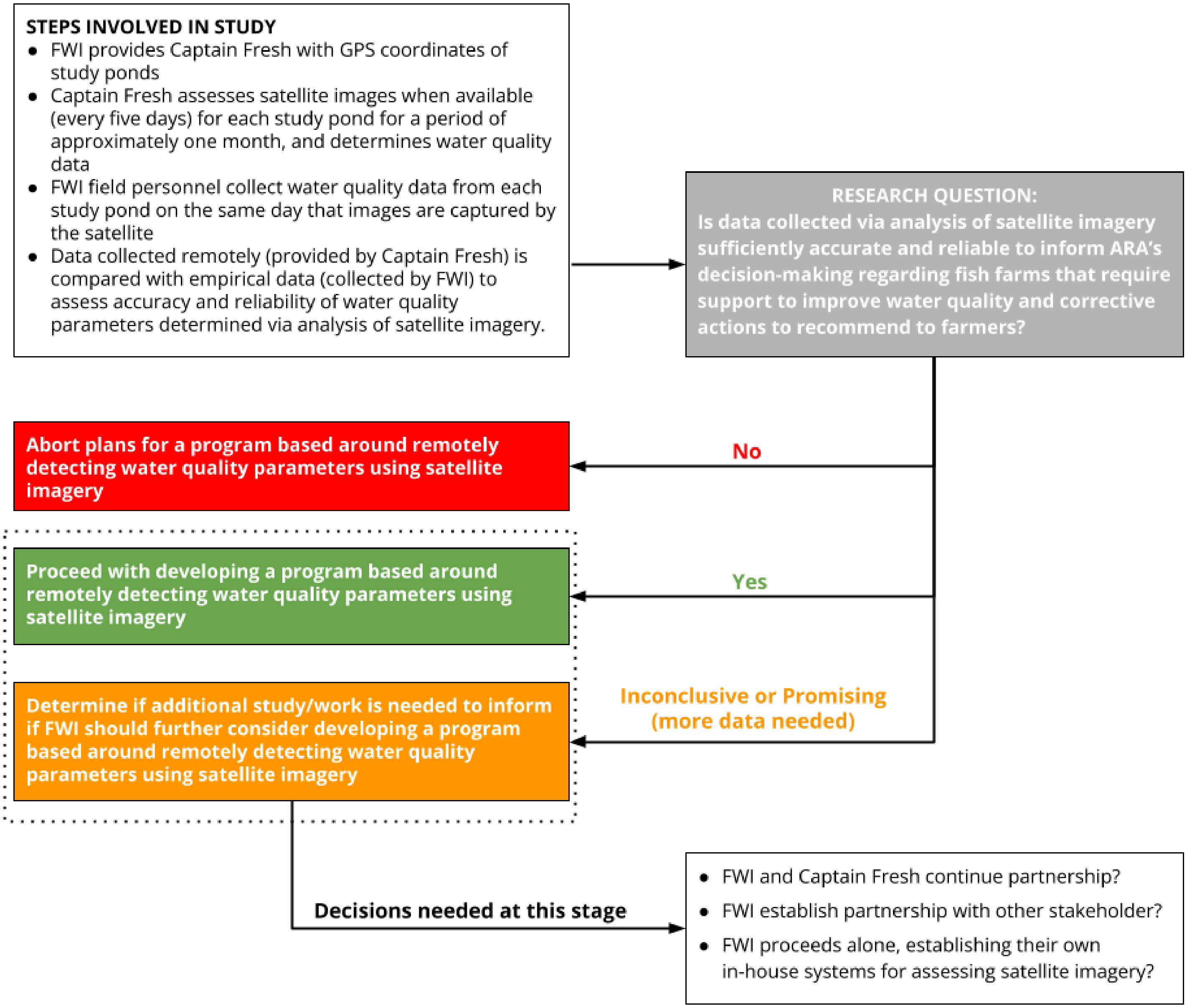

Figure 1. Overview of proof-of-concept study to assess the viability of, and inform FWI's decisions for, using satellite imagery for remote monitoring of water quality at fish farms.

Methodology

Selection of Study Ponds

Twenty ponds were selected purposively, taking into account logistics of data collection (for each day of data collection, it was critical that all 20 ponds could be visited during a narrow time window to match as closely as possible to the flyover schedule of the Sentinel-2 satellite). ARA ponds in the Kolleru region were considered for selection. Ponds below 3.5 acres in size, and ponds not actively farming at the time (i.e. no, or low levels, of water due to the pond preparation activities in-between cycles) were excluded from the selection process.

Ponds were chosen in two clusters such that a schedule could be created allowing for two data collectors to visit ten ponds each in the desired time window (approximately 2.5 hours; Table S1). Practice runs were conducted in advance of the study to ensure that the data could be collected from the 20 selected ponds in the desired time window.

Data Collection at Study Ponds

Water quality data were collected at the 20 study ponds using both empirical data collection (i.e. data collected directly from ponds) and remote data collection (i.e. data determined through analysis of satellite imagery). Data for six water quality parameters were collected: ammonia, DO, Chl-a, PC, pH, and temperature. Water quality parameters were collected every five days, corresponding to the flyover schedule for the Sentinel-2 satellite, with five rounds of data collection for each pond (once every five days).

Remote data was captured every five days between 10:25 am to 10:45 am, according to the flyover schedule of the Sentinel-2 satellite. Empirical data collection occurred on the same days as the remote data collection, but with a wider time window (approx 9:00 am to 11:20 am). Perfectly aligning the time of empirical data collection with the satellite flyover schedule was impossible due to resource constraints. While the time windows for the two components of data collection could not be perfectly matched, all empirical data was collected during an approximate 2.5-hour window in the morning spanning the time window for which satellite data was captured, and did not go past 11:30 am to minimize the influence of the sun on some of the water quality parameters (notably, DO, Chl-a, PC, and temperature).

Empirical Data Collection

On each of the 5 data collection days, the 20 ponds were visited in a predetermined sequence (Table S1). Two data collectors were assigned 10 ponds each, and worked in tandem to ensure that the ponds were visited in the same order and at approximately the same time each day. On each of the five data collection days, each of the two data collectors collected data from their first assigned pond at approximately 9:00 am, and their final assigned pond at approximately 11:05 am (data collector 1; cluster 1) and 11:20 am (data collector 2; cluster 2).

At each pond, a YSI ProDSS handheld meter was used to collect data for five of the six water quality parameters of focus for this study: DO, Chl-a, PC, pH, and temperature. Standing at the edge of a pond, the sensors of the ProDSS handheld meter were submerged in the water, per the manufacturer's instructions.[1] The day before data collection, all sensors on the ProDSS meter were calibrated as per the manufacturer's instructions.[2] After data collection at each pond, all sensors, as well as the cables, on the ProDSS meter were disinfected with 3% hydrogen peroxide to minimize the chances of contamination of other ponds with potential pathogens. Ammonia levels were determined by collecting a sample of water from each pond at the time of the visit, storing it in an airtight container, and analyzing the sample upon returning to the laboratory using a Hanna spectrophotometer.[3]

Remote Data Collection

Data for each of the six water quality parameters of focus at each of the study ponds were determined by Captain Fresh, applying proprietary algorithms to extract data from images collected on each of the five days of data collection (Figure 2). For each image, the focus of attention for analysis corresponded to the GPS coordinates for the relevant pond provided by FWI, corresponding to the same location from where data collectors collected the empirical data.

