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Effect of Climate Variability on Carbon Biomass in Lake Kivu : ARDL Model Approach

Kintu Mayaka Doudou [1,2] , Isumbisho Mwapu Pascal [1,6] , Ngonzo Luwesi Cush [1,3] , Riziki Walumona Jacques [5],
Masilya Mulungulu Pascal [5], Rodric Mérimé Nonki [1,4]

1.Regional School of water at the University of Kinshasa, (Democratic Republic of Congo).
2.University of Kindu ;
3.African University of management and Technology, Congo-Brazzaville ;
4.Environmental Modelling and Atmospheric Physics Laboratory, University of Yaoundé 1, Cameroon ;
5.Applied Hydrobiology Teaching and Research Unit (UERHA), Biology Department, Higher Pedagogical Institute of Kinshasa of Bukavu, (Democratic Republic of Congo) ;
6.Laboratory for the Study of Aquatic Environments (LEMA), Biology Department, Higher Pedagogical Institute of Kinshasa, (Democratic Republic of Congo) .

Abstract

The effectiveness of climate change around Lake Kivu in the Democratic Republic of Congo has been verified using time series of climate data spanning more than 3 decades. This study aims to analyse the effects of climate variability on the carbon biomass of Lake Kivu, which have not been documented to date. The biological data and physico-chemical parameters were collected from documentary sources in the Unité d'Enseignement et de Recherche en Hydrobiologie Appliquée (UERHA) database from 2002 to 2022 and from personal analysis in the laboratory. The climate data was downloaded from the NASA website (https://power.larc.nasa.gov) and covers a period from 1981 to 2023. We applied the Auto Regressive Distributed Lag model (ARDL). The results indicate that only the mean annual temperature has changed, but not significantly over the period 1981 to 2023, with an increase of 1.13°C in the Lake Kivu catchment area, rising from 18.04°C in 1981 to 19.17 in August 2023 (R2=0.633). This has a significant negative influence (t:-2.156404 and Prob.: 0.0327) on the carbon biomass of Lake Kivu. On the other hand, the other synchronous explanatory variables (Conductivity, rainfall, Secchi depth value and Turbidity) have statistically null coefficients because they have probabilities greater than 5%. They therefore have no effect on carbon biomass. Furthermore, 51.9% of the biomass was explained by the explanatory variables included in the synchronous and lagged model, with an adjusted determination coefficient of 46.3%. The Fisher F probability (F:9.439 and Prob. 0.0000), being less than the 5% margin of error, shows that the model is globally and statistically significant.

Keywords: Ecological functioning, Phytoplankton, Photosynthesis, Anthropogenic activities, Eutrophication, Atmospheric temperature, Modelling.

Effet de la Variabilité Climatique sur la Biomasse en Carbone du Lac Kivu : approche par le modèle ARDL

Résumé

L'effectivité du changement climatique autour du lac Kivu en République Démocratique du Congo a été vérifiée à partir des séries chronologiques des données climatiques de plus de 3 décennies. Cette étude vise à analyser les effets de la variabilité climatique sur la biomasse en carbone du lac Kivu, non documentés à ce jour. Les données biologiques et les paramètres physico-chimique ont été collectées à partir des sources documentaires de la base des données d'Unité d'Enseignement et de Recherche en Hydrobiologie Appliquée (UERHA) de 2002 à 2022 et de l'analyse personnelle au Laboratoire. Les données climatiques ont été téléchargées sur le site de la NASA (https://power.larc.nasa.gov) et couvre une période de 1981 à 2023. Nous avons appliqué le modèle dynamique autorégressif à retards distribués, en sigle ARDL (Auto Regressive Distributed Lag model). Les résultats indiquent que, seule, la température moyenne annuelle a évolué mais pas de manière significative au cours des années 1981 à 2023 avec une augmentation de 1.13°C dans le Bassin versant du Lac Kivu passant de 18.04°C en 1981 à 19.17 en août 2023 (R2=0.633). Ce qui, influence, négativement et significativement la biomasse en carbone du Lac Kivu (t :-2.156404 et Prob. : 0.0327). Par contre, les autres variables explicatives (la Conductivité, les précipitations, la valeur de la profondeur du Secchi et la Turbidité) synchrones possèdent des coefficients statistiquement nuls parce que disposant des probabilités supérieures à 5%. Elles n'exercent donc pas d'effet sur la biomasse en Carbone. Par ailleurs, la biomasse se trouve expliquée à 51.9% par les variables explicatives reprises dans le modèle synchrones et retardés avec un coefficient de determination ajusté de 46.3%. La probabilité F de Fisher (F :9.439 et Prob. 0.0000), étant inférieure à la marge d'erreur de 5%, montre que le modèle est globalement et statistiquement significatif.

