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Modeling the Water Quality of Lake Itasy by Long Short-Term Memory (LSTM) using Landsat 8 Data

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Abstract

Modeling lake water quality is very important to preserve and protect this resource. Several algorithms can be used to model lake water quality using in-situ measurement data. This work used The Long Short-Term Memory (LSTM) deep learning (DL) architecture to obtain models for modeling and predicting water quality parameters of Lake Itasy depending on the reflectance of Landsat8 OLI. The main purpose of this study was to identify the appropriate LSTM model in function of the optimization algorithms: Adagrad, RMSprop and Adam, in order to do the estimation on the date provided, according to the date of satellite image acquisition. The obtained results showed the performance of the developed LSTM model, with an Adaptive Moment Estimation (Adam) optimization algorithm that provided an excellent concordance between the collected and simulated water quality parameters. Moreover, the correlation coefficient (R^2) was 0.993 for the conductivity and 0.977 for the dissolved oxygen concentration. The root mean square error (RMSE) values for conductivity and dissolved oxygen concentration were 0.898 and 0.228 respectively. After choosing the best model, the water quality parameters of the Lake Itasy were estimated on May 25th 2020. The conductivity ranged from 46.8 µS.cm-1 to 66.5 µS.cm-1, and the dissolved oxygen concentration from 6.5 mg/L to 9.1 mg/L. These values indicate that the water from Lake Itasy respects the Malagasy norms in terms of conductivity and dissolved oxygen concentration

1. Introduction

In Surface waters, such as the sea, rivers and lakes are important for long-term economic development and environmental sustainability (Al-Shaibah et al., 2021; Nagy-Kovács et al., 2019). However, the prediction of lake water quality has attracted the attention of researchers due to its effect on the life of biodiversity. Therefore, modeling lake water quality is necessary to monitor, preserve and manage this resource. Modeling water quality with traditional methods, such as in situ-measurements, sample collection from the site and laboratory analyses is impractical. These methods are very expensive, time consuming and limit the assessment of spatial and temporal trends of the water quality (Jerry et al., 2019).

In this study, the conductivity of Lake Itasy water and its dissolved oxygen concentration were modeled. Lake Itasy is the third largest lake in Madagascar (approximately 35 km²) and plays an important role in the economic development of the Itasy region, thanks to tourism, which brings benefits to the local population through related activities, and fish farming (I. et al., 2020). Therefore, it is necessary to seek a new approach to

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avoid the limitations of the traditional monitoring method, as mentioned above, in order to preserve and protect this resource. Remote sensing techniques and machine learning offer opportunities and approaches for modeling and monitoring lake water quality. Remote sensing modeling of lake water quality requires the establishment of a reliable relationship between surface reflectance measured by remote sensing and water quality parameters collected in situ (Barrett & Frazier, 2016).

Previous research on water quality such as Srivastava et al. (2024), are still focused on utilizing the visible, Infrared (NIR), and Thermal Infrared (TIR) spectra to detect water characteristics such as suspended sediment and algae growth. Then Ness et al. (2025), the development of mathematical models based on remote sensing data has been carried out extensively to analyze more than 26,000 water samples to understand the dynamics of environmental parameters. As well as research conducted by Gao (2024) which focused on monitoring industrial and agricultural waste pollution to see the quality of the aquatic environment. However, most of the research that has been done in the past is limited to spectral analysis approaches and the development of conventional statistical or regression models. Another studies, which have been conducted in Lake Itasy, utilized deep learning to analyze water quality including parameters such as Ph and turbidity (Jerry et al., 2019), as well as the use of Landsat 8 in water surface temperature monitoring which showed results that normal temperatures lie in the range of 18.1°C to 22.6°C (Jerry et al., 2018). Based on previous research, the application of Long Short-Term Memory (LSTM) on environmental research has become more and more extensive (Huang & Kuo, 2018) due to its good performance in time-series prediction , but no one of that using this model to water quality assessment.

The application of deep learning models such as LSTM in the use of machine learning techniques, is still relatively rare in quality modeling, especially in Lake Itasy. Based on that gap, it found that there has been no research that specifically utilizes the use of deep learning LSTM model in Itasy Lake. The use of LSTMs can provide a deeper understanding of temporal patterns in environmental data that cannot be fully captured by static models or traditional approaches. To enrich the knowledge about implementation of LSTM model, this study aimed to convey the improvement of water quality model using LSTM to show the new development of LSTM based on deep neural networks, branches of machine learning. In detail, the model utilized Landsat 8 satellite imagery to get some advantages of free and open-source data.

2. Data and Methods

2.1. Study Area

Lake Itasy is located in the Itasy region, the Miarinarivo district and the rural commune of Ampefy. It is sited within the volcanic field of Itasy and geographically located between 19° 04' latitude South and 46° 47' longitude East (Figure 1).