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[1] ProDIGITIAL User Manual, Xylem. Manual available at https://www.ysi.com/file%20library/documents/manuals/ysi_prodss_user_manual_english.pdf
[2] Ibid.
[3] Ammonia Low Range Photometer, Instruction Manual, Hanna Instruments. Manual available at https://www.hannainst.com/hubfs/product-manuals/MAN97700_12_19.pdf

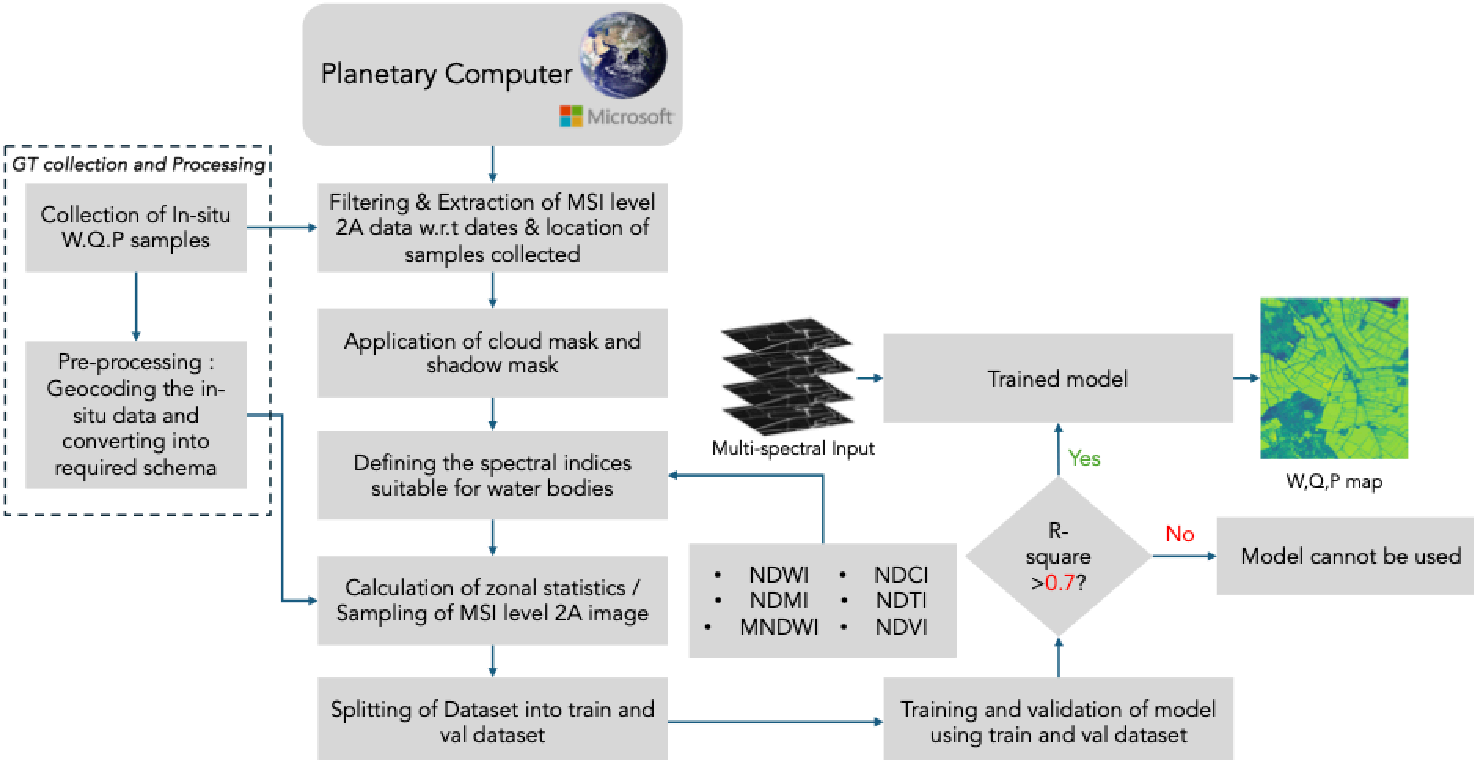

Figure 2. Determination of water quality data from analysis of satellite imagery. NDWI=normalized difference water index; NDMI=normalized difference moisture index; MNDWI=modified normalized difference water index; NDCI=normalized difference chlorophyll index; NDTI=normalized difference turbidity index; NDVI=normalized difference vegetation index.

Training and Validation of Remote Data Collection Models

For each of the six water quality parameters, matched data points (i.e. data points collected by both methods—empirically and remotely—at a given pond at a given time point) were split randomly into two groups. One of the two groups ("train dataset") was used to train the model to predict the relevant water quality parameter, and the other group ("val dataset") was subsequently used to validate the trained model (Figure 2). Validating the models (i.e. assessing how closely the predicted and empirical values matched) involved log, square root, and Box-Cox transformation of the data, assessing the data normality by Q-Q plots and shapiro wilk test, and selection of the transformation that best approximates a normal distribution for the data. After having this information, we determined a Pearson correlation coefficient (r) to assess the strength and direction of the linear relationship between predicted and empirical data. To further understand how well the data fit the linear model, we determined the coefficient of determination (R^2). R^2 explains the proportion of the variance in the dependent variable that is predictable from the independent variable. While r and R^2 are related (the coefficient of determination is the square of the Pearson correlation coefficient) they provide different perspectives on the data: r gives a direct measure of the linear correlation, while R^2 provides an indication of the explanatory power of the linear relationship. Both coefficients are complementary, indicating whether the relationship is strong or weak, but R^2 provides a more intuitive sense of how much of the variability in the predicted satellite is explained by the empirical data. Values of r range from -1 to 1, and R^2 values range from 0 to 1, with values closer to ±1 and 1, respectively, indicating that the model's predictions are close to the actual values, implying a good predictive model.

To further evaluate the performance of the models for each water quality parameter, we calculated the root mean squared error (RMSE), a commonly used metric to evaluate the accuracy of a predictive model. RMSE measures the average difference between predicted and actual (ground-truthed) values, indicating how tightly the actual values cluster around the predicted values. RMSE provides a measure in the same scale/units as the variable being assessed (i.e. the respective water quality parameters). To provide a measure in percentage terms, we calculated the mean absolute percentage error (MAPE). MAPE measures the average percentage deviation of the predicted values from the actual values. Low RMSE and MAPE values indicate that the model's predictions are close to the actual values, implying a good fit, whereas high RMSE and MAPE values suggest a poor fit.

Generally, large r and R^2 values, and small RMSE and MAPE values, are associated with the best predictive models.

Results

Data collection took place every five days, starting on February 19, 2024, and ending on March 10, 2024. For empirical data collection, 20 ponds were visited every five days by FWI data collectors to collect data for the six water quality parameters (Table 1). The plan was to collect 100 data points in total for each of the 6 water quality parameters over the course of the study (1 data point at 20 ponds every 5 days). On the final day of data collection (March 10), data from one pond—PKR 1—could not be collected as the water levels had been significantly reduced as part of the pond preparation process for the next cycle of farming. As such, 99 data points were collected for each of the water quality parameters. The actual times at which data were collected from each pond are shown in Table S2; the data collected for each of the six water quality parameters are shown in Table S3-S8.

For remote data collection, satellite images taken by the Sentinel-2 satellite for each of the 20 study ponds were analyzed every five days, and data for each of the six water quality parameters of focus were determined using proprietary algorithms (Table 2). The plan was to collect 100 data points in total for each of the 6 water quality parameters over the course of the study (1 data point at 20 ponds every 5 days). However, data could not be extracted from some satellite images due to poor imaging resulting from direct cloud cover, or shadowing caused by overhead clouds, at the time the images were taken (Table 2 and Table S9). In total, 81 data points were determined for each of the water quality parameters via analysis of satellite images.

Of the 81 empirical data points for each water quality parameter that could be matched with data obtained through analysis of satellite imagery, 51 were randomly selected by Captain Fresh analysts to train their model (Figure 3). The remaining matched 30 data points for each water quality parameter were used to validate the trained model by directly comparing the “ground-truthed” data (i.e. the empirical data) with the predicted data (i.e. the data collected remotely by analysis of satellite images).

Table 1. Water quality data collected directly at study ponds by FWI data collectors. Time window indicates the time at which data collectors began/ended their work on each data collection day; see Table S2 for actual time of data collection at individual study ponds, and Table S3-S8 for the actual values obtained. NH_3=ammonia.

