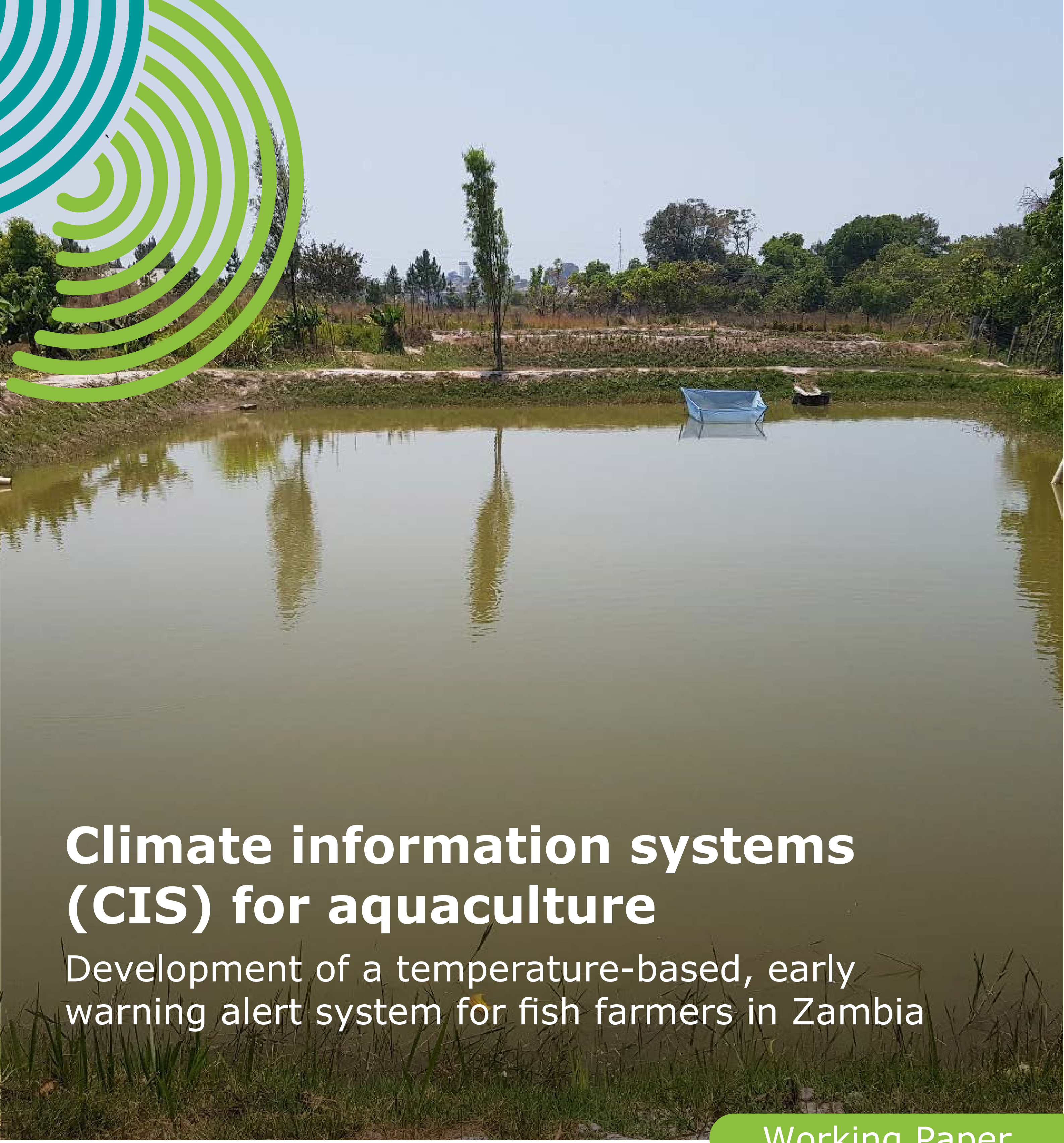

# Climate information systems (CIS) for aquaculture

## Development of a temperature-based, early warning alert system for fish farmers in Zambia

Working Paper

AICCRA
Accelerating Impacts of CGIAR Climate Research for Africa

CGIAR

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## About AICCRA

AICCRA Accelerating Impacts of CGIAR Climate Research for Africa

Accelerating Impacts of CGIAR Climate Research for Africa (AICCRA) is a project that helps deliver a climate-smart African future driven by science and innovation in agriculture. It is led by the Alliance of Bioversity International and CIAT and supported by a grant from the International Development Association (IDA) of the World Bank. Explore our work at **aiccra.cgiar.org**

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# List of abbreviations

| | |
|---|---|
| AICCRA | Accelerating Impacts of CGIAR Climate Research for Africa |
| DO | dissolved oxygen |
| DNN | deep neural networks |
| iSAT | Intelligent Agricultural Systems Advisory Tool |
| MAE | mean absolute error |
| MAPE | absolute percentage error |
| MSE | mean square error |

# Abstract

Zambia is one of the most vulnerable countries in the world to climate change. Smallholder tilapia farmers in the country are particularly vulnerable, as they lack the expertise and resources to implement mitigation strategies in response to adverse weather conditions. Among climate-driven environmental stressors, such as water supply and temperature variability, temperature can lead to loss of production and low growth among tilapia farmers in the short term. As such, it is important to observe and manage fluctuations in pond temperature beyond favorable production conditions.

The AICCRA project developed an air-water temperature relationship algorithm used to forecast pond water temperatures for integration with the data hub of the Intelligent Agricultural Systems Advisory Tool (iSAT) and an early temperature warning decision tree matrix. The project team will develop the matrix into a dashboard based on input data and water quality parameter thresholds for critical scenarios for tilapia and catfish (*Clarius Gariepinus*). When predicted temperatures approach their thresholds, this activates a color-coded alarm corresponding with a specific action protocol to regulate pond temperatures. The purpose is to mitigate the impact of high-risk (24°C for minimum and 32°C for maximum) and emergency (12°C for minimum and 40°C for maximum) temperature scenarios on cultured stock.

In each case, the messages include information about the current temperature, predictions, the impact of temperature on fish health, monitoring parameters, monitoring frequency and mitigation steps. The prediction tool's early warning system is based on thresholds derived from mean pond temperatures. It is, however, important to note that normal pond temperatures between 12°C and 18°C are not optimal for growth and feed conversion efficiency in tilapia. Future work will focus on developing priority, low-cost pond monitoring equipment for temperature, oxygen levels and pH that can store data in an online database. Additionally, hydrological data for surface water and pond water replacement rates needs to be integrated.

# 1. Introduction

The largest number of small-scale farmers in Zambia are found in Northern and North-Western provinces (Figure 1), where knowledge transfer largely stimulates sector growth (DOF 2015; Genschick et al. 2017; Kaminski et al. 2018). However, some wetlands of international importance, such as the Bangweulu, Lake Tanganyika and Lake Mweru-wa-Ntipa wetlands, are located in Northern and Luapula provinces and need protection against unnecessary impact from aquaculture (Hoevenaars and Ng'ambi 2019). In Northern Province, culturing Nile tilapia is not allowed, as they are able to escape from the facilities and disturb the ecology of native tilapia species (Bhole 2014). Best management practices promote the culture of green-headed tilapia (*Oreochromis macrochir*)*,* Tanganyika bream (*O. tanganicae*) and red-breasted tilapia (*Coptodon rendalli*) in Luapula, Northern and Muchinga provinces (Hoevenaars and Ng´ambi 2019). From site visits, species farmed in Northern and Luapula provinces include red-breasted tilapia*,* green-headed tilapia and banded tilapia (*Tilapia sparmanii*).