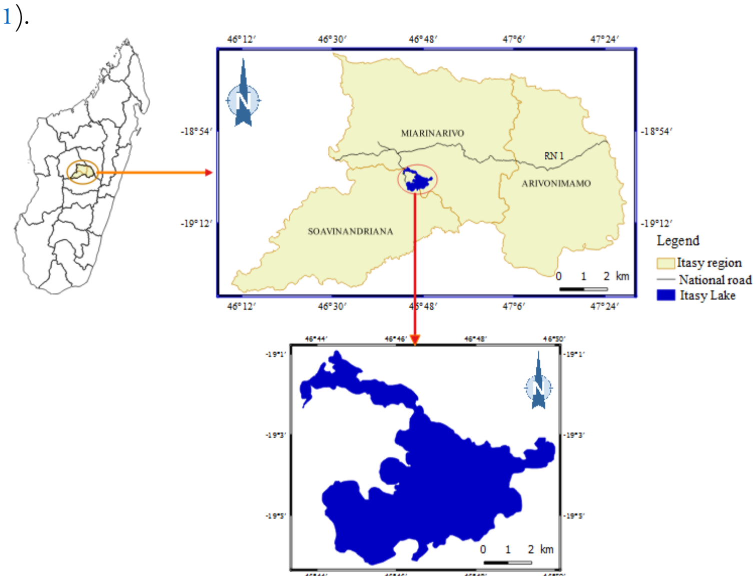

Figure 1. Location of the Study Area

2.2. Data Used

In this study, images from the Landsat8 satellite were used. They were obtained the same day as the in-situ measurements of the water quality parameters of Lake Itasy. The images can be freely downloaded from the United States Geological Survey (USGS) website. Landsat8 carries two sensors: OLI (Operational Land Imager) and TIRS (Thermal Infrared sensors). The characteristics of Landsat 8 OLI/TIRS are given in Table 1.

Table 1. Landsat 8 Characteristics

Band Designations	Wavelength (µm)	Spatial Resolution (m)
Band 1 (Coastal Aerosol)	0.43 – 0.45	30
Band 2 (Blue)	0.45 – 0.51	30
Band 3 (Green)	0.53 – 0.59	30
Band 4 (Red)	0.64 – 0.67	30
Band 5 (Near Infrared)	0.85 – 0.88	30
Band 6 (Short wave infrared)	1.57 – 1.65	30
Band 7 (Short wave infrared)	2.11 – 2.29	30
Band 8 (Panchromatic)	0.50 – 0.68	15
Band 9 (Cirrus)	1.36 – 1.39	30
Band 10 (Thermal infrared)	10.6 – 11.19	100
Band 11 (Thermal infrared)	11.50 – 12.51	100

Source: Landsat 8 Data Users Handbook, 2015

2.3. Water Quality Parameters

2.3.1. Conductivity

Conductivity is the capability of the water to carry electric current and serves as a tool to assess the purity of water (Murugesan et al., 2006). The ions like chloride (Cl^-), sodium (Na^+), calcium (Ca^{2+}), phosphate (PO_4^{3-}) etc. are responsible for electric current conduction.

2.3.2. Dissolved Oxygen

Dissolved oxygen is one of the key parameters in water quality analysis. It is used by most aquatic organisms to survive (Gholizadeh et al., 2016). Dissolved oxygen concentration is influenced by the temperature, the rate of photosynthesis, the turbidity, and the concentration of organic matters, such as industrial waste (Arief, 2017).

2.4. Method

2.4.1. Image pre-Processing

The Dark Object Subtraction (DOS1) atmospheric correction method was used in this work to reduce the atmospheric effects and to calculate the values of surface reflectance. This method can provide an accurate mapping for wetland areas and is well accepted by the geospatial community (Song et al., 2001). The Quantum GIS (QGIS) software was used to carry out the DOS1 atmospheric correction and to draw the maps shown in this article.

2.4.2. Long Short-Term Memory (LSTM)

The deep neural network is the branch of machine learning introduced to approach the objective of automatic learning. These methods were developed in the 1980s but were quickly left because they were considered as not promising (Blier, 2017). With the introduction of computers, which can make quick calculations, new big data databases, and the progress in the optimization techniques, deep learning has become the most competitive algorithm for different tasks (LeCun et al., 2015), such as voice recognition and face recognition. In deep learning, there are many architectures that can be used, such as Convolutional Neural

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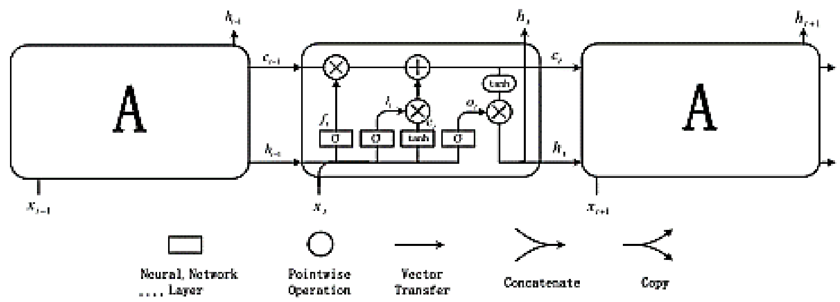
Network (CNN), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM) which was introduced by Hochreiter and Schmid Huber in 1997 (Hochreiter & Schmidhuber, 1997) to remedy the vanishing and exploding gradient problem that is encountered in RNN. LSTM was the architecture used in this study.

a. The LSTM Architecture

As an improvement of recurrent neural network, LSTMs are capable of learning long-term dependencies and remembering past information, while predicting future values and taking them into account (Hochreiter & Schmidhuber, 1997) LSTMs that use purpose-built the memory cells to store information also have this chained in similar structure, but the repeating module is structured differently (Liu et al., 2019). There are four interacting layers in an LSTM cell (Olah, 2015) as depicted in Figure 2.