Date	Time window (approx)	No. of data points collected across 20 study ponds						Comment
		NH_3	DO	Chl-a	PC	pH	Temp	
Feb 19, 2024	9:00-11:20 am	20	20	20	20	20	20	Data collected from all 20 study ponds
Feb 24, 2024	9:00-11:20 am	20	20	20	20	20	20	Data collected from all 20 study ponds
Feb 29, 2024	9:00-11:20 am	20	20	20	20	20	20	Data collected from all 20 study ponds
Mar 5, 2024	9:00-11:20 am	20	20	20	20	20	20	Data collected from all 20 study ponds
Mar 10, 2024	9:00-11:20 am	19	19	19	19	19	19	Data could not be collected from 1 of the 20 study ponds due to low water levels as a result of the pond being prepared for the next cycle of farming.
Total data points collected		**99**	**99**	**99**	**99**	**99**	**99**	

Table 2. Water quality data determined by analysis of satellite imagery by Captain Fresh analysts. Images of study ponds were taken by Sentinel-2 satellite between 10:25 am and 10:45 am every five days. NH_3=ammonia.

Date	Time window	No. of data points determined from analysis of satellite imagery						Comment
		NH_3	DO	Chl-a	PC	pH	Temp	
Feb 19, 2024	10:25-10:45 am	20	20	20	20	20	20	Data determined from images for all 20 study ponds as planned
Feb 24, 2024	10:25-10:45 am	7	7	7	7	7	7	Cloud cover or shadowing caused by clouds precluded analysis of images from 13 of the 20 study ponds
Feb 29, 2024	10:25-10:45 am	20	20	20	20	20	20	Data determined from images for all 20 study ponds as planned
Mar 3, 2024	10:25-10:45 am	18	18	18	18	18	18	Cloud cover or shadowing caused by clouds precluded analysis of images from 2 of the 20 study ponds
Mar 10, 2024	10:25-10:45 am	16	16	16	16	16	16	Cloud cover or shadowing caused by clouds precluded analysis of images from 3 of the 20 study ponds. For 1 study pond data could not be collected due to low water levels as a result of the pond being prepared for the next cycle of farming.
Total data points collected		**81**	**81**	**81**	**81**	**81**	**81**	

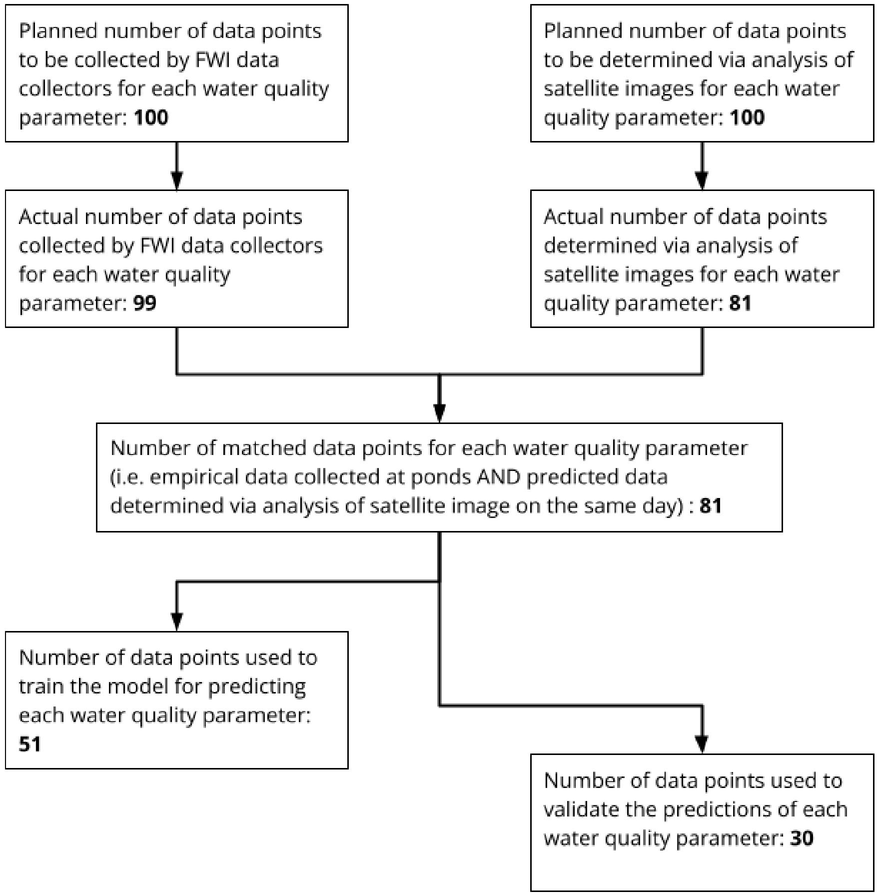

Figure 3. Collection and use of empirical and predicted data for each of the six water quality parameters of focus for the study.

To assess how closely the predicted and empirical values matched for each of the six water quality parameters, we determined a Pearson correlation coefficient (r). The correlation between satellite-derived and on-site measurements for four of the six water quality parameters—ammonia, DO, Chl-a, and PC—were all above 0.90, indicating very strong linear relationships (Figure 4 and Table 3). This was further supported by the coefficient of determination (R^2), which exceeded 0.81 for these four water quality parameters, indicating that over 81% of the variance in on-site measurements can be explained by satellite data (Table 3). In contrast, pH and temperature did not show a significant correlation, with r and R^2 values close to zero, indicating no linear relationship between the satellite data and on-site measurements for these parameters.

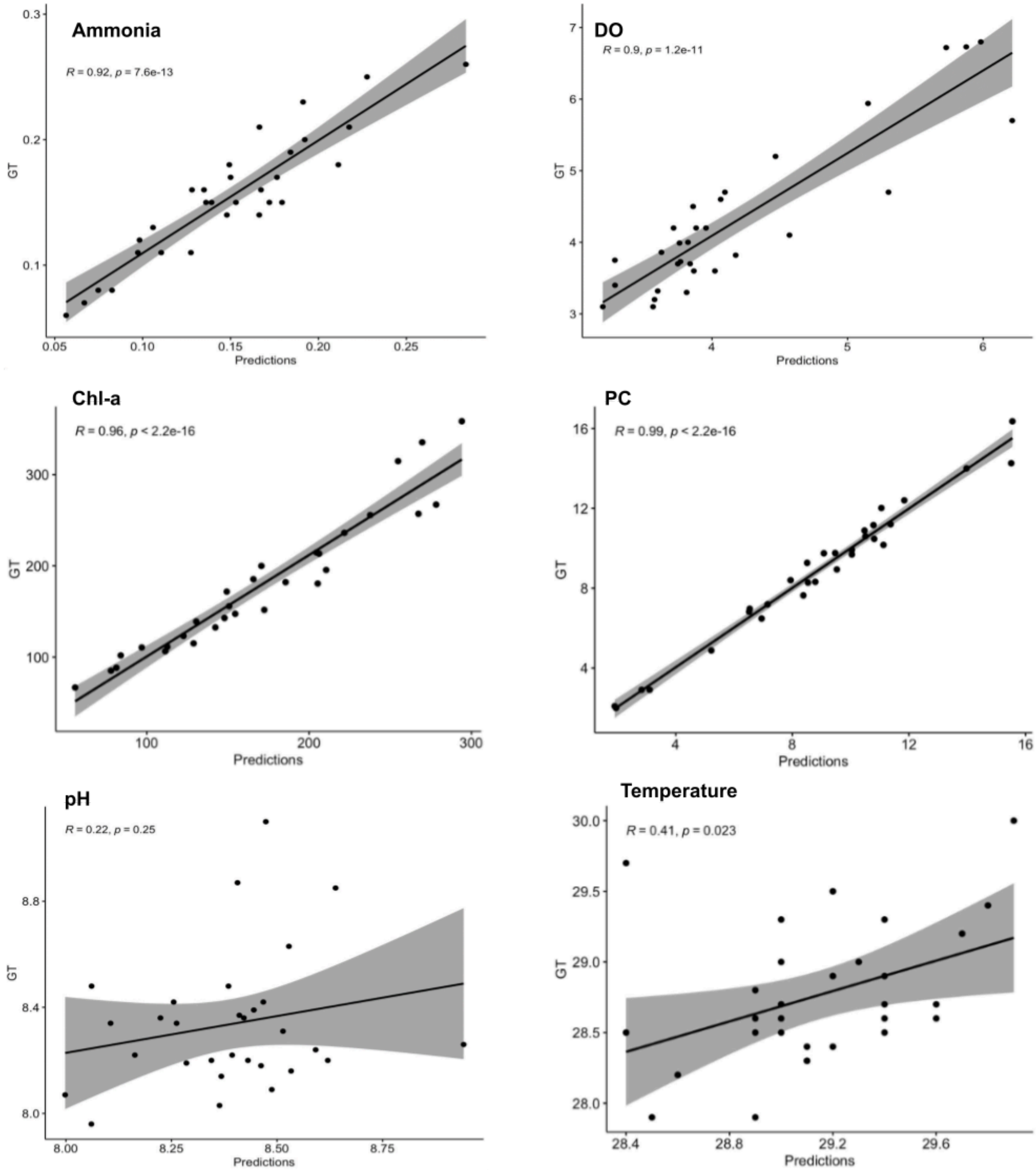

Figure 4. Correlation of empirical, ground-truthed (GT) data with predicted data determined from analysis of satellite imagery for each water quality parameter.