The National Adaptation Programme of Action on Climate Change (2007) promotes the development of aquaculture, while the National Aquaculture Development Plan of Zambia has identified aquaculture zones in the north as target development areas because of their water availability (MOAL and FAO 2015). Lack of technical skills and quality inputs such as fingerlings and feed are some of the main challenges in promoting smallholder growth (Avadí et al. 2022). Farmers learn aquaculture practices from WorldFish workshops and from each other. With adequate support, some farms (such as Hopeways) have developed into hatcheries to further support income and obtain a beneficial position in the value chain. Smallholder farmers often lack the resources and information needed to manage environmental variables that affect their fish culture systems. As one of the most vulnerable countries to climate change (Eckstein et al. 2018), Zambia was classified as being at high to extreme risk in the 2018 Climate Change Vulnerability Index (Maplecroft 2017). The change in temperature in Zambia is projected to increase 1.9°C by 2050, while rainfall will decrease, with the northern region experiencing the least change in water availability (Hamududu et al. 2020). Climate-related weather changes, such as flooding and insufficient rain, lead to dried up ponds and compromised water quality, adversely affecting aquaculture and fisheries in the rural Northern and Luapula provinces.

Drought, flooding and cold temperatures in winter are key environmental risks, while high temperatures pose an occasional risk. Not all farms measure their pond temperature, and frequency is low among those that do. Additionally, farmers have limited knowledge of the physiological and ecological responses of fish and culture systems to temperature changes. However, farmers believe drought poses the highest risk, as its impacts have increased in recent years along with low oxygen measurements and increasingly stressed fish. Climate-smart priority activities include harvesting rainwater (GIZ 2020), while some farmers have indicated that they intend to drill boreholes and pump water during times of drought. Technology and seasonal environmental monitoring will, however, provide more reliable information for implementing mitigation strategies.

Aquaculture farmers must become more resilient and responsive to climate change by planning for and reacting quickly to adverse weather events and changes in environmental trends. The National Sustainable Development Goals promote climate-smart agriculture practices and enhance investment in water capture. Most farmers have access to surface water streams and springs that flow year-round, as well as community wells. However, drilling boreholes equipped with solar pumps would serve as a long-term intervention to provide a reliable water source. It is also possible to store surface water upstream for water replacement purposes for both operation and emergency protocols. Additionally, readily available pond fertilizer can improve overall pond health and nutrient cycling, while integrating aquaculture with small livestock, particularly chickens, provides fertilizer for culture ponds.

Under the World Bank-funded Accelerating Impact of CGIAR Climate Research for Africa project, WorldFish leads the work on integrated aquaculture–agriculture systems to promote resilience to climate change for smallholder fish farmers in Northern and Luapula provinces. Small-scale aquaculture in the north practices integrated farming systems by combining fish farming with crop and livestock farming to obtain optimal productivity in land use, despite unfavorable seasonal weather conditions (ACF and FSRP 2009). Modeling optimization strategies of land use outputs will improve production viability to ensure sustainable livelihoods for smaller-scale commercial farms.

Climate-smart farming relies on accurate environmental information and temperature predictions to proactively implement mitigation measures to improve the resilience of farming operations to adverse events. Continuous monitoring will also ensure that farming systems recover fully from environmental challenges by learning how long to apply mitigation measures.

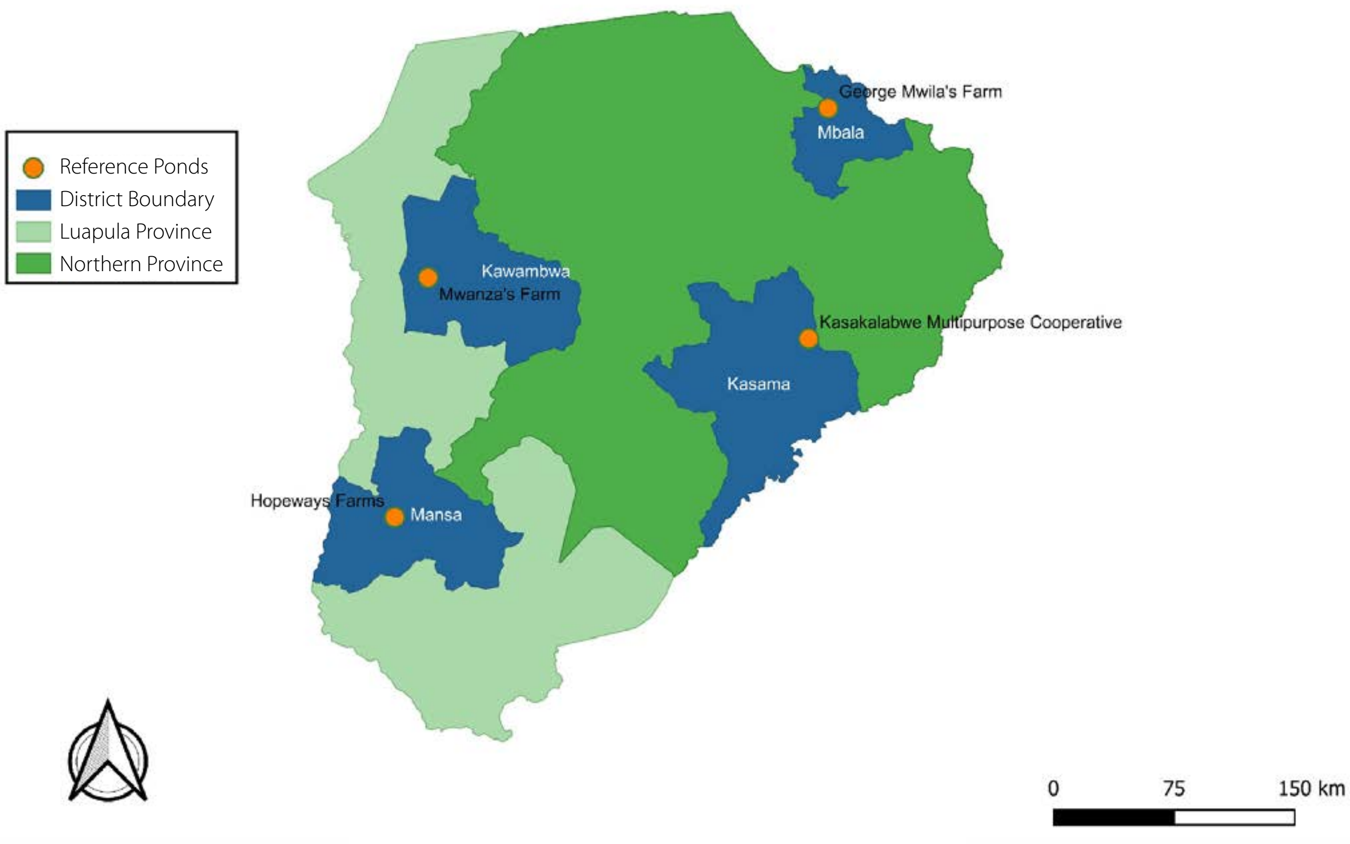
This report describes the technical approach and results of WorldFish's journey toward providing climate-smart information systems (CIS) for aquaculture by developing a temperature-based, early warning alert system for fish farmers in Zambia. WorldFish is working toward improving access to CIS for farmers in Northern and Luapula provinces. Specifically, WorldFish aims to integrate aquaculture climate advisories into iSAT, which is managed by the International Crops Research Institute for the Semi-Arid Tropics.