Mots clés : Fonctionnement écologique, Phytoplancton, Photosynthèse, Activités anthropiques, Eutrophisation, Température atmosphérique, Modélisation.

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[1] Corresponding author: mayakadoudou@gmail.com

1. INTRODUCTION

The massive release of greenhouse gases into the Earth's atmosphere by human activities over the last one hundred and fifty years (IPCC, 2023) has resulted in a warming of the surface layers of the oceans, acidification and a reduction in the concentration of dissolved oxygen (Petitgas et al., 2020).

By the end of the 21st century, the warming of the climate system will continue and could reach values ranging from +0.3°C to +4.8°C for a reference period going back to 1980 (IPCC, 2013 ; Jacquemin, 2019). These environmental changes are leading to profound alterations in the biodiversity of ecosystems, their functioning and their evolutionary trajectories (Carpenter et al., 2006 ; Polunin, 2008).

Freshwater aquatic environments are among the most threatened ecosystems according to the Millennium Ecosystem Assessment (MEA, 2005) and the Intergovernmental Panel on Climate Change (IPCC) (Rosenzweig et al., 2007 ; Jacquemin, 2019). Lakes are considered 'sentinels' because of their sensitivity and rapid response to environmental change.

The work of Stockner and Antia (1986), Peterson and Seligman (1987), Keller and Suzuki (1988); Thyssen et al. (2008); Sardet (2015) and Benaziza (2018), has shown that phytoplankton accounts for more than half of terrestrial biomass, and plays an essential role in climate control because it is responsible for producing a large proportion of atmospheric oxygen and is a veritable carbon dioxide pump. It is illustrated as the main primary producer that forms the basis of the food chain in aquatic ecosystems, and any qualitative and quantitative changes that occur in phytoplankton communities will consequently influence the entire trophic chain.

According to Hugo (2006), the most common phytoplankton species found in Lake Kivu were the pinnate diatoms Nitzschia bacata Hust. and Fragilaria danica (Kütz.) Lange-Bert, and the cyanobacteria Planktolyngbya limnetica (Lemm.) Komárková-Legnerová and Cronberg and Synechococcus sp. The mean annual chlorophyll a in the mixing zone is estimated at 2.2 mg m-3 and a primary productivity of 0.71 g C m2 d-1 (~ 260 g C m2 a-1), which contributes to the mitigation of greenhouse gases by sequestering atmospheric CO2. Spatial, seasonal and vertical variations have been relatively slight.

Recently, there has been strong anthropogenic pressure on Lake Kivu (Aleke, 2016), and the cumulative effects of climate variability have had a major impact on Ichthyological productivity (Balagizi, 2017). On a such context, it is quite justified to think that this anthropogenic pressure associated with climate change would have an effect on phytoplankton biomass in this lake, as has been demonstrated in Lake Tanganyika (O'Reilly et al, 2003). Here, however, the evaluation of this effect has so far not attracted the attention of researchers. This study therefore seeks to assess the combined effects of climate variability and physico-chemical parameters on the carbon biomass sequestered by Lake Kivu by applying the autoregressive time lag model (ARDL).

The choice of the ARDL model is justified by its belonging to the class of dynamic models (Kibala, 2018) and allows temporal effects to be captured in the explanation of a variable. In this context, a dependent variable (Yt) can be explained both by its own past values, present values of independent variables (Xt) and their time-lagged values (Xt-i) (Adama and Mamadou, 2023).

The aim of this study is to assess the combined effects of climate variability and physico-chemical parameters on the carbon biomass sequestered by Lake Kivu by applying the autoregressive time lag model (ARDL).

2. Materials and methods

2.1. Study site

Lake Kivu is from volcanic origin (Isumbisho, 2006). It is deep, meromictic lake with very specific limnological characteristics. This lake combines a relatively shallow euphotic zone (more or less 18 m), usually less than the mixing zone (20 to 60 m), with a low thermal gradient in the mixolimnion and is clearly oligotrophic (Hugo, 2006). It is located south of the equator between 1°34'- 2°30'S and 28°50'- 29°23'E. With a surface area of 2370 km2, a maximum depth of 489 m and an average depth of 240 m (Marshall 1993), it forms a natural boundary between the Democratic Republic of Congo and the Republic of Rwanda. It is one of the four great lakes of the East African "Rift". It has 102 km of length and 50 km of wide (at its widest point). It is located at an altitude of 1463 m above sea level (Descy, 1991).