Table 3. Analysis of accuracy of the models for predicting the six water quality parameters.

Water quality parameter	Coefficient of correlation (r)	Coefficient of determination (R^2)	Root mean squared error (RMSE)	Mean absolute percentage error (MAPE)
Ammonia	0.92	0.85	0.02 mg/L	10.28%
DO	0.90	0.81	0.49 mg/L	13.35%
Chl-a	0.96	0.92	23.95 μg/L	8.20%
PC	0.99	0.98	0.52 μg/L	3.63%
pH	0.22	0.05	0.28	25.03%
Temperature	0.41	0.17	0.61 ^{O}C	29.06%

The four water quality parameters with high r and R^2 values—ammonia, DO, Chl-a, and PC—also had low RMSE and MAPE values, implying the models' predictions are close to the actual values (Table 3). The MAPE for these four parameters ranged from 3.63% (PC) to 13.35% (DO). In contrast, the high MAPE values for pH and temperature—25.03% and 29.06%, respectively—imply significant deviation of the predicted values from the actual values, limiting the utility of the models for remote monitoring.

Discussion

The primary objective of this proof-of-concept study was to determine if key water quality parameters determined through analysis of satellite imagery are sufficiently accurate and reliable to inform decisions on the ground. To answer this question, values for six water quality parameters—ammonia, DO, Chl-a, PC, pH, and temperature—were determined via analysis of satellite imagery, and compared to empirical values to assess how closely the predicted and empirical values matched.

For four of the six water quality parameters—ammonia, DO, Chl-a, and PC—predicted and empirical data were sufficiently correlated to suggest that remote monitoring may have utility. The R^2 values for these four water quality parameters ranged from 0.81 to 0.98, all significantly exceeding the minimum target value of 0.70 (Figure 2). These findings indicate that amongst these four water quality parameters, at least 81% of the variance in the dependent variable is predictable from the independent variable (as high as 98% in the case of PC). DO levels measured on-site correlated highly with satellite data (r value of 0.90 and R^2 value of 0.81), with a MAPE below 14%, suggesting to some extent that satellite imagery can reliably estimate oxygen concentrations—a crucial indicator for fish health and optimal conditions—in ponds. DO has been considered perhaps the single most critical water quality parameter in the Kolleru region of Andhra Pradesh by the ARA program, being the water quality parameter recorded out of range the most frequently by ARA data collectors, with some farms exhibiting consistent DO issues. The ability to remotely monitor DO levels offers real potential to improve the scalability and impact of the ARA. Ammonia levels—a crucial indicator of water quality and fish stress—measured on-site correlated highly with measurements made from analysis of satellite imagery (r value of 0.92 and R^2 value of 0.85) with an error of approximately 10% of the predicted measurements, indicating the potential of remote monitoring of nitrogenous waste in aquaculture environments. Ammonia has recently become a water quality parameter of increased importance for the ARA program, so the potential to remotely monitor ammonia levels, particularly in association with DO levels, offers intriguing possibilities for improving the scalability and impact of the ARA. Chl-a levels—an indicator of phytoplankton abundance—also were highly correlated (r value of 0.96 and R^2 value of 0.93). Phytoplankton is an essential parameter for assessing primary productivity and ecological balance in ponds. The high correlation and a low error (~8%) between empirical and predicted measurements for Chl-a indicate the potential for using satellite imagery to detect and quantify phytoplankton concentrations effectively. Additionally, PC—a pigment present in cyanobacteria, a component of phytoplankton—also exhibited a high correlation and low error (r value of 0.99 and R^2 value of 0.98; MAPE of ~3.7%), indicating that satellite technology could be a valuable tool for remotely monitoring harmful algal blooms.

In contrast, our results indicated no significant correlation between satellite data and on-site measurements for pH (r value of 0.22 and R^2 value of 0.05) and temperature (r value of 0.41 and R^2 value of 0.17). Both these parameters showed a high level of error (29% and 25%, respectively) between predicted and actual data. The lack of correlation for these two water quality parameters suggests that satellite imagery may not yet have the precision required to accurately measure the acidity, alkalinity, or temperature—which is highly sensitive to localized environmental factors and rapid changes—of pond water.

Chl-a and PC are pigments with specific light absorption and reflection properties that satellites can effectively detect based on water color. Alongside DO and ammonia, these water quality parameters are closely related to biological activity at the pond's surface. For instance, high levels of Chl-a (indicating algal blooms) can serve as a proxy for estimating DO levels because photosynthesis by algae increases DO. Ammonia is also related to algae activity and nutrient loads. In contrast, pH and temperature do not have direct optical signatures that satellites can measure, with fluctuations in pH and temperature not resulting in changes to water color or turbidity, making them more challenging to predict accurately.

This proof-of-concept study provided encouragement that remote monitoring of fish farms using satellite imagery of four of the studied water quality parameters—ammonia, DO, Chl-a, and PC—may be a viable option for FWI to consider incorporating into the ARA. However, before rolling this technology out as part of the ARA, further work is required to further validate the accuracy and reliability of the models for predicting these four water quality parameters. It would be prudent to collect more data to further train the models for predicting each of these four water quality parameters with a view to further boosting the r and R^2 values, and decreasing the RMSE and MAPE values. Although this current study indicates that the models for predicting pH and temperature are not reliable, further data collection—easily conducted concomitant to collecting data for ammonia, DO, Chl-a and PC—could help to improve the models for predicting pH and temperature. While temperature is not a key parameter for the ARA—no corrective actions based on temperature have been issued to farmers by ARA personnel since the program’s inception—being able to predict pH may have value for the ARA.

The results of the current study are based on a relatively small data set, collected over a short time window—five data collection days over a three-week period. To further test the accuracy and reliability of remote sensing using satellite imagery before making a decision to incorporate this technology into the ARA, it would be prudent to further train the models with (i) larger data sets, and (ii) data sets that have been collected over a longer period of time to avoid any bias that may result from the short time window of the original study.

It’s also important to note that the methodology used to train and subsequently validate the models may have resulted in correlations that are higher than they should be. Specifically, ponds used for training the models were not separated from ponds used for validating the models. Using data from the same ponds—albeit collected at different time points—to train and validate the models may have overfit the models to specific characteristics of those pools. As further work is carried out to further test the accuracy and reliability of the model, it will be important to ensure that data used for training the models comes from a different set of ponds than data used for validating the models.

The current study utilized a single data point (for each water quality parameter) at each of the 20 study ponds on each of the five days of data collection. Collecting more than one data point from each pond may help to improve the spatial variability within the models for predicting each of the water quality parameters. Similarly, collecting data points from locations more central within the water body of the ponds may help with improving the reliability and accuracy of each of the models. The current study collected data from a point at the side of each of the 20 ponds, as this was logistically easier to manage, especially with the need to collect data from 20 ponds within a tight time window. However, such logistical concerns are important to factor into future data collection plans; due to resource limitations, there is a need to balance time constraints with increasing the number of data collection points at each pond.

Spatial variability effects may also be improved by training the models with data sets collected from a wider geographical area. Variations in environmental conditions, water chemistry, and ecological dynamics across different geographic areas can influence the performance and reliability of these models. Before utilizing these models for the ARA, additional work is needed to improve the models for predicting these water quality parameters, and to show that they are accurate and reliable for remotely monitoring farms across the ARA's targeted geography.