This key objectives of the project were as follows:

- Develop an air–water temperature relationship algorithm to forecast pond water temperatures using air temperature trend data.
- Develop a decision support tree that translates risk scenarios for water temperature forecasts into an early warning alert system with associated mitigation measures.
- Integrate the alert system into iSAT with the ability to send real-time alerts to farmers in Northern and Luapula provinces.
- Optimize environmental monitoring protocols and equipment, and conceptualize medium- and long-term interventions needed to build resilience to climate change trends.

Once piloted in Northern and Luapula provinces, WorldFish will update the advisory to include other fish species, such as catfish (*Clarius Gariepinus*), and then upscaled to other provinces in Zambia and Malawi. Social inclusion of rural women was a key consideration during the development of the advisory tool, particularly in overcoming known barriers to access technology and technical knowledge by incorporating local languages (Kwaku et al. 2023). Advisories will be available both on smartphones and via USSD protocols to allow those without smartphones to access the advisories.

***Figure 1**. The location of reference ponds in the Northern and Luapula provinces of Zambia.*



# 2. Climate-smart information systems for fish farmers in Zambia and climate-smart agriculture

CIS use technology to provide farmers with climate-related information to promote resilience to climate change. They integrate environmental information with enhanced productivity, adaptive capacity to climate variability and risk management. CIS collect weather data from various sources to illustrate patterns and predict changes, and they communicate (in advance) mitigation measures linked to specific environmental scenarios. Therefore, historical and real-time data are implemented in models that are continuously optimized to support informed decision-making. Empirical models are site-specific and serve as predictive tools when applied to situations that resemble the input parameters for which the model was developed.

Models have been used to analyze data on aquaculture ponds, describe pond dynamics and develop decision support systems for management purposes (Piedrahita et al. 1997). Decision tree models provide a structured and systematic approach to decision-making based on the analysis of historical climatic conditions. Through WorldFish, the aim of the current project is to develop an algorithm of the air–water temperature relationship to link the decision tree to the iSAT decision support system. Existing datasets of past climate information and aquaculture pond monitoring data from four pilot monitoring farms (provided by WorldFish) were analyzed by the team at the University of Stellenbosch to estimate trends for the relationship between water temperature and air temperature.

# 3. Environmental tolerances and monitoring

## 3.1. Thermal tolerances

The exotic Nile tilapia (*O. Niloticus*) (farmed in the southern provinces), three-spotted bream (*O. andersonii*), green-headed bream (*O. macrochir*), red-breasted bream (*C. rendalli*) and Tanganyika bream (*O. tanganicae*) all have an optimal thermal temperature within 24°C–32°C (Table 1). Nile tilapia, three-spotted bream and Tanganyika bream are fast-growing and omnivorous, and they tolerate a wide range of environmental conditions and temperatures between 8°C and 42°C, though Tanganyika bream does not tolerate cold (Hoevenaars and Ng'ambi 2019). Their upper lethal limits are near 42°C (Table 1), and their lower lethal limits are approximately 8°C–12°C.

Several authors have summarized the general influence of temperature, including Balarin and Haller (1982), Chervinski (1982), Philippart and Ruwet (1982) and Wohlfarth and Hulate (1983). The preferred range is between 28°C and 35°C, with no reproduction occurring below 20°C and poor growth between 10°C and 15°C. Temperature effects can also be reflected in reduced productivity at altitudes up to 1000 m. When fish are fed to satiation, growth at the preferred temperature is typically three times greater than at 22°C. Genetic selection for heat-tolerant tilapia strains should be considered in ecoregions with a high risk for warm temperature stress.

## 3.2. Monitoring abiotic (water quality) and biotic (fish stress) factors

Ponds are carefully managed for a balanced environment between algae, fish, microbes and nutrient cycling, so it is important to monitor water quality. Phytoplankton and nitrifying bacteria remove toxic ammonia from the water, while bacteria convert organic nutrients into inorganic forms (such as nitrogen, phosphorus and carbon) through a mineralization process that allows phytoplankton to absorb them. Nitrifying bacteria derive nitrate from ammonia, while denitrifying bacteria convert nitrate to nitrogen gas under anaerobic conditions. Rural pond farmers lack appropriate monitoring equipment and methods, and they often do not monitor critical variables, such as ammonia. This leaves them at risk for missing a water quality scenario (Table 2) that may impair fish growth (and thus production) or result in loss of stock because of fish deaths. Temperature fluctuations beyond the optimal thermal range cause stress, which is exacerbated by high stocking densities and other environmental stressors, such as pH, ammonia and low dissolved oxygen (DO), ultimately impacting production performance. Sufficient DO levels of more than 5 mg/L optimize the thermal growth coefficient in tilapia when food macronutrient levels are adequate (Mengistu et al. 2020). Aeration influences DO levels, so it is important that farmers manage it in parallel with temperature, as the partial pressure capacity of DO decreases with rising temperatures. Fish will come to the water's surface to gasp for air when oxygen levels are low (less than 2 mg/L), especially in the early morning. Temperature drives the demand for oxygen, but tilapia is relatively resilient to limited oxygen by obtaining it at the air-water interface (Lowe-McConnell 1957).

From site visits to smallholder farms in the northern provinces, it was evident that Hopeways monitors water quality, including temperature, conductivity, pH, DO and total dissolved solids, twice daily (morning and afternoon), while the other farms do not. Three other farms, which were not visited, collect water quality data.

There are several tools and devices available for recording water temperature in pond aquaculture systems.

There are traditional thermometers that are simple and inexpensive, thermometers that float on the surface of the water and submersible thermometers that are lowered into the pond at different depths. Data loggers are another option, as are wireless sensors, which farmers can deploy in different areas of the pond to transmit temperature data to a central receiver or a computer system. All of these options provide farmers with real-time monitoring, and farmers can integrate them into automated systems for better control or to implement mitigation strategies. These actions include adjusting feed inputs, modifying aeration systems, changing water circulation or taking any necessary steps to improve the water quality and conditions in the pond. Through training and international support, rural farmers already implement climate mitigation strategies. During drought, farmers will relocate fish to ponds that retain water better, often because of recharge from groundwater. Additionally, farmers aim for a minimum pond depth of 1.5–2 m to help regulate the temperature.