Source: Ping Liu et al. (2019)

Figure 2. LSTM unit structure

Forget gate f_t (Equation 1) (Aslam et al., 2019): It decides what kind of information will be removed and how much information will be kept (Hafezparast Mavadat & Marabi, 2021). This process was carried out by the application of the sigmoid function σ which takes the preceding output value h_{t-1} at $t-1$ and the input value x_t at t. The output value of f_t varies from 0 to 1.

$$f_t = \sigma(W_f * [h_{t-1}, x_t] + b_f) \text{ .... } (Eq.\ 1)$$

Input gate i_t (Equation 2) (Liu et al., 2019): It acts as a filter because it decides which information will be added to the memory cell. It takes the values h_{t-1} and x_t, and its value is also included between 0 and 1 by using the sigmoid function σ.

$$i_t = \sigma(W_i * [h_{t-1}, x_t] + b_i) \text{ .... } (Eq.\ 2)$$

Memory cell: It contains two elements, which are the new memory cell C_t (Equation 3) and the final memory cell C_t (Equation 4). The new memory cell is used to carry the information which comes being's updates and the final memory cell is used to update the state of the new memory cell.

$$C_t = \tanh(W_c * [h_{t-1}, x_t] + b_c) \text{ .... } (Eq.\ 3)$$

$$C_t = f_t \otimes C_{t-1} + i_t \otimes C_t \text{ .... } (Eq.\ 4)$$

Here, C_t and C_{t-1} are the cell states at times t and $t-1$.

The output gate o_t (Equation 5) (Liu et al., 2019):'It decides which information can be sent to the output of the cell state. Finally, the output of the LSTM unit was obtained by multiplying the output gate by the hyperbolic tangent of the cell state (Equation 6).

$$o_t = \sigma\left(W_o * \left[h_{t-1}, x_t\right] + b_o\right) \text{............ (Eq. 5)}$$

$$h_t = o_t \otimes \tanh(C_t) \text{............ (Eq. 6)}$$

Note that W_f, W_i, W_c, W_o are the matrix weights associated with f, i, c, o. The terms b_f, b_i, b_c, b_o are the biases that were obtained during the training and testing process. The sign * represents the matrix multiplication and ⊗ indicates the multiplication element by element.

b. Optimization Algorithm

Three optimization algorithms based on the gradient descent were used to optimize the deep neural network parameters, i.e. to update network weights iterative in training data: Adagrad (Adaptive gradient method) (Wang et al., 2019), RMSprop (Root Mean Square Propagation) (Hinton et al., 2011) and Adam (Adaptive moment Estimation) (Kingma, 2014).

c. Activation Function

The Rectified Linear Unit (ReLU) proposed by Nair and Hinton in 2010 was the activation function used in this work. ReLU is the most widely used activation function in the deep learning network (Nair V. & Hinton, G.E., 2010). It has proved to be the most successful and offers the best performance (Dahl et al., 2013; Zeiler et al., 2013). It is given by the following Equation 7:

$$f(x) = \max(0, x) = \begin{cases} x, \ if\ x \geq 0 \\ \quad and \\ x, \ if\ x < 0 \end{cases} \qquad \text{....... (Eq. 7)}$$

2.4.3. Model evaluation

A model without validation criteria is not a model. The performance of the models used in this study was evaluated according to two common evaluation indicators: The correlation coefficient (R^2) and the root mean square error $(RMSE)$.

a. The Correlation Coefficient

The correlation coefficient measures the relationship degree between two variables. Its value ranges between -1 and +1. If it is near -1 or close to +1, it indicates that the correlation between two variables is strong. It is given by (Equation 8).

$$R^2 = \frac{\sum_{i=1}^{n}(t_i - \bar{t})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(t_i - \bar{t})^2} * \sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \text{................ (Eq. 8)}$$

Where t_i and $\bar{t}$ represent the in-situ measurements and their average, y_i and $\bar{y}$ represent the obtained values from the model and their average, n is the observation number.

b. Root Mean Square Error (RMSE)

RMSE is often used to calculate the difference between the predicted value and the observed value. The smaller the RMSE value, the smaller the distance between the two values (prediction and observation). RMSE can be calculated using Equation 9.

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$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(t_i - y_i)^2}{n}} \qquad (Eq.\ 9)$$

where t_i is the in-situ measurement of the value of the water quality parameter, y_i is the prediction from the models and n is the observation number.