Collecting additional data to train the models with larger data sets would simultaneously allow us to assess if weather is a concern that may limit the utility of the remote monitoring approach. On one of the data collection days—February 24—only 7 (35%) of the study ponds could be analyzed remotely (Table 2 and Table S9). Over the five days of data collection, cloud conditions prevented remote monitoring of 13 (65%) of the ponds, with 4 (20%) of the ponds impacted on two or more days (Table S9). The effect of clouds is a well-recognized limitation of utilizing satellite imagery for remote data collection, and understanding how significant a limitation this would be for FWI programming is an important factor to consider before adding this to the ARA program.

Overall, the findings from this proof-of-concept study are highly encouraging, indicating real potential to utilize satellite imagery for the remote monitoring of ammonia, DO, Chl-a, and/or PC as part of FWI's flagship ARA program. However, before incorporating remote monitoring of fish farms into the ARA, additional work is needed. To ensure that the models are sufficiently predictive, a larger data set collected over a longer period of time with more geographical diversity is needed. In future data analysis, we will also ensure the separation of ponds used for training the models from ponds used for validation. Beyond improving the accuracy and reliability of the predictive models, additional work is also needed to understand how problematic cloud cover issues may be.

This study was designed as a proof of concept, not to develop a product to take forward directly into a program. The study has provided us with sufficient confidence to take this concept further and invest additional resources. We recognize that it's not yet ready to integrate within the ARA, but we are greatly encouraged by the findings.

Supporting Information

Table S1. Daily schedule for data collection at study ponds. 20 ponds were purposively selected in two clusters, with 10 ponds per cluster. One data collector was assigned to each cluster, with the two data collectors working in parallel. This predetermined time and sequence for collection of data was followed as closely as possible on each of the five days of data collection. The actual time that data was collected at each pond is shown in Table S2. Times shown in hh:mm format.

Cluster 1		Cluster 2	
Pond	**Time to reach pond**	**Pond**	**Time to reach pond**
NSR 1	09:00	SNR 2	09:00
JAG 1	09:15	JKS 1	09:15
VPS 3	09:30	PNR 1	09:35
NRO 1	09:45	GOW 2	09:55
VMS 1	10:00	SRV 1	10:10
GRA 1	10:15	SRK 1	10:25
PKR 1	10:25	VVR 1	10:40
SRI 1	10:45	KIS 1	10:55
SRI 2	10:55	PRA 1	11:05
GIL 2	11:05	SBR 1	11:20

Table S2. Time of data collection at study ponds. Data collectors followed a predetermined daily schedule for data collection at study ponds, which provided guidance for the times they should collect data at each study pond (see Table S1). Times shown below are the actual times at which data were collected at each pond on each of the five days of data collection. Times shown (hh:mm:ss format) were recorded automatically by the ProDSS meter at the time of data collection. ND=not determined (i.e. data could not be collected at time of visit to the pond).

Pond ID	Time pond water was sampled				
	Day 1 (Feb 19, 2024)	Day 2 (Feb 24, 2024)	Day 3 (Feb 29, 2024)	Day 4 (Mar 5, 2024)	Day 5 (Mar 10, 2024)
Cluster 1					
NSR 1	9:04:18	9:05:48	9:02:26	9:02:05	9:01:44
JAG 1	9:15:25	9:18:09	9:16:57	9:16:28	9:16:33
VPS 3	9:27:13	9:37:49	9:31:13	9:31:23	9:31:26
NRO 1	9:42:43	9:49:30	9:46:24	9:46:16	9:46:50
VMS 1	9:54:46	10:01:34	10:01:25	10:01:49	10:01:32
GRA 1	10:06:25	10:17:35	10:16:25	10:17:06	10:16:27
PKR 1	10:16:19	10:29:12	10:27:18	10:27:31	ND
SRI 2	10:33:37	10:48:07	10:45:54	10:46:30	10:46:27
SRI 1	10:42:06	10:59:47	10:56:18	10:57:32	10:57:19
GIL 2	10:52:58	11:11:06	11:06:01	11:06:04	11:06:16
Cluster 2					
SNR 2	9:03:03	9:02:47	9:03:11	9:03:01	9:09:15
JKS 1	9:15:09	9:18:08	9:18:10	9:18:03	9:17:13
PNR 1	9:32:49	9:38:07	9:38:11	9:38:01	9:37:22
GOW 2	9:50:02	9:58:07	9:58:09	9:58:00	9:57:37
SRV 1	10:02:34	10:13:11	10:13:14	10:13:22	10:12:31
SRK 1	10:15:22	10:28:09	10:28:10	10:28:00	10:27:12
VVR 1	10:26:33	10:43:11	10:43:08	10:43:01	10:42:06
KIS 1	10:38:09	10:58:10	10:58:01	10:57:35	10:57:32
PRA 1	10:47:23	11:08:47	11:08:07	11:09:02	11:07:33
SBR 1	11:02:13	11:23:10	11:22:43	11:22:31	11:22:16

Table S3. Levels of ammonia determined by direct analysis of water at the 20 study ponds. Ammonia levels were determined by an FWI data collector taking a sample of water from the pond in the morning, storing it in an air-tight sample bottle, and assessing ammonia levels in a laboratory in the afternoon using a Hanna spectrophotometer. ND=not determined (i.e. data could not be collected at time of visit to the pond).

Pond ID	Ammonia (mg/L)				
	Day 1 (Feb 19, 2024)	Day 2 (Feb 24, 2024)	Day 3 (Feb 29, 2024)	Day 4 (Mar 5, 2024)	Day 5 (Mar 10, 2024)
Cluster 1					
NSR 1	0.23	0.12	0.14	0.17	0.3
JAG 1	0.25	0.03	0.25	0.21	0.41
VPS 3	0.18	0.17	0.28	0.16	0.18
NRO 1	0.26	0.2	0.21	0.18	0.43
VMS 1	0.28	0.31	0.24	0.21	0.24
GRA 1	0.12	0.12	0.17	0.15	0.18
PKR 1	0.21	0.17	0.25	1.08	ND
SRI 2	0.08	0.08	0.15	0.13	0.24
SRI 1	0.44	0.66	0.54	0.14	0.15
GIL 2	0.06	0.06	0.13	0.09	0.11
Cluster 2					
SNR 2	0.01	0.05	0.07	0.07	0.15
JKS 1	0.16	0.03	0.11	0.1	0.1
PNR 1	0.14	0.14	0.16	0.2	0.15
GOW 2	0.33	0.17	0.11	0.14	0.13
SRV 1	0.06	0.08	0.11	0.13	0.13
SRK 1	0.07	0.07	0.08	0.09	0.3
VVR 1	0.06	0.04	0.12	0.05	0.05
KIS 1	0.03	0.04	0.08	0.1	0.17
PRA 1	0.19	0.08	0.17	0.23	0.29
SBR 1	0.14	0.1	0.15	0.11	0.2

Table S4. Levels of DO determined by direct analysis of water at the 20 study ponds. DO levels were determined by an FWI data collector using a handheld ProDSS meter. ND=not determined (i.e. data could not be collected at time of visit to the pond).

Pond ID	Dissolved Oxygen (mg/L)				
	Day 1 (Feb 19, 2024)	Day 2 (Feb 24, 2024)	Day 3 (Feb 29, 2024)	Day 4 (Mar 5, 2024)	Day 5 (Mar 10, 2024)
Cluster 1					
NSR 1	3.7	5.7	7.6	9.6	4.1
JAG 1	2.1	2.1	2.8	4.5	3.6
VPS 3	3.7	3.1	4.6	4	4.2
NRO 1	1.6	6.5	1.1	5.3	5.2
VMS 1	2.7	2.8	5.8	5.7	6.8
GRA 1	3.2	3	3.3	4	4.7
PKR 1	4.8	6.6	8.1	2.8	ND
SRI 2	3.1	0.8	7	6.3	2.2
SRI 1	2.7	6.4	4.2	4.2	7.7
GIL 2	3.4	2.5	7.7	4.2	2.2
Cluster 2					
SNR 2	4.7	3.58	3.73	3.82	6.72
JKS 1	2	1.21	3.17	3.6	2.35
PNR 1	2.87	5.94	12.94	5.4	8.77
GOW 2	8.79	6.73	11.04	11.51	7.5
SRV 1	3.75	4.57	3.32	5.4	6.75
SRK 1	7.65	2.04	3.86	9.18	4.66
VVR 1	5.51	7.62	13.44	3.25	7.57
KIS 1	3.3	3.84	6.88	5.55	7.06
PRA 1	3.3	9.28	3.9	4.39	11.59
SBR 1	3.99	7.55	13.87	9.08	10.1

Table S5. Levels of Chl-a determined by direct analysis of water at the 20 study ponds. Chl-a levels were determined by an FWI data collector using a handheld ProDSS meter. ND=not determined (i.e. data could not be collected at time of visit to the pond).