# 4. Environmental mitigation strategies

## 4.1. Elevated temperatures

During extended hot periods, farmers typically observe the response of their fish to factors such as reduced DO and, if needed, will relocate their fish to other ponds. Additionally, tank water flow rates increase during times when the temperature appears to affect the fish (Table 2). During elevated temperatures, farmers need to lower both the stocking density and feeding rate, as fish eat less when they are stressed. Typically, adult fish are fed twice daily, while small fish are fed four times per day to maintain a positive energy balance to invest metabolic energy in growth (Riche et al. 2004), while optimal water temperature promotes feed conversion efficiency (Mengistu et al. 2020).

To buffer and control warm water temperatures, farmers can optimize shading to reduce the amount of direct sunlight on the water surface, use aerators or sprayers to increase water circulation within the pond, or add ice during emergencies.

## 4.2. Cold temperatures

During extended cold periods, farmers must take close note of the well-being and decreased growth of their fish and harvest or relocate their fish to ponds where they seem to perform better. When water temperature drops below 20°C, tilapia eat less, and feeding stops entirely at about 16°C (Balarin and Haller 1982; Chervinski 1982). To guard against cold temperatures, farmers should consider the following factors:

- Choose a location for your tilapia pond with maximum sunlight exposure. This helps warm the water naturally during the day.
- Insulate the sides and bottom of the pond to reduce heat loss. Use materials like expanded polystyrene foam or geotextile liners to provide thermal insulation.
- Consider using supplemental heating techniques during extreme cold periods. If needed, use electric heaters or solar-powered heaters to raise the water temperature.
- Constructing a greenhouse can create a microclimate that traps heat and protects the pond.

For mitigation strategies during high-risk scenarios, farmers can flush their ponds with warm water and increase the mixing of warmer water, move fish to ponds with more sunlight, or reduce feeds (Table 2).

# 5. The relationship between air temperature and pond water temperature

Most smallholder farms do not use sophisticated water quality monitoring equipment and can likely only access air temperature information from local weather stations. Several factors can influence the relationship between air temperature and pond temperature, including sunlight exposure, wind speed, pond depth and the presence of vegetation or other thermal regulators. However, in general, some patterns can help understand their relationship. One is the lag effect, where water has a higher heat capacity than air, making it longer to heat up or cool down. Another is solar radiation, where the sun's energy directly warms the surface of the pond. Wind can also affect the rate of heat exchange between the air and water. In shallow ponds, the water temperature is more likely to closely follow variations in air temperature.

***Table 1***. *Temperature thresholds for tilapia from the literature.*

| | **Red-breasted bream*** | **Three-spotted bream** | **Green-headed bream** | **Tanganyika bream** | **Genetically Improved Farmed Tilapia**** | **Nile tilapia** | **Nile tilapia***** | **Nile tilapia****** |
|---|---|---|---|---|---|---|---|---|
| Growth | Slow | Fast | Average | Fast | | Fast | Fast | Fast |
| Minimum optimal temperature (°C) | 24 | 24 | 24 | 24 | 25 | 24 | 27 | 28 |
| Minimum growth temperature (°C) | | | | | 25 | | 27 | 15 |
| Minimum survival temperature (°C) | 8 | 9 | 12 | not cold-tolerant | 18 | 8 | 10 | 12 |
| Maximum optimal temperature (°C) | 32 | 32 | 32 | 32 | | 32 | 31 | 35 |
| Maximum growth temperature (°C) | | | | | 30 | | 31 | |
| Max survival temperature (°C) | 41 | 41 | 41 | | 37 | 42 | 40 | 42 |
| Minimum optimal DO (mg/L = ppm) | | | | | | | 5 | 2 (0.1) |
| Maximum optimal DO (mg/L = ppm) | | | | | | | 8 | |
| Minimum optimal pH | | | | | | | 7 | 7 (5) |
| Maximum optimal pH | | | | | | | 9 | 8 (11) |

* Hoevenaars and Ng'ambi (2019).
** Pant et al. (2019).
*** Fregene et al. (n.d.).
**** Lim and Webstr (2006).

***Table 2**. Short-term mitigation strategies in high risk and emergency scenarios.*

| | Frequency of monitoring water temperature, DO, pH and ammonia (and nitrite) and observing fish behavior | Option 1: Flushing at water quality thresholds | Option 2: Reducing feeding times by 1 at water quality thresholds |
|---|---|---|---|
| HIGH RISK: Predicted water temperature under 32°C over the next 24 hours | Every 4 hours during the day and once during the night | 1. Temp > 35°C<br>2. DO < 6 mg/L<br>3. pH ≤ 7 or ≥ 9<br>4. Ammonia < 3.0 / nitrite <1, 0.1 in soft water | 1. Temp > 35°C<br>2. DO < 6 mg/L<br>3. pH ≤ 7 or ≥ 9<br>4. Ammonia < 3.0 / nitrite <1, 0.1 in soft water |
| EMERGENCY: Predicted water temperature under 41°C over the next 8 hours | Every 2 hours during the day and every 4 hours during the night | 1. Temp > 35°C<br>2. DO ≤ 6 mg/L<br>3. pH ≤7 or ≥ 9<br>4. Ammonia < 3.0 / nitrite <1, 0.1 in soft water | 1. Temp > 35°C<br>2. DO ≤ 6 mg/L<br>3. pH ≤ 7 or ≥ 9<br>4. Ammonia < 3.0 / nitrite <1, 0.1 in soft water |
| HIGH RISK: Predicted water temperature under 24°C over the next 24 hours | Every 6 hours during the day and at night | 1. Temp < 14°C<br>2. DO < 6 mg/L<br>3. pH ≤ 7 or ≥ 9<br>4. Ammonia < 3.0 / nitrite <1, 0.1 in soft water | 1. Temp < 14°C<br>2. DO < 6 mg/L<br>3. pH ≤ 7 or ≥ 9<br>4. Ammonia < 3.0 / nitrite <1, 0.1 in soft water |
| EMERGENCY: Predicted water temperature under 12°C over the next 8 hours | Every 4 hours during the day and at night | 1. Temp < 14°C<br>2. DO < 6 mg/L<br>3. pH ≤ 7 or ≥ 9<br>4. Ammonia < 3.0 / nitrite <1, 0.1 in soft water | 1. Temp < 14°C<br>2. DO < 6 mg/L<br>3. pH ≤ 7 ≥ 9<br>4. Ammonia < 3.0 / nitrite <1, 0.1 in soft water |

Option 1: Add freshwater and continue monitoring water parameters at the outlet until normal values are obtained.
Option 2: Reduce the number of feeding times and feed the fish slowly until they stop eating.
Option 3: Harvest or move fish that appear stressed to another pond with safe water parameters.

Note: Stress indicators include gasping for air at the surface and fish swimming or lying on their sides or floating at the surface with minimal movement.