2.4.4. Research Diagram

A summary of the methodology used to conduct this research is shown in Figure 3. The images used in this study were Landsat8 imagery, downloaded from USGS. When the data were obtained, the pre-processing included the atmospheric correction, and the extraction of the study area was performed on the QGIS software. Then, the bands 2,3,4,5 were selected and these pixels were extracted because the spectral response for these bands is related to water quality (Jerry et al., 2019). The pixels extracted from the in-situ measurements data were integrated into the LSTM model to train the network. The following step was to evaluate the performance of the LSTM model using RMSE and R2 to choose the appropriate model that will be used to estimate the conductivity and the dissolved oxygen in order to create the map distribution of these parameters.

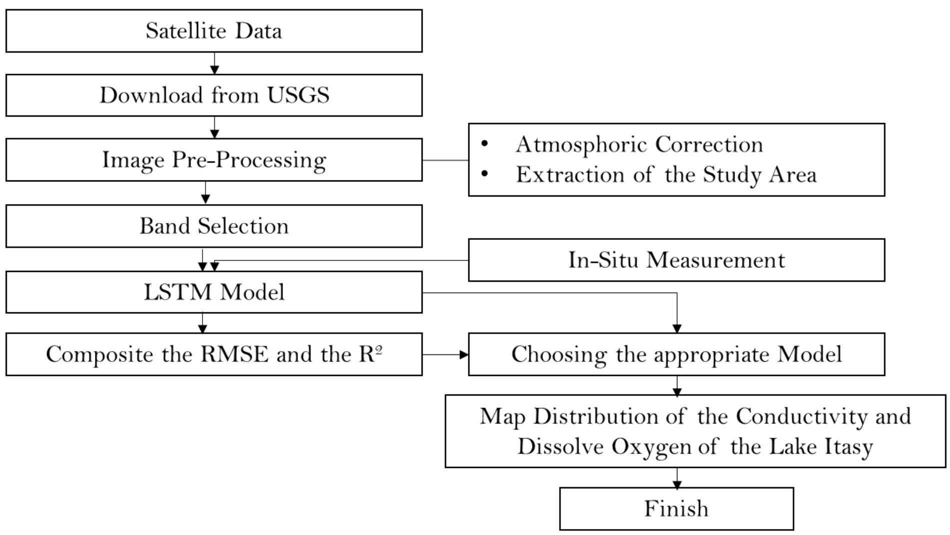

Figure 3. Research Flow Chart of the Study

3. Result and Discussion

This section presents the findings derived from the application of the LSTM model to predict water quality parameters, specifically conductivity and dissolved oxygen, based on remote sensing data. The discussion also covers the interpretation of the results in relation to the objectives of the study. The performance of the model is evaluated using RMSE and R^2 metrics to assess the accuracy and reliability of the predictions. The results are organized in subsections to clearly explain the model output and its implications.

3.1. Result

3.1.1. Conductivity

The LSTM architecture deep neural network used for modeling the conductivity of Lake Itasy water was constituted of 20 inputs, 3 LSTM layers containing 15, 24 and 16 elements respectively, followed by 2 dense layers of 20 and 10 elements, and by 20 output layers. The number of epochs was 10000.

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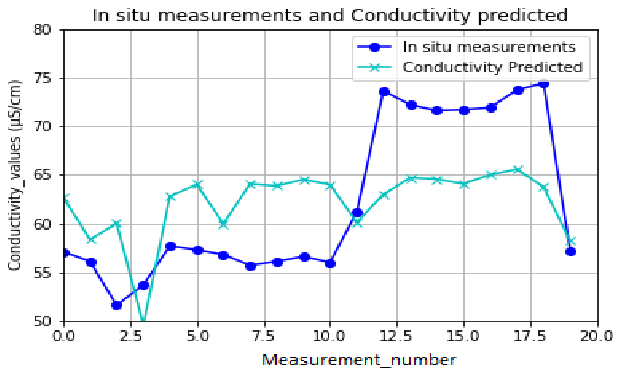

Figure 4. In-situ Measurements and Conductivity Predicted using the Adagrad Optimization

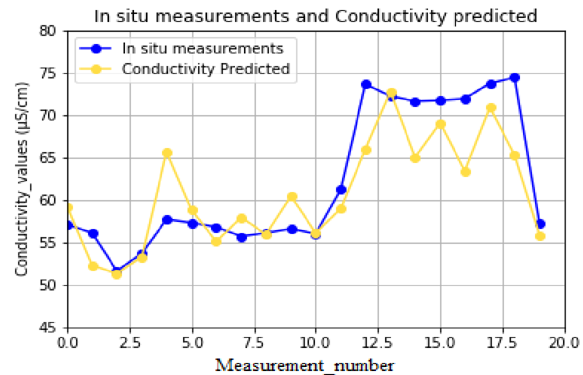

Figure 5. In-situ Measurements and Conductivity Predicted using the RMSprop Optimization

The curves in the Figure 4 show the in-situ measurement conductivity and the predicted conductivity from this architecture with the Adagrad optimization. The correlation coefficient between the two values was 0.500. It can be concluded that the model is inadequate. The Figure 5 shows the measured conductivity and the predicted conductivity when the RMSprop optimization was used. This is an acceptable model with a correspondence rate of 85.9% between the in-situ values and the predicted values.