The most common phytoplankton species in pelagic Lake Kivu were pinnate diatoms (Nitzschia bacata Hust. and Fragilaria danica Lange-Bert.) and the cyanobacteria Planktolyngbya limnetica (Lemm.) Komárková-Legnerová and Cronberg and Synechococcus sp. Centric diatoms Urosolenia sp. and various species of Microcystis can also be very abundant (Hugo, 2006).

Although fishing is less important than elsewhere in the region, it still accounts for 10,000 tonnes of fish per year, and is a cheap source of animal protein for the local population of the two riparian countries (Lecrenier, 2016).

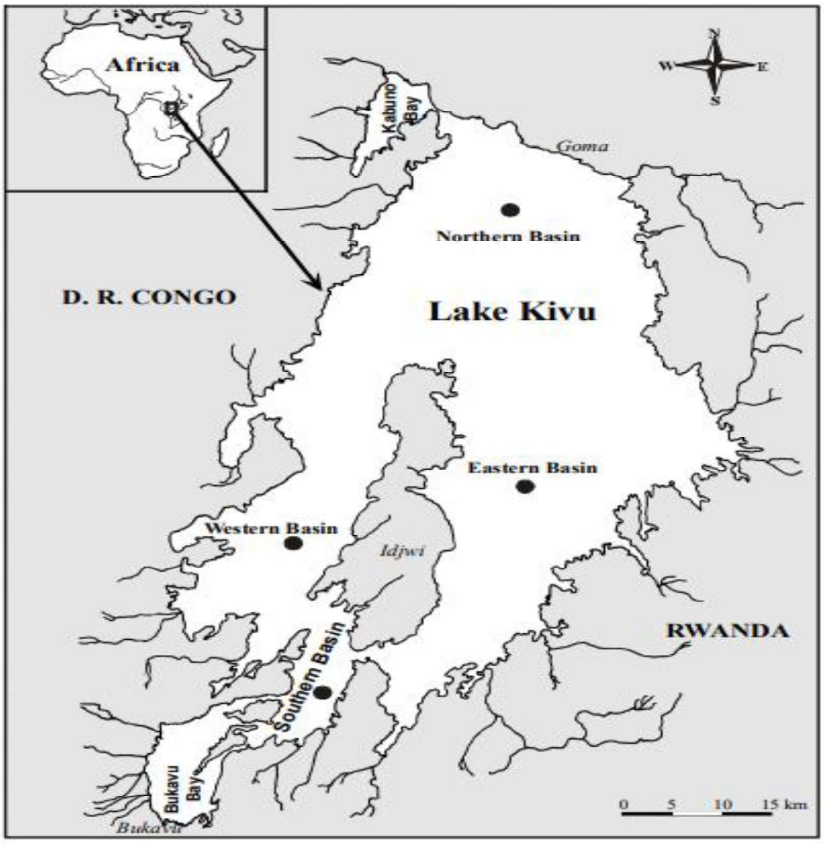


Figure 2 : Lake Kivu geographic situation and sampling sites location. (Isumbisho, 2006).

2.2. Data sources and sampling strategies

To verify the combined effects of climatic and physico-chemical variables on the biomass of Lake Kivu, we used data on phytoplankton biomass and physico-chemical parameters (O'Reilly et al, 2003) from 2002 to 2023. The data for 2002 to 2022 were retrieved from the database of the Unité d'Enseignement et de Recherche en Hydrobiologie Appliquée (UERHA) of the Department of Biology and Chemistry at the Institut Supérieur (ISP) in Bukavu, while the data for 2023 were collected in the field by ourselves. The climatic data was downloaded from the NASA website (https://power.larc.nasa.gov) and covers a period from 1981 to 2023, 2 m above the surface at coordinates 28°512392 and - 2° 281121, and was validated by meteorological data from various stations in the area.

Physico-chemical characteristics were sampled in situ at various depths (0, 5, 10, 20, 30, 40, 50 and 60 m). Measurements of dissolved oxygen (D.O), temperature (TE), conductivity (Cond.), turbidity (Turd.), pH and pressure were made using a PRODSS multiparameter probe. Similarly, the sequi disc (SE) enabled us to determine the transparency of the water in Lake Kivu.