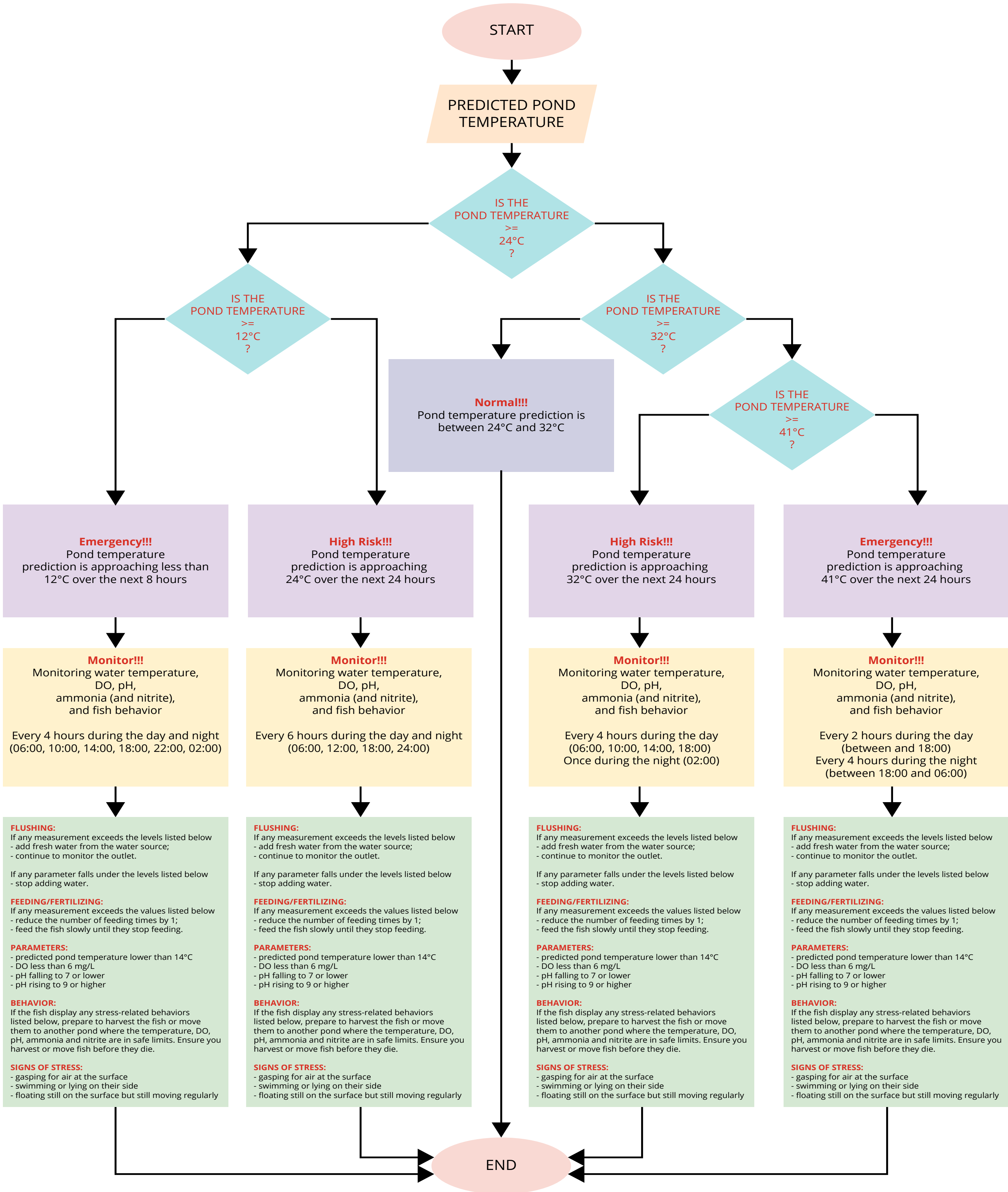
# 6. Decision support tool

We developed a decision support matrix/tool by analyzing existing knowledge of the temperature thresholds for tilapia, as well as the potential effects of temperature on other water quality variables (Figure 2). A decision matrix tool provides decision-making support in pond management strategies in response to adverse weather conditions. There are various strategies available for managing pond temperatures, and each has its advantages and disadvantages.

The decision matrix was developed using python language, and it can be replicated with other programming languages. The main components of a decision tree model are root or decision nodes, chance nodes, representing one of the possible choices available at that point in the tree structure, and the result of a combination of decisions or events. The decision matrix tool entails a combination of conditional statements that generate different warning messages based on a predictive pond temperature value. It evaluates the value of the predicted pond temperature against predefined temperature levels and, depending on the result, prints different messages with instructions for monitoring and mitigation.

Tables 1 and 2 employ four levels of predefined temperatures (12°C, 24°C, 32°C and 40°C) to classify the risk levels of pond temperature alert messages. These messages are broadly classified into three categories: (1) high risk, (2) emergency and (3) normal (Figure 2). The specific temperature levels and response strategies may vary depending on the aquaculture setup and the species being cultivated. In each case, the messages include information about the current temperature, predictions, the impact of temperature on fish health, monitoring parameters, monitoring frequency and mitigation steps.

***Figure 2***. *The decision support tool.*

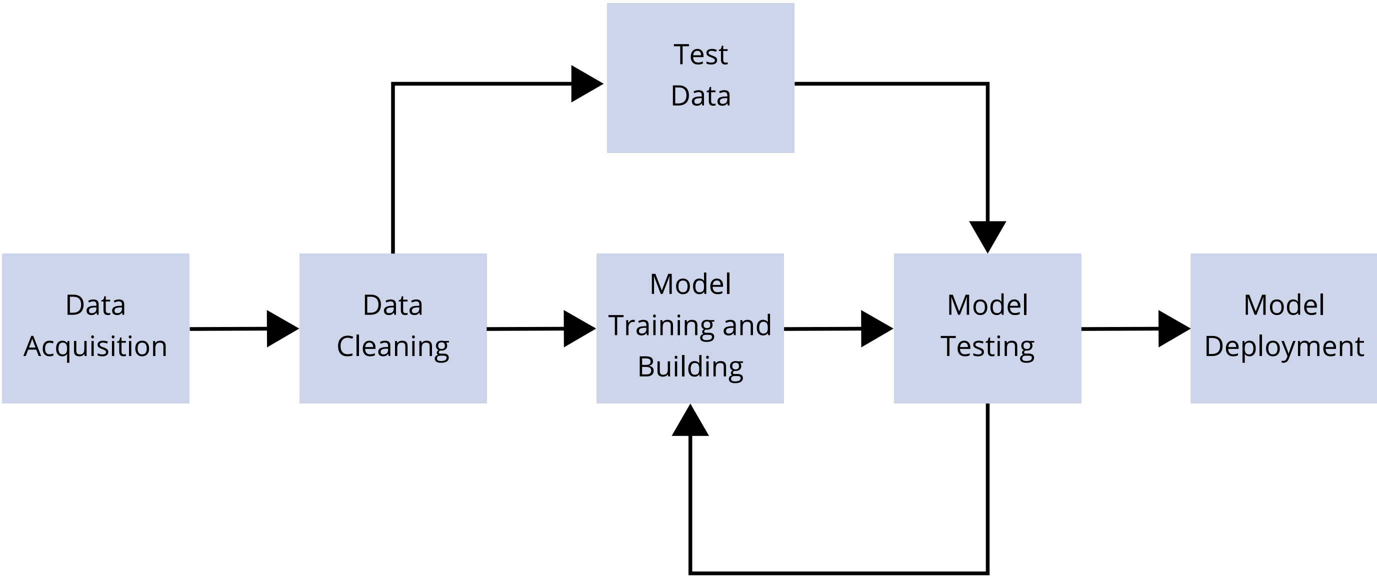



Note: created with BioRender (https://biorender.com/).