Pond ID	Chlorophyll-a (µg/L)				
	Day 1 (Feb 19, 2024)	**Day 2 (Feb 24, 2024)**	**Day 3 (Feb 29, 2024)**	**Day 4 (Mar 5, 2024)**	**Day 5 (Mar 10, 2024)**
Cluster 1					
NSR 1	52.33	42.25	73.02	96.64	103.71
JAG 1	253.65	158.34	138.85	154.75	182.92
VPS 3	126.37	126.34	85.9	105.07	88.27
NRO 1	267.14	189.65	137.97	134.54	104.24
VMS 1	335.43	258.82	238.28	371.9	356.37
GRA 1	276.81	148.63	111.26	132.52	114.96
PKR 1	257.05	190.67	228.51	36.69	ND
SRI 2	118.74	170.45	95.73	155.79	170.53
SRI 1	138.97	85.36	177.07	101.82	101.43
GIL 2	61.55	55.76	56.81	66.67	75.52
Cluster 2					
SNR 2	314.77	195.48	214.55	199.88	308.93
JKS 1	110.52	52.38	81.72	85.07	74.61
PNR 1	182.11	106.35	77.2	86.14	105.6
GOW 2	185.36	123.2	131.93	127.99	99.03
SRV 1	213.31	98.44	185.66	139.9	132.31
SRK 1	621.83	377.58	477.38	383.74	401
VVR 1	236.18	136.97	142.82	139.85	80.05
KIS 1	95.45	44.31	52.15	32.1	41.81
PRA 1	358.49	151.73	180.58	171.74	124.1
SBR 1	255.62	132.7	147.42	129.88	113.92

Table S6. Levels of PC determined by direct analysis of water at the 20 study ponds. Chl-a levels were determined by an FWI data collector using a handheld ProDSS meter. ND=not determined (i.e. data could not be collected at time of visit to the pond).

Pond ID	Phycocyanin (µg/L)				
	Day 1 (Feb 19, 2024)	Day 2 (Feb 24, 2024)	Day 3 (Feb 29, 2024)	Day 4 (Mar 5, 2024)	Day 5 (Mar 10, 2024)
Cluster 1					
NSR 1	10.6	12.09	12.02	11.57	10.89
JAG 1	7.19	7.17	6.22	6.48	7.41
VPS 3	3.97	5.28	4.04	3.4	3.7
NRO 1	14.88	16	12.4	10.82	6.31
VMS 1	10.17	11.41	11.16	14	13.46
GRA 1	10.47	7.61	5.64	5.78	5.27
PKR 1	7.33	7.32	9.81	1.13	ND
SRI 2	4.97	8.01	6.84	6.97	8.28
SRI 1	4.88	6.82	8.4	6.74	7.05
GIL 2	1.6	2.1	2	2.09	2.08
Cluster 2					
SNR 2	8.74	9.76	9.75	8.94	14.26
JKS 1	6.8	5.6	4.79	2.91	4.99
PNR 1	7.64	8.78	9.27	8.71	9.88
GOW 2	6.53	8.32	9.69	6.82	6.67
SRV 1	6.27	4.68	8.58	4.9	5.84
SRK 1	16.36	19.03	22.65	18.03	17.01
VVR 1	6.89	6.81	6.49	4.16	3.65
KIS 1	2.91	2.5	2.49	1.06	2.78
PRA 1	11.2	10.74	10.31	8.65	6.84
SBR 1	11.06	12.73	12.66	9.92	10.37

Table S7. pH determined by direct analysis of water at the 20 study ponds. pH was determined by an FWI data collector using a handheld ProDSS meter. ND=not determined (i.e. data could not be collected at time of visit to the pond).

Pond ID	pH				
	Day 1 (Feb 19, 2024)	**Day 2 (Feb 24, 2024)**	**Day 3 (Feb 29, 2024)**	**Day 4 (Mar 5, 2024)**	**Day 5 (Mar 10, 2024)**
Cluster 1					
NSR 1	8.24	8.42	8.51	8.57	8.51
JAG 1	8.22	8.3	8.28	8.33	8.3
VPS 3	8.16	8.22	8.21	8.22	8.24
NRO 1	8.07	8.28	8.13	8.24	8.26
VMS 1	8.2	8.28	8.28	8.33	8.37
GRA 1	8.37	8.43	8.48	8.54	8.57
PKR 1	8.18	8.25	8.33	8.25	ND
SRI 2	8.14	8.19	8.19	8.27	8.2
SRI 1	8.2	8.27	8.23	8.17	8.23
GIL 2	8.19	8.23	8.33	8.28	8.25
Cluster 2					
SNR 2	8.26	8.2	8.63	8.38	8.62
JKS 1	8.34	7.89	8.36	7.94	7.96
PNR 1	8.34	8.48	9.1	8.67	8.73
GOW 2	8.48	8.42	8.87	8.55	8.35
SRV 1	8.31	8.09	8.66	8.33	8.31
SRK 1	8.85	8.66	8.96	8.69	8.6
VVR 1	8.39	8.54	9.04	8.66	8.85
KIS 1	8.03	8.06	8.53	8.1	8.11
PRA 1	8.36	8.42	8.61	8.23	8.29
SBR 1	7.96	8.22	8.77	8.25	8.26

Table S8. Temperature determined by direct analysis of water at the 20 study ponds. Temperature was determined by an FWI data collector using a handheld ProDSS meter. ND=not determined (i.e. data could not be collected at time of visit to the pond).

Pond ID	Temperature (^{o}C)				
	Day 1 (Feb 19, 2024)	Day 2 (Feb 24, 2024)	Day 3 (Feb 29, 2024)	Day 4 (Mar 5, 2024)	Day 5 (Mar 10, 2024)
Cluster 1					
NSR 1	27.9	28.5	28.9	29.2	29.7
JAG 1	28.4	29.2	28.9	29.3	29.8
VPS 3	28.8	29.2	29.4	29.5	30.1
NRO 1	28.7	29.6	29.3	30	30.5
VMS 1	28.7	29.2	29.6	29.6	30.2
GRA 1	28.3	28.9	29.2	28.4	30.1
PKR 1	29.7	29.9	30.5	30.5	ND
SRI 2	28.5	28.6	29.7	29.4	29.8
SRI 1	28.6	29.5	29.2	29.7	30.6
GIL 2	28.4	28.7	29.2	29	29.6
Cluster 2					
SNR 2	28.2	29	28.5	28	29.2
JKS 1	28.6	29.3	29.3	29.4	30.3
PNR 1	28.3	28.6	29.3	28.6	29.8
GOW 2	28.5	29.4	29.5	30.1	30.3
SRV 1	28.6	28.7	29.4	29.3	30.2
SRK 1	27.9	28.7	28.6	29.1	29.6
VVR 1	28.5	29.5	29.3	28.3	29.7
KIS 1	28.9	29.5	30.1	29.9	31
PRA 1	29	30	29.8	29.6	31.2
SBR 1	28.9	29.7	30.4	30.4	30.9

Table S9. Ponds for which water quality data were successfully determined by analysis of satellite imagery. Green tick marks (✔) indicate ponds from which satellite images were collected and successfully used for determining water quality parameters. Red "x" marks ( ) indicate ponds from which data could not be determined from analysis of satellite images. For pond PKR 1 on day 5 of data collection, no data could be determined as the pond had been emptied of water in preparation for the next cycle of fish farming. All other incidences of failure to determine water quality data from satellite images resulted from cloud cover or shadowing causing obstruction of the pond surface.