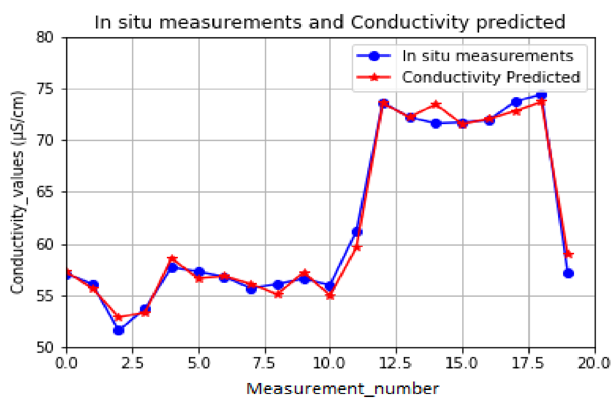

Figure 6. In-situ Measurements and Conductivity Predicted using the Adam Optimization

After changing the optimization algorithm to Adam, the similarity between measured conductivity and predicted conductivity was obtained as shown in the Figure 6. With a 99.3% correspondence between two values, the model is appropriate.

The performance of the model according to the optimization algorithm is given in Table 2. According to this table, the best optimization algorithm that can be used to model the conductivity of Lake Itasy is the Adam optimization algorithm since the correlation between collected values and estimated values is high (R^2=0.993) and the RMSE value is weak (RMSE=0.898).

Table 2. Model Performance

Optimization Algorithm	R^2	RMSE
Adagrad	0.500	6.940
RMSprop	0.859	4.432
Adam	0.993	0.898

The Figure 7 shows the estimation of the conductivity of Lake Itasy using LSTM with the Adam optimization. The spatial distribution of water conductivity ranged from 46.8 µS.cm-1 to 66.5 µS.cm-1. It indicates that the Lake Itasy water respects the Malagasy norm which is inferior to 250 µS.cm-1, and that it is of good quality (Class A) (Water surface classifications according to decree n°2003/464 in 15/04/03).

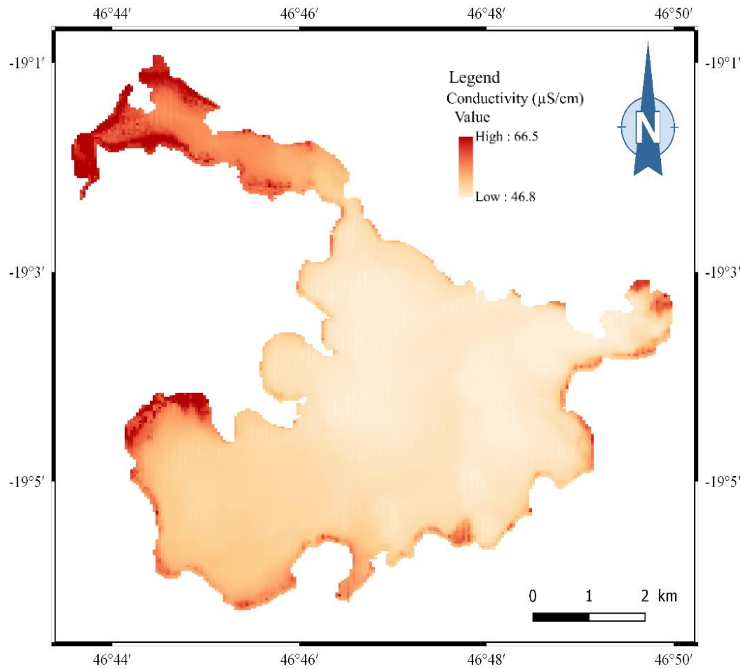

Figure 7. Map Distribution of the Conductivity of Lake Itasy (05/25/2020)

3.1.2. Dissolved Oxygen

On the other hand, for the modeling of the Lake Itasy dissolved oxygen concentration, an architecture composed of 18 inputs, 3 LSTM hidden layers of 33, 23 and 15 elements, 2 dense layers of 17 and 15 elements and one output layer of 18 elements was constructed. The number of iterations was 10000.