# 7. Air–water temperature relationship algorithm

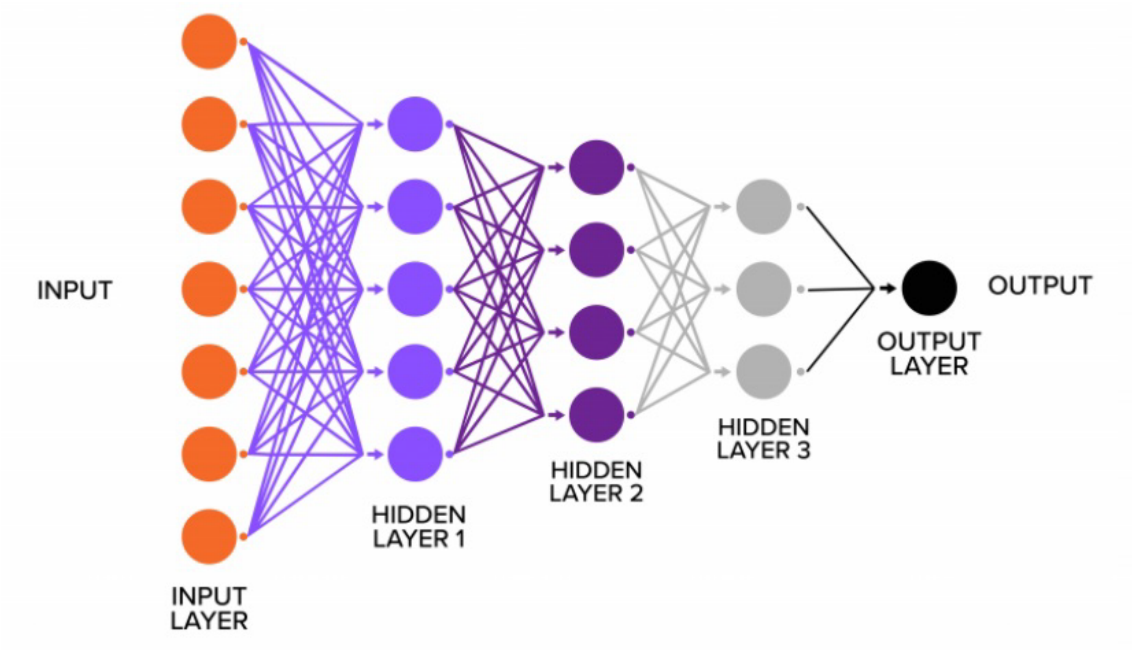
We employed the widely used model generation process to develop the machine learning models used to predict pond temperature. Herein, Figure 3 illustrates the model generation process. During the data acquisition phase, temperatures of the pond water and the surrounding air at specific times of the day are recorded for several months. The data acquisition period in this instance spans from March to the end of September 2022, with temperature measurements taken twice daily in degrees centigrade. Additionally, the model is flexible and capable of accommodating hourly temperature data.

***Figure 3**. Model generation process.*




The cleaning process in this work takes place within a Python Pandas environment. It involves data wrangling techniques to eliminate null cells and employs various data engineering processes. Using the train-test-split method from the sklearn libraries, the dataset is divided into training and testing subsets. In this study, 70% of the dataset is allocated for model training, while the remaining 30% is designated for the testing phase. In building the machine learning models, the TensorFlow framework (Abadi et al. 2016), Keras (Chollet 2015) and scikit-learn libraries were employed within a Python environment. For instance, the deep learning model, which is based on deep neural networks (DNN) is constructed using a sequential model because of its simplicity, featuring five hidden layers. Figure 4 illustrates the architecture of a DNN. Each layer consists of four rectified linear unit activation neurons (Glorot et al. 2015). We selected an Adam-based optimization algorithm (Kingma and Ba 2015), as it offers advantages such as rapid convergence and efficient handling of memory and sparse gradients, making it a preferable choice over the traditional stochastic gradient descent. This first-order optimization algorithm iteratively updates the weights of the neurons based on the training data to optimize the loss function.

***Figure 4****. An illustration of the DNN architecture.*




*Source: Smartboost 2020.*

During model development, we compared five models, including linear regression, stochastic regression, deep learning, random forest and decision tree.

Deep learning, a subset of machine learning, uses neural networks, often referred to as DNNs, as function approximators. It places a significant focus on stacking numerous layers composed of structurally similar components, including neurons, activations, biases, weights and layers. This layering approach defines the multilayer perceptron, a straightforward model constructed iteratively from these fundamental components (Collobert and Bengio 2004).

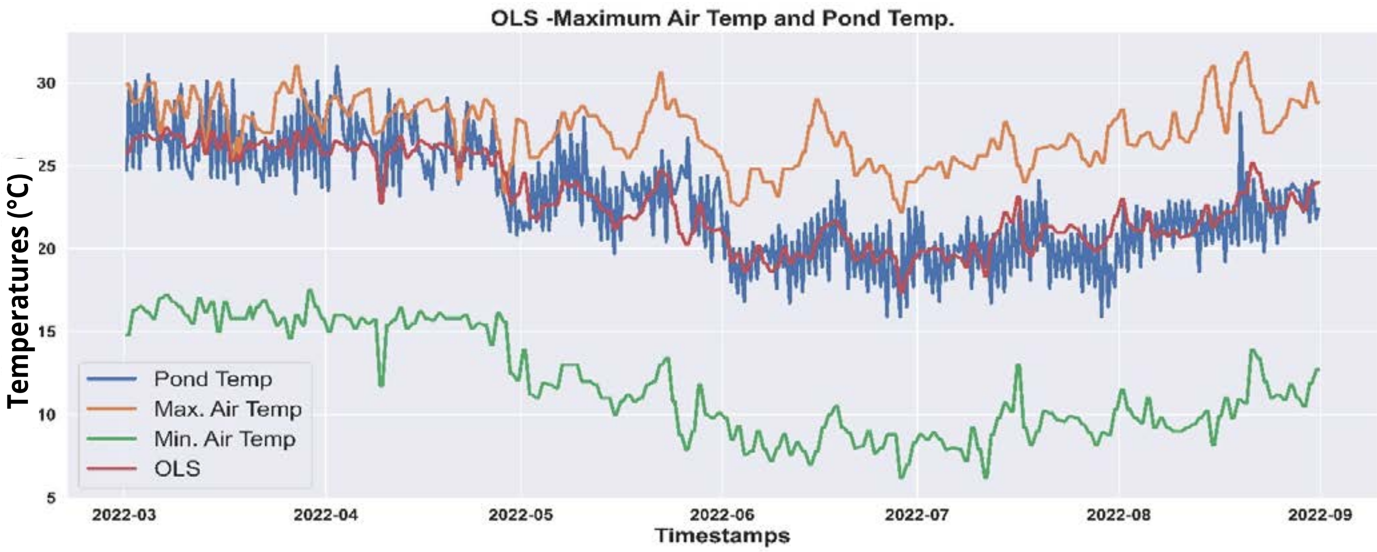
A decision tree algorithm is a machine learning algorithm that uses a decision tree to make predictions. The algorithm employs a recursive function by using a previous term to calculate subsequent terms to split the data into subsets based on the most significant feature at each node of the tree. The decision tree model displays an algorithm that only contains conditional control statements, which were temperature thresholds. The model variables to predict pond temperature included time of day, maximum and minimum air temperature, where both temperatures displayed a linear relationship with pond temperature. The Random Forest algorithm, trademarked by Leo Breiman (Breiman 2001) and Adele Cutler (Cutler et al. 2012), is a widely used machine learning technique. It amalgamates the outputs of numerous decision trees to produce a singular result. Its widespread adoption is driven by its user-friendliness and adaptability, making it suitable for handling both classification and regression tasks.