Pond ID	Ponds for which data was successfully determined by analysis of satellite images				
	Day 1 (Feb 19, 2024)	Day 2 (Feb 24, 2024)	Day 3 (Feb 29, 2024)	Day 4 (Mar 5, 2024)	Day 5 (Mar 10, 2024)
Cluster 1					
NSR 1	✔		✔	✔	✔
JAG 1	✔		✔	✔	✔
VPS 3	✔	✔	✔	✔	✔
NRO 1	✔		✔	✔	✔
VMS 1	✔		✔	✔	✔
GRA 1	✔	✔	✔	✔	✔
PKR 1	✔		✔	✔	
SRI 2	✔		✔	✔	✔
SRI 1	✔		✔	✔	✔
GIL 2	✔		✔	✔	✔
Cluster 2					
SNR 2	✔	✔	✔	✔	✔
JKS 1	✔		✔	✔	✔
PNR 1	✔	✔	✔	✔	✔
GOW 2	✔	✔	✔	✔	✔
SRV 1	✔	✔	✔	✔	✔
SRK 1	✔		✔		
VVR 1	✔		✔	✔	
KIS 1	✔		✔		
PRA 1	✔	✔	✔	✔	✔
SBR 1	✔		✔	✔	✔
Total number of of ponds from which data could be determined remotely	**20**	**7**	**20**	**18**	**16**

Table S10. Validation of model for predicting ammonia levels in ponds. Ammonia levels collected directly at ponds (empirical data) were compared with levels determined from analysis of satellite images (predicted data) collected at the same day as the empirical data to assess how closely they matched. 30 matched data sets were used for statistical analysis to determine how closely the predicted and empirical values matched (see Figure 4, and Table 3).

Date	Pond ID	Empirical Data: Ammonia (mg/L)	Predicted Data: Ammonia (mg/L)	Relative Difference (%)
19-02-2024	JKS 1	0.16	0.1280463423	-19.97
19-02-2024	PRA 1	0.19	0.1841080096	-3.10
19-02-2024	SBR 1	0.14	0.1478974564	5.64
19-02-2024	NSR 1	0.23	0.1912176855	-16.86
19-02-2024	VPS 3	0.18	0.1492835654	-17.06
19-02-2024	NRO 1	0.26	0.2838544814	9.17
19-02-2024	PKR 1	0.21	0.1664030543	-20.76
19-02-2024	GIL 2	0.06	0.05645680402	-5.91
24-02-2024	PRA 1	0.08	0.07474142861	-6.57
29-02-2024	JKS 1	0.11	0.1274401419	15.85
29-02-2024	PNR 1	0.16	0.1673171666	4.57
29-02-2024	VVR 1	0.12	0.09823420771	-18.14
29-02-2024	KIS 1	0.08	0.08258916764	3.24
29-02-2024	PRA 1	0.17	0.1763992365	3.76
29-02-2024	SBR 1	0.15	0.1530441706	2.03
29-02-2024	NRO 1	0.21	0.2174669404	3.56
29-02-2024	PKR 1	0.25	0.2276331528	-8.95
29-02-2024	SRI 2	0.15	0.1720673688	14.71
29-02-2024	GIL 2	0.13	0.1058899825	-18.55
05-03-2024	SNR 2	0.07	0.0668161869	-4.55
05-03-2024	PNR 1	0.2	0.1922183812	-3.89
05-03-2024	SBR 1	0.11	0.09727032731	-11.57
05-03-2024	NSR 1	0.17	0.150000871	-11.76
05-03-2024	VPS 3	0.16	0.1348810898	-15.70
05-03-2024	NRO 1	0.18	0.21128398	17.38
05-03-2024	GRA 1	0.15	0.1360239757	-9.32
05-03-2024	SRI 1	0.14	0.1663028507	18.79
10-03-2024	PNR 1	0.15	0.1792719311	19.51
10-03-2024	SRI 1	0.15	0.1391692562	-7.22
10-03-2024	GIL 2	0.11	0.1105543538	0.50

Table S11. Validation of model for predicting DO levels in ponds. DO levels collected directly at ponds (empirical data) were compared with levels determined from analysis of satellite images (predicted data) collected at the same day as the empirical data to assess how closely they matched. 30 matched data sets were used for statistical analysis to determine how closely the predicted and empirical values matched (see Figure 4, and Table 3).

Date	Pond ID	Empirical Data: DO (mg/L)	Predicted Data: DO (mg/L)	Relative Difference (%)
19-02-2024	SNR 2	4.7	4.095487632	-12.86
19-02-2024	SRV 1	3.75	3.283972659	-12.43
19-02-2024	SBR 1	3.99	3.760460775	-5.75
19-02-2024	NSR 1	3.7	3.838627575	3.75
19-02-2024	VPS 3	3.7	3.748208006	1.30
19-02-2024	GRA 1	3.2	3.576526488	11.77
19-02-2024	SRI 2	3.1	3.565482353	15.02
19-02-2024	GIL 2	3.4	3.284993788	-3.38
24-02-2024	PNR 1	5.94	5.150863449	-13.29
24-02-2024	GOW 2	6.73	5.875147735	-12.70
24-02-2024	VPS 3	3.1	3.194796847	3.06
29-02-2024	SNR 2	3.73	3.767447305	1.00
29-02-2024	SRV 1	3.32	3.600025801	8.43
29-02-2024	SRK 1	3.86	3.627343669	-6.03
29-02-2024	VPS 3	4.6	4.0642293	-11.65
29-02-2024	GRA 1	3.3	3.813188487	15.55
29-02-2024	SRI 1	4.2	3.956017267	-5.81
05-03-2024	SNR 2	3.82	4.175092003	9.30
05-03-2024	JKS 1	3.6	3.866484531	7.40
05-03-2024	JAG 1	4.5	3.860716131	-14.21
05-03-2024	VPS 3	4	3.822977334	-4.43
05-03-2024	VMS 1	5.7	6.214344876	9.02
05-03-2024	SRI 1	4.2	3.883038265	-7.55
10-03-2024	SNR 2	6.72	5.727210043	-14.77
10-03-2024	NSR 1	4.1	4.571546852	11.50
10-03-2024	JAG 1	3.6	4.021715609	11.71
10-03-2024	VPS 3	4.2	3.716743364	-11.51
10-03-2024	NRO 1	5.2	4.468701626	-14.06
10-03-2024	VMS 1	6.8	5.982508569	-12.02
10-03-2024	GRA 1	4.7	5.301841786	12.81

Table S12. Validation of model for predicting Chl-a levels in ponds. Chl-a levels collected directly at ponds (empirical data) were compared with levels determined from analysis of satellite images (predicted data) collected at the same day as the empirical data to assess how closely they matched. 30 matched data sets were used for statistical analysis to determine how closely the predicted and empirical values matched (see Figure 4, and Table 3).

Date	Pond ID	Empirical Data: Chl-a (µg/L)	Predicted Data: Chl-a (µg/L)	Relative Difference (%)
19-02-2024	SNR 2	314.77	254.8013907	-19.05
19-02-2024	JKS 1	110.52	96.93554833	-12.29
19-02-2024	PNR 1	182.11	185.4986322	1.86
19-02-2024	GOW 2	185.36	165.6628166	-10.63
19-02-2024	SRV 1	213.31	206.192187	-3.34
19-02-2024	VVR 1	236.18	221.7090478	-6.13
19-02-2024	PRA 1	358.49	294.0687161	-17.97
19-02-2024	SBR 1	255.62	237.6477221	-7.03
19-02-2024	NRO 1	267.14	278.2152405	4.15
19-02-2024	VMS 1	335.43	269.6364859	-19.61
19-02-2024	PKR 1	257.05	267.3054852	3.99
19-02-2024	SRI 1	138.97	130.4541806	-6.13
24-02-2024	SNR 2	195.48	210.4875376	7.68
24-02-2024	PNR 1	106.35	111.4064543	4.75
24-02-2024	GOW 2	123.2	122.6149872	-0.47
24-02-2024	PRA 1	151.73	172.388157	13.62
29-02-2024	SNR 2	214.55	204.5442676	-4.66
29-02-2024	VVR 1	142.82	147.8755464	3.54
29-02-2024	PRA 1	180.58	205.2787842	13.68
29-02-2024	SBR 1	147.42	154.4584696	4.77
29-02-2024	GRA 1	111.26	112.6655026	1.26
05-03-2024	SNR 2	199.88	170.6191529	-14.64
05-03-2024	JKS 1	85.07	77.94993082	-8.37
05-03-2024	PRA 1	171.74	149.2485512	-13.10
05-03-2024	GRA 1	132.52	142.2519232	7.34
05-03-2024	SRI 2	155.79	150.7425023	-3.24
05-03-2024	SRI 1	101.82	83.95620346	-17.54
05-03-2024	GIL 2	66.67	55.86186117	-16.21
10-03-2024	VPS 3	88.27	81.2974343	-7.90
10-03-2024	GRA 1	114.96	128.8203651	12.06