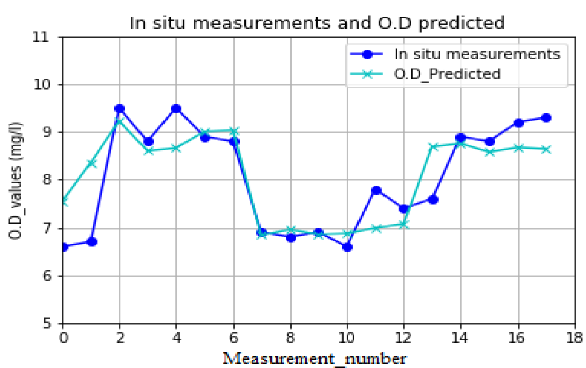

Figure 8. In-situ Measurements and Dissolved Oxygen Concentration Predicted using the Adagrad Optimization

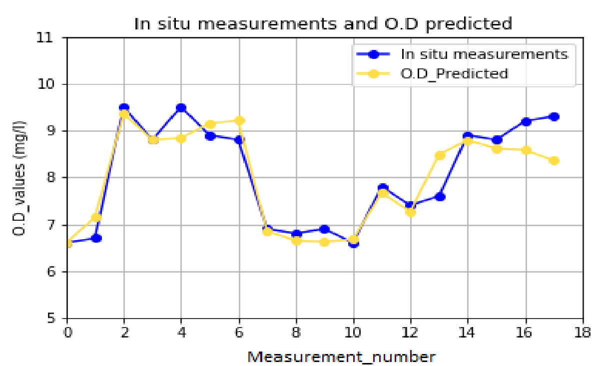

Figure 9. In-situ Measurements and Dissolved Oxygen Concentration Predicted using the RMSprop optimization

The dissolved oxygen concentration measured in situ and the dissolved oxygen concentration estimated using the Adagrad optimization are represented in Figure 8. It is an acceptable model as the correlation coefficient between measured values and predicted values is 0.775. The Figure 9 shows the measurements of the dissolved oxygen concentration collected in situ and the concentrations predicted by replacing the Adagrad optimization by RMSprop. According to this figure, the concentrations measured are almost similar to the concentrations estimated, with a 92.5% correspondence. Thus, this combination can be considered to be a good model. The curves in the Figure 10 show the collected data on the dissolved oxygen concentration and the estimations when the optimization is Adam. They are in good concordance, with a correlation coefficient of 0.997, the model is then adequate.

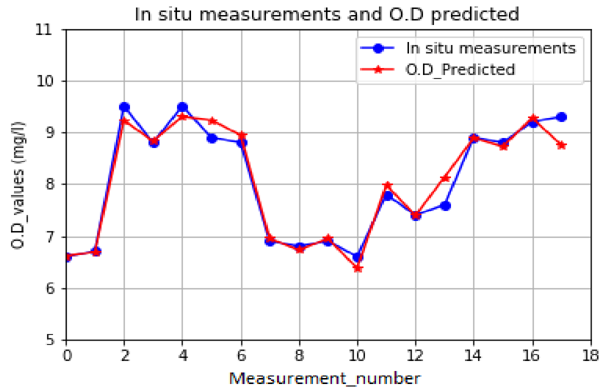

Figure 10. In-situ Measurements and Dissolved Oxygen Concentration Predicted using the Adam Optimization

Table 3. Model Performance

Optimization Algorithm	R²	RMSE
Adagrad	0.775	0.683
RMSprop	0.925	0.417
Adam	0.977	0.228

Table 3 depicts the performance of the model according to the optimization algorithm. This table indicates that the LSTM architecture utilizing the Adam optimization is the most adapted model to estimate the dissolved oxygen concentrations of Lake Itasy.

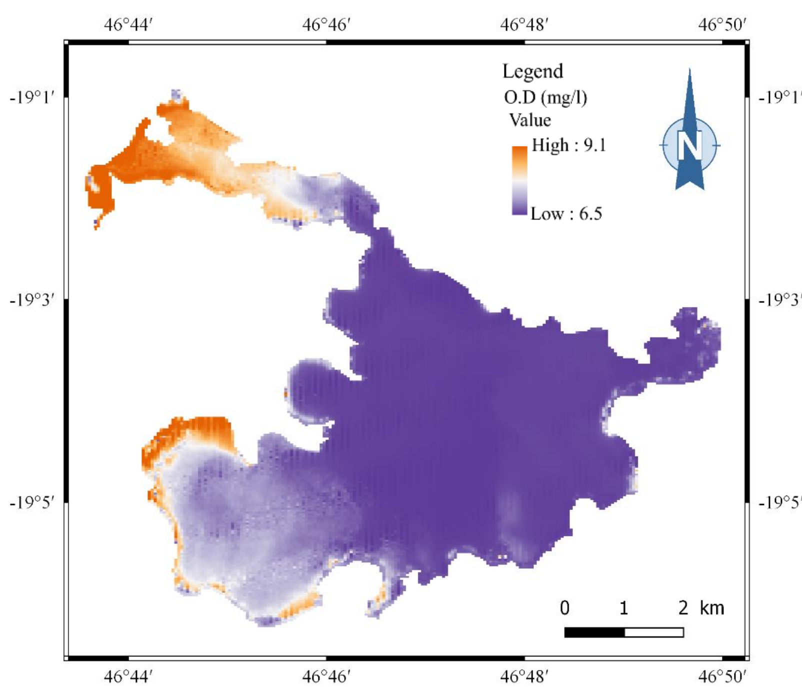

Figure 11. Map Distribution of Dissolved Oxygen of Lake Itasy (05/25/2020)

The spatial distribution of surface water dissolved oxygen of Lake Itasy is shown in the Figure 11 after applying the best model, dated May 25th 2020. Regarding the Lake Itasy water class, it is good because the concentration of dissolved oxygen is superior to 5 mg/L everywhere (Water surface classifications according to the decree n°2003/464 in 15/04/03).