The data was modeled for a pond designed according to best aquaculture practices, with size and pond depth as constants. A linear regression model for pond temperature is expressed as follows:

$Y(t) = \alpha X1 + \beta X2 + C + Y,$

Where α and β are the gradients (coefficients) of the maximum and minimum air temperature features, respectively. Additionally, C denotes the intercept and Y is the error coefficient. Y(t) is the predicted pond temperature in degrees centigrade at time t. The R-squared value for the linear regression was 0.6, so the linear regression was a good fit. An ordinary least squares regression was fitted to best describe the relationship between the air temperature predictor variables and the pond temperature response variable. The seasonal pattern of pond temperatures and predicted pond temperatures using the linear regression model displayed a close resemblance (Figure 5).

***Figure 5****. Seasonal pattern of the air temperature, pond temperature and predicted pond temperature using the linear regression model.*




We also compared three machine learning models: deep learning, decision tree and random forest. Figures 6, 7 and 8 provide a visual representation of the seasonal fluctuations in air temperature, pond temperature and forecasted pond temperature. These forecasts were generated through the application of machine learning models, with a specific focus on two distinct approaches: a decision tree model and deep learning.

For a more detailed performance evaluation of these models, please refer to Table 3 for a comprehensive summary of their capabilities. In assessing the quality of these predictive models, one crucial metric to consider is the $R^2$ value. This metric, often referred to as the coefficient of determination, serves as an indicator of how effectively a model captures and explains the underlying data patterns. A higher $R^2$ value signifies a closer alignment between the model's predictions and the actual data, with a value of 1 indicating perfect alignment. Mean square error (MSE) is a risk metric that corresponds to the anticipated value of the squared (quadratic) error or loss. The mean absolute error (MAE) is a common metric used in statistics and machine learning to measure the average magnitude of errors between predicted values and actual (observed) values and is calculated by taking the absolute differences between the predicted values and the actual values and then averaging these differences. The mean absolute percentage error (MAPE), alternatively referred to as mean absolute percentage deviation, serves as an evaluation metric primarily employed in regression problems. Its core principle revolves around its sensitivity to relative errors. The mathematical expressions for model performance metrics (Pedregosa et al. 2011) are as follows:

$R^2(y,\hat{y}) = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\hat{y})^2}$

Where $y_i$ denotes the actual pond temperature and $\hat{y}_i$ is the predicted pond temperature value of the $i_{th}$ sample of a total *n* samples, with

$\hat{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$

The mathematical expression for the MSE metric for $n_{samples}$ (number of samples) is given as

$MSE_{(y,\hat{y})} = \frac{1}{n_{samples}}\sum_{i=0}^{n_{samples}-1}(y_i - \hat{y}_i)^2$

The expression for the MAE over a given number of $n_{samples}$ is expressed as

$MAE_{(y,\hat{y})} = \frac{1}{n_{samples}}\sum_{i=0}^{n_{samples-1}} |y_i - \hat{y}_i|$

Finally, the MAPE is defined as

$MAPE_{(y,\hat{y})} = \frac{1}{n_{samples}}\sum_{i=0}^{n_{samples-1}} \frac{|y_i-\hat{y}_i|}{max(\epsilon,|y_i|)}$

Where ϵ is a strictly positive number with a small value to prevent having an undefined solution when the y is zero.

It is worth highlighting that the deep learning model outperformed the others, demonstrating an impressive value of 0.84 in its predictions of pond temperature. This outcome underscores the deep learning model's remarkable accuracy and precision, making it a notable standout in our study.

***Figure 6**. Seasonal pattern of the air temperature, pond temperature and predicted pond temperature using a deep learning model.*

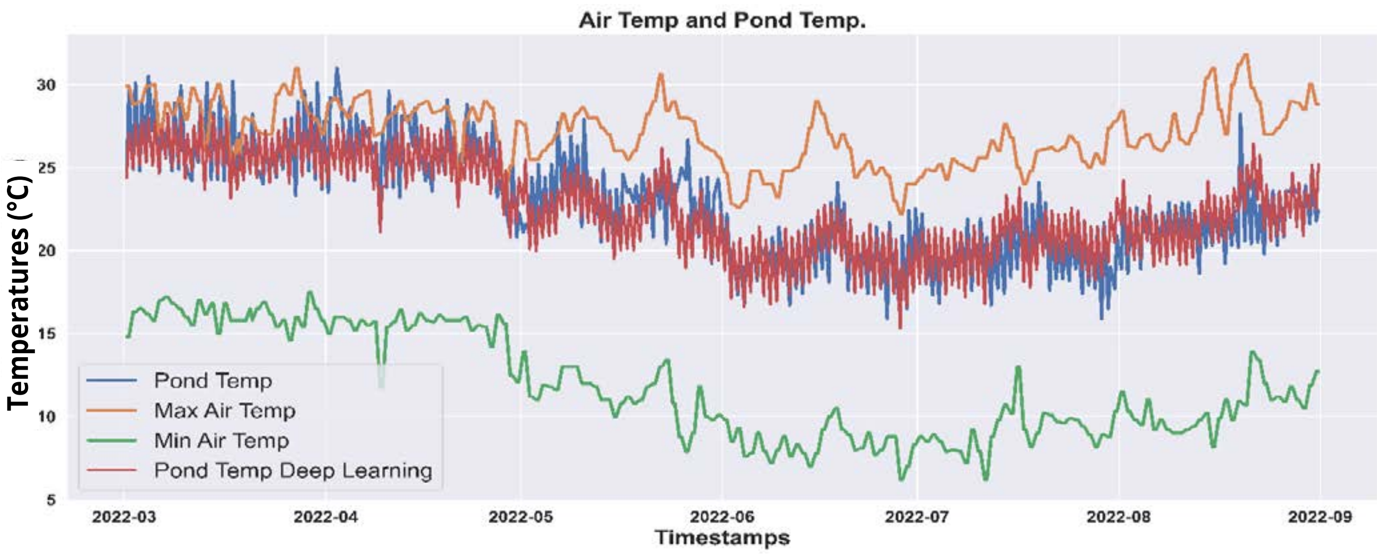


***Figure 7**. Seasonal pattern of the air temperature, pond temperature and predicted pond temperature using a random forest model.*