Table S13. Validation of model for predicting PC levels in ponds. PC levels collected directly at ponds (empirical data) were compared with levels determined from analysis of satellite images (predicted data) collected at the same day as the empirical data to assess how closely they matched. 30 matched data sets were used for statistical analysis to determine how closely the predicted and empirical values matched (see Figure 4, and Table 3).

Date	Pond ID	Empirical Data: PC (µg/L)	Predicted Data: PC (µg/L)	Relative Difference (%)
19-02-2024	PNR 1	7.64	8.376616194	9.64
19-02-2024	SRK 1	16.36	15.55051875	-4.95
19-02-2024	KIS 1	2.91	2.825499172	-2.90
19-02-2024	PRA 1	11.2	11.37103189	1.53
19-02-2024	NSR 1	10.6	10.50412289	-0.90
19-02-2024	JAG 1	7.19	7.146107472	-0.61
19-02-2024	VMS 1	10.17	11.12355628	9.38
19-02-2024	GRA 1	10.47	10.80568215	3.21
19-02-2024	SRI 1	4.88	5.217432495	6.91
24-02-2024	SNR 2	9.76	9.466211705	-3.01
24-02-2024	GOW 2	8.32	8.783799398	5.57
29-02-2024	SNR 2	9.75	9.080233995	-6.87
29-02-2024	PNR 1	9.27	8.504911179	-8.25
29-02-2024	GOW 2	9.69	10.04115568	3.62
29-02-2024	NSR 1	12.02	11.05427927	-8.03
29-02-2024	NRO 1	12.4	11.83980334	-4.52
29-02-2024	VMS 1	11.16	10.78073889	-3.40
29-02-2024	SRI 1	8.4	7.937796044	-5.50
29-02-2024	GIL 2	2	1.948359883	-2.58
05-03-2024	SNR 2	8.94	9.523978053	6.53
05-03-2024	JKS 1	2.91	3.102491388	6.61
05-03-2024	GOW 2	6.82	6.514361992	-4.48
05-03-2024	SBR 1	9.92	10.04077507	1.22
05-03-2024	JAG 1	6.48	6.943526971	7.15
05-03-2024	VMS 1	14	13.97622404	-0.17
05-03-2024	SRI 2	6.97	6.535313119	-6.24
05-03-2024	GIL 2	2.09	1.900515311	-9.07
10-03-2024	SNR 2	14.26	15.50960499	8.76
10-03-2024	NSR 1	10.89	10.47397682	-3.82
10-03-2024	SRI 2	8.28	8.536150094	3.09

Table S14. Validation of model for predicting pH in ponds. pH values collected directly at ponds (empirical data) were compared with values determined from analysis of satellite images (predicted data) collected at the same day as the empirical data to assess how closely they matched. 30 matched data sets were used for statistical analysis to determine how closely the predicted and empirical values matched (see Figure 4, and Table 3).

Date	Pond ID	Empirical Data: pH	Predicted Data: pH	Relative Difference (%)
19-02-2024	SNR 2	8.26	8.941894251	8.26
19-02-2024	JKS 1	8.34	8.105737833	-2.81
19-02-2024	PNR 1	8.34	8.262095401	-0.93
19-02-2024	GOW 2	8.48	8.06077531	-4.94
19-02-2024	SRV 1	8.31	8.514074568	2.46
19-02-2024	SRK 1	8.85	8.638602085	-2.39
19-02-2024	VVR 1	8.39	8.444981769	0.66
19-02-2024	KIS 1	8.03	8.363760807	4.16
19-02-2024	PRA 1	8.36	8.421465749	0.74
19-02-2024	SBR 1	7.96	8.060240186	1.26
19-02-2024	NSR 1	8.24	8.591430782	4.26
19-02-2024	JAG 1	8.22	8.393665466	2.11
19-02-2024	VPS 3	8.16	8.533291783	4.57
19-02-2024	NRO 1	8.07	7.998135907	-0.89
19-02-2024	VMS 1	8.2	8.344534753	1.76
19-02-2024	GRA 1	8.37	8.410715057	0.49
19-02-2024	PKR 1	8.18	8.462072588	3.45
19-02-2024	SRI 2	8.14	8.368029153	2.80
19-02-2024	SRI 1	8.2	8.431153758	2.82
19-02-2024	GIL 2	8.19	8.285416748	1.17
24-02-2024	SNR 2	8.2	8.620186994	5.12
24-02-2024	PNR 1	8.48	8.38503177	-1.12
24-02-2024	GOW 2	8.42	8.467491661	0.56
24-02-2024	SRV 1	8.09	8.487509606	4.91
24-02-2024	PRA 1	8.42	8.255223124	-1.96
24-02-2024	VPS 3	8.22	8.163298818	-0.69
29-02-2024	SNR 2	8.63	8.528139006	-1.18
29-02-2024	JKS 1	8.36	8.223858186	-1.63
29-02-2024	PNR 1	9.1	8.473435605	-6.89
29-02-2024	GOW 2	8.87	8.406355022	-5.23

Table S15. Validation of model for predicting temperature in ponds. Temperature values collected directly at ponds (empirical data) were compared with values determined from analysis of satellite images (predicted data) collected at the same day as the empirical data to assess how closely they matched. 30 matched data sets were used for statistical analysis to determine how closely the predicted and empirical values matched (see Figure 4, and Table 3).

Date	Pond ID	Empirical Data: Temperature (^{o}C)	Predicted Data: Temperature (^{o}C)	Relative Difference (%)
19-02-2024	SNR 2	28.2	28.6	1.42
19-02-2024	JKS 1	28.6	29.4	2.80
19-02-2024	PNR 1	28.3	29.1	2.83
19-02-2024	GOW 2	28.5	29.4	3.16
19-02-2024	SRV 1	28.6	28.9	1.05
19-02-2024	SRK 1	27.9	28.5	2.15
19-02-2024	VVR 1	28.5	28.4	-0.35
19-02-2024	KIS 1	28.9	29.4	1.73
19-02-2024	PRA 1	29	29	0.00
19-02-2024	SBR 1	28.9	29.2	1.04
19-02-2024	NSR 1	27.9	28.9	3.58
19-02-2024	JAG 1	28.4	29.1	2.46
19-02-2024	VPS 3	28.8	28.9	0.35
19-02-2024	NRO 1	28.7	29.4	2.44
19-02-2024	VMS 1	28.7	29	1.05
19-02-2024	GRA 1	28.3	29.1	2.83
19-02-2024	PKR 1	29.7	28.4	-4.38
19-02-2024	SRI 2	28.5	29	1.75
19-02-2024	SRI 1	28.6	29	1.40
19-02-2024	GIL 2	28.4	29.2	2.82
24-02-2024	SNR 2	29	29.3	1.03
24-02-2024	PNR 1	28.6	29.6	3.50
24-02-2024	GOW 2	29.4	29.8	1.36
24-02-2024	SRV 1	28.7	29.6	3.14
24-02-2024	PRA 1	30	29.9	-0.33
24-02-2024	VPS 3	29.2	29.7	1.71
29-02-2024	SNR 2	28.5	28.9	1.40
29-02-2024	JKS 1	29.3	29.4	0.34
29-02-2024	PNR 1	29.3	29	-1.02
29-02-2024	GOW 2	29.5	29.2	-1.02