3.2. Discussion

The focus of the present study was to compare the performances of the LSTM model when the optimization algorithm was changed while keeping the numbers of LSTM layers and the epoch number. The results showed that the LSTM model using a Rectified Linear Unit (ReLU) activation function and the Adam optimizer was the best model with a high-level R^2. This result is in accordance with the research of Dheda & Cheng (2020) based on both multivariate single and multiple step LSTM models using ReLU activation and RMSprop optimizer, and confirmed the abilities of the LSTM model in water quality prediction (A et al., 2021; Liu et al., 2019; Wang et al., 2023; Wang et al., 2017). One weakness of this work was that the number of data collections was little.

This study is a further response to various studies that have been conducted previously by Gao (2024); Jerry et al. (2018, 2019); Ness et al. (2025); and Srivastava et al. (2024). Although these studies have made important contributions to water quality assessment through the use of remote sensing and deep learning models, none have specifically utilized the use of LSTM in temporally modeling water quality. The use of LSTM in this study provides a new perspective due to its ability to capture the patterns and dynamics of time series data that are relevant in monitoring changes in water quality over time. As such, this approach not only complements previous research, but also offers the potential to improve and understand long-term fluctuations in water quality.

Based on the results of the research that has been done, it can be seen that the advantages of the results obtained using LSTM show results that are close to real conditions. Possible future works include improving the number of in situ measurements and expanding the study to incorporate ensemble modeling techniques, combining LSTM with another deep learning architecture, such as CNN (Barzegar et al., 2020), RNN, to further improve the accuracy and robustness of the predictions. This is not only useful for environmental management, but can be maximized for infrastructure provision planning in supporting the availability of water resources.

4. Conclusion

Lake biodiversity plays an important role for aquatic life, for humans and for appropriate development. In Madagascar, surface waters are used for human consumption after treatment and for other activities, such as fish farming. To protect this resource, modeling about the quality of the water is necessary. This work showed that the Long Short-Term Memory (LSTM) with the Adam optimization was the most appropriate model for modeling and predicting the quality of the Lake Itasy water using remote sensing (Landsat 8). This model reached a high level of correlation coefficient $R^2>0.95$ for the conductivity and the dissolved oxygen concentration, which is trustworthy. The obtained results indicate that Lake Itasy respects the Malagasy norms regarding conductivity and dissolved oxygen concentrations. This work is a contribution to avoiding the problems associated with the traditional method of monitoring water quality, and to enabling the monitoring and evaluation of changes in conductivity and dissolved oxygen in the surface water of Lake Itasy. The two parameters that were modeled in this work are among the key parameters for determining surface water quality. Therefore, it is highly recommended that future research model other water quality parameters such as turbidity, pH, temperature etc. to gather more knowledge about this lake.

5. References

A, O. C., A, B. W., Mayowa, A., & Olajide, O. M. (2021). Forecasting of water quality index using long short-term memory (LSTM) networks. *International Journal of Advances in Engineering and Management (IJAEM, 3*(10), 1007–1017.

Al-Shaibah, B., Liu, X., Zhang, J., Tong, Z., Zhang, M., El-Zeiny, A., Faichia, C., Hussain, M., & Tayyab, M. (2021). Modeling Water Quality Parameters Using Landsat Multispectral Images: A Case Study of Erlong Lake, Northeast China. *Remote Sensing*, *13*(9), 1603. [Crossref]

Arief, M. (2017). Development of dissolved oxygen concentration extraction model using Landsat data case study: Ringgung coastal waters. *International Journal of Remote Sensing and Earth Sciences (IJReSES)*, *12*(1), 1–12.

Aslam, M., Lee, J.-M., Kim, H.-S., Lee, S.-J., & Hong, S. (2019). Deep Learning Models for Long-Term Solar Radiation Forecasting Considering Microgrid Installation: A Comparative Study. *Energies*, *13*(1), 147. [Crossref]

Barrett, D., & Frazier, A. (2016). Automated Method for Monitoring Water Quality Using Landsat Imagery. *Water*, *8*(6), 257. [Crossref]

Barzegar, R., Aalami, M. T., & Adamowski, J. (2020). Short-term water quality variable prediction using a hybrid CNN–LSTM deep learning model. *Stochastic Environmental Research and Risk Assessment*, *34*(2), 415–433. [Crossref]

Blier, L. (2017). Apprentissage profond et théorie de l'information. *Université Paris-Saclay*.