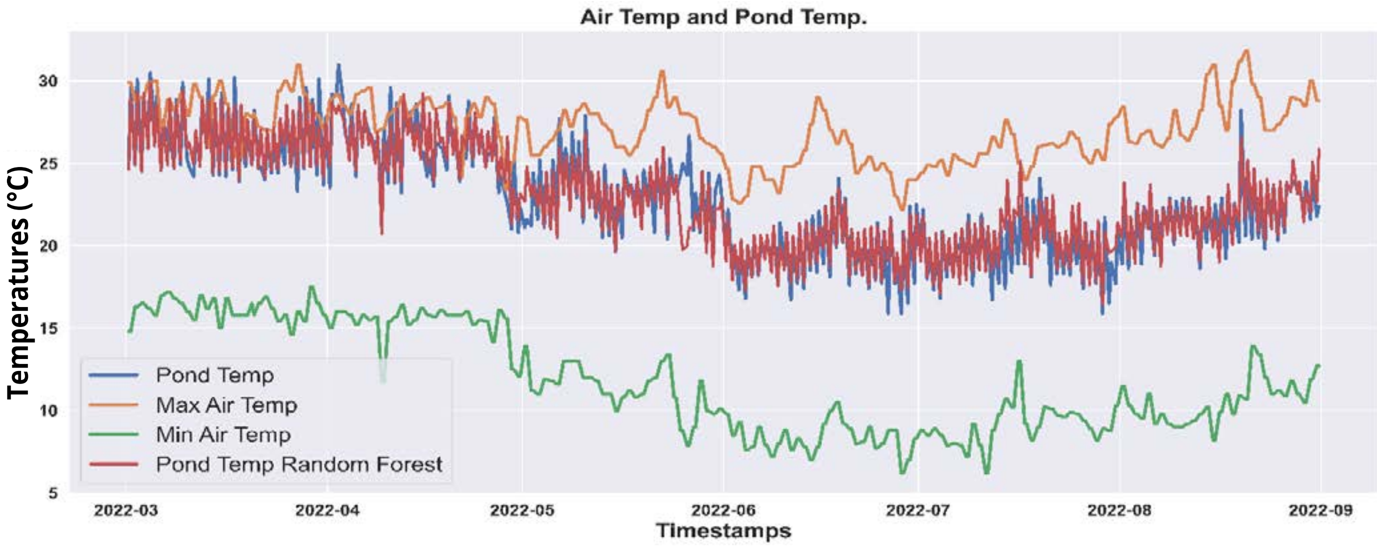



***Figure 8**. Seasonal pattern of the air temperature, pond temperature and predicted pond temperature using a decision tree model.*

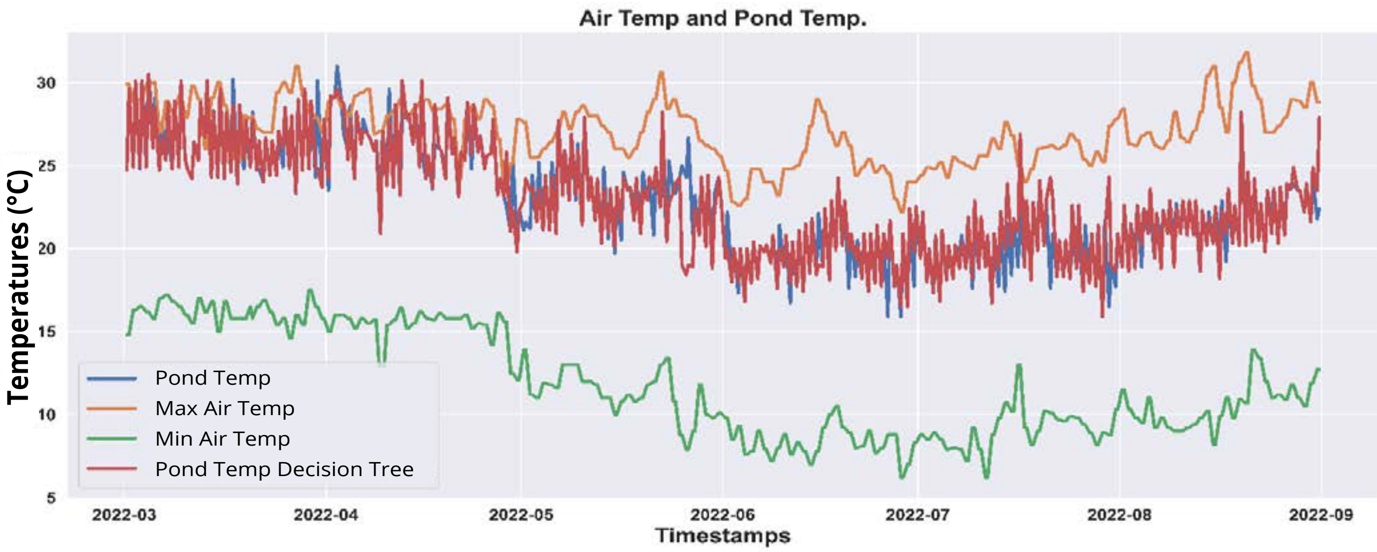



***Table 3**. Summary statistics for the different model performance metrics.*

| Model | $R2$ | MSE | RMSE | MAE | MAPE |
|---|---:|---:|---:|---:|---:|
| Linear regression | 0.61 | 4.37 | 2.09 | 1.75 | 0.08 |
| Stochastic regression | -17.6<br>-4.52 | 9.66<br>41.91 | 3.11<br>6.47 | 2.50<br>5.34 | 0.11<br>0.26 |
| Deep learning | 0.84 | 1.83 | 1.35 | 1.07 | 0.05 |
| Random forest | 0.77 | 2.89 | 1.70 | 1.28 | 0.06 |
| Decision tree | 0.61 | 4.89 | 2.21 | 1.54 | 0.07 |

In summary, from Table 3, the deep learning model is the top performer, with the highest $R^2$ value, followed closely by the random forest model. The choice between these two models may depend on other factors, such as interpretability, computational resources and specific requirements of the task at hand. However, the decision tree model is a good foundation for farmers to understand and predict pond temperatures on their farms. The model is flexible and can be refined for specific operations so that farmers can update scenarios, actions and their predicted outcomes.

# 8. Conclusions and recommendations

## 8.1. Short-term recommendations

- Integrate the algorithm and decision tree into iSAT and link to live weather data.
- Pilot the early warning system with a set of selected farmers.
- Provide the selected farmers with equipment to continuously monitor temperature as a minimum.
- Initiate a project and team to conduct regular reviews and improve the algorithm to include temperature data from more ponds, as well as start to include data on pond-specific variables.
- Provide selected farmers with other monitoring equipment to take intermittent readings of other critical variables such as pH, ammonia, DO and the water source, as well as flow-through rates and overall water availability over time, and then integrate them into the existing algorithm.
- Improve the farmer interface to allow for farmer-led data input (pond information and water quality and flow-through data).

## 8.2. Medium-term recommendations

- Develop tailor-made, low-cost pond monitoring equipment at various stages of development by increasing the number of parameters to measure as well as the systems to store or send data.

## 8.3. Long-term recommendations

- Develop interventions to support farmers in establishing reliable water sources for flow-through, such as upstream storage (scaled to operational and emergency needs) and/or drilling and equipping boreholes with solar (and battery) pumps.
- Develop feasibility models that consider farming inputs and outputs and assist with understanding minimum scales to achieve minimum viable production. (This is critical not only for commercial production but also for ensuring sustainable livelihood strategies for smaller-scale commercial farms or those that combine commercial, subsistence and polyculture systems.)

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