Dahl, G. E., Sainath, T. N., & Hinton, G. E. (2013). Improving deep neural networks for LVCSR using rectified linear units and dropout. *2013 IEEE International Conference on Acoustics, Speech and Signal Processing*, 8609–8613. [Crossref]

Dheda, D., & Cheng, L. (2020). A multivariate water quality parameter prediction model using recurrent neural network. *ArXiv Preprint ArXiv:2003.11492*.

Gao, H. (2024). Application and Effect Evaluation of Remote Sensing Technology in the Monitoring of Water Pollution. *Transactions on Environment, Energy and Earth Sciences*, *3*, 186–191.[Crossref]

Gholizadeh, M., Melesse, A., & Reddi, L. (2016). A Comprehensive Review on Water Quality Parameters Estimation Using Remote Sensing Techniques. *Sensors*, *16*(8), 1298. [Crossref]

Hafezparast Mavadat, M., & Marabi, S. (2021). Prediction of SAR and TDS parameters using LSTM-RNN model: A case study on Aran station, Iran. *Journal of Applied Research in Water and Wastewater*, *8*(2), 88–97.

Hinton, G., Nitish, S., & Swersky, K. (2011). Divide the gradient by a running average of its recent magnitude. *Neural Networks for Machine Learning*.

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation*, *9*(8), 1735–1780. [Crossref]

Huang, C.-J., & Kuo, P.-H. (2018). A Deep CNN-LSTM Model for Particulate Matter (PM2.5) Forecasting in Smart Cities. *Sensors*, *18*(7), 2220. [Crossref]

I., R. R., F., J. J. C., & Fils, L. R. (2020). Reinforcement of Knowledge of Some Parameters of Lake Itasy in Order to Establish Its Current State of Health. *Resources and Environment*, *10*(2), 19–25.

Jerry, R., Rija, R., Jean, R., Lahatra, R., & Fils, R. (2018). Temperature Retrieval of Lake Itasy Using Remote Sensing. *Resources and Environment*, *8*(6), 241–244. [Crossref]

Jerry, R., Rija, R., Jean, R., Lahatra, R., & Fils, R. (2019). Modelling of Lake Water Quality Parameters by Deep Learning Using Remote Sensing Data. *American Journal of Geographic Information System*, *2019*(6), 221–227. [Crossref]

Kingma, D. P. (2014). Adam: A method for stochastic optimization. *ArXiv Preprint ArXiv:1412.6980*.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444. [Crossref]

Liu, P., Wang, J., Sangaiah, A. K., Xie, Y., & Yin, X. (2019). Analysis and Prediction of Water Quality Using LSTM Deep Neural Networks in IoT Environment. *Sustainability*, *11*(7), 2058. [Crossref]

Murugesan, A., Ramu, A., & Kannan, N. (2006). Water quality assessment from Uthamapalayam municipality in Theni District, Tamil Nadu, India. *Pollution Research*, *25*(1), 163.

Nagy-Kovács, Z., Davidesz, J., Czihat-Mártonné, K., Till, G., Fleit, E., & Grischek, T. (2019). Water Quality Changes during Riverbank Filtration in Budapest, Hungary. *Water*, *11*(2), 302. [Crossref]

Ness, E., Fatima, A., Maktabdar-Oghaz, M., & Luca, C. (2025). An investigation into water quality monitoring models using remote sensing. *International Journal of Remote Sensing*, *46*(4), 1742–1772. [Crossref]

Olah, C. (2015). *Understanding lstm networks*.

Song, C., Woodcock, C. E., Seto, K. C., Lenney, M. P., & Macomber, S. A. (2001). Classification and Change Detection Using Landsat TM Data. *Remote Sensing of Environment*, *75*(2), 230–244. [Crossref]

Srivastava, M. K., Gaur, S., Ohri, A., Srivastava, P. K., & Singh, N. (2024). Applications of remote sensing in water quality assessment. In *Remote Sensing in Precision Agriculture* (pp. 217–236). Elsevier. [Crossref]

Wang, H., Zhou, J., Wang, Y., Wei, J., Liu, W., Yu, C., & Li, Z. (2019). Optimization Algorithms of Neural Networks for Traditional Time-Domain Equalizer in Optical Communications. *Applied Sciences*, *9*(18), 3907. [Crossref]

Wang, X., Li, Y., Qiao, Q., Tavares, A., & Liang, Y. (2023). Water Quality Prediction Based on Machine Learning and Comprehensive Weighting Methods. *Entropy*, *25*(8), 1186. [Crossref]

Wang, Y., Zhou, J., Chen, K., Wang, Y., & Liu, L. (2017). Water quality prediction method based on LSTM neural network. *2017 12th International Conference on Intelligent Systems and Knowledge Engineering (ISKE)*, 1–5. [Crossref]

Zeiler, M. D., Ranzato, M., Monga, R., Mao, M., Yang, K., Le, Q. V., Nguyen, P., Senior, A., Vanhoucke, V., Dean, J., & Hinton, G. E. (2013). On rectified linear units for speech processing. *2013 IEEE International Conference on Acoustics, Speech and Signal Processing*, 3517–3521. [Crossref]