After these measurements, water samples were taken (once a month) using a Van Dorn-type hydrological bottle with a capacity of 6,000 ml, stored in jars (1,000 ml) kept in a cooler at 4°C and then brought back to the laboratory (Lalèyè et al., 2022). In the laboratory, the carbon biomass was assayed for chl a using a GENESYS20 spectrophotometer. The methods used were those described by Rodier et al (2009).

Chl a is the only pigment capable of producing the chemical energy (Groga, 2012) required for carbon fixation from light energy. Calculations of average chlorophyll biomass (in g C m-2) were based on Chl a concentrations, and converted into weight of sequestered organic carbon using the conversion factor C/Chl a = 40 (Sagan and Thouzeau 1998).

2.3. Statistical analysis of data

The main aim of plankton modelling is to predict the impacts of environmental changes on its production, composition and associated ecosystem functions (Benedetti, 2018).

To this end, an autoregressive distributed lag model (ARDL) (Boubonnais, 2018) was applied to assess the effects of climate variability and physico-chemical parameters on carbon biomass. The model considered one dependent variable (carbon biomass) and several independent variables (physico-chemical parameters : dissolved oxygen, temperature, conductivity, turbidity, pH and transparency, as well as climatic data : temperature, precipitation, wind speed and relative humidity).

The ARDL model belongs to the class of dynamic models (Kibala, 2018) and captures time effects (adjustment lag, expectations, etc.) in the explanation of a variable. In a dynamic model, a dependent variable (Yt) can be explained both by its own lagged values, the present values of the independent variables (Xt) and their time-lagged values (Xt-i) (Adama and Mamadou, 2023). The Autoregressive Distributed Lag (ARDL) model makes it possible, on the one hand, to test long-term relationships on series that do not have the same order integration and, on the other hand, to provide more reliable estimates even with small sample sizes. In addition, the ARDL model makes it possible to deal simultaneously with long-term dynamics and short-term adjustments (Capri, 2019).

To avoid spurious regressions between different variables in the model to be tested, it is necessary to carry out a preliminary analysis of the data (Kibala, 2018). To do this, we used exploratory data analysis, stationarity tests (Hamisultane, 2016), Akaike-AIC (1973), Shwarz-SIC and Hannan-Quin-HQ (1979) information criteria to determine the optimal lags (p, q) of the ARDL model by parsimony (Akaike, 1973). We then tested the causality of the variables in the sense of TODA YAMAMOTO (1995) and verified the statistical validity of the model using the residual autocorrelation test of Breusch-Godfrey (1978), the Heteroscedasticity test of Breusch-Pagan-Godfrey (1979), the normality test of Jarque-Bera (1980), the functional specification test of Ramsey (1928) and the stability test (CUSUM).

Using the Pesaran et al (2001) cointegration test, we verified the existence of a cointegrating relationship between the variables, one of the conditions of validity of the ARDL model. The variables we are analysing are time series. Our research is carried out using EViews 12 software.

The theoretical model used in our research takes the following form :

$$\mathbf{BC_t} = \sum_{i=1}^{p} \mathrm{a}\,1iBCt - i + \sum_{i=1}^{p} a2i\,CONDt - i + \sum_{i=1}^{p} \mathrm{a}\,3iDOt - i + \sum_{i=1}^{p} \mathrm{a}\,4ipHt - i + \sum_{i=1}^{p} \mathrm{a}\,5iPMMt - 1 + \sum_{i=1}^{p} \mathrm{a}\,6iSE\,t - i + \sum_{i=1}^{p} \mathrm{a}\,7iTAt - i + \sum_{i=1}^{p} \mathrm{a}\,8iTurb.t - i + b1BCt - 1 + b2CONDt - 1 + b3DOt - 1 + b4pHt - 1 + b5PMMt - 1 + b6SEt - 1 + b7TAt - 1 + b8Turb.t - 1 + \varepsilon$$

With :

BCt: represents the carbon biomass sequestered by Lake Kivu over a given period, expressed in mgC/L ; COND : Electrical conductivity of Lake Kivu water (mg/L) ; DO : Oxygen dissolved in water ; pH : Hydrogen Potential ; PMM: rainfall (mm) ; SE: Secchi ; TA: Air temperature (°C) ; TE: Water temperature (°C) ; Turb. Water turbidity (NTU) ; a0: the Constant ; a1i.........a8i: short-term effects (Parameter to be estimated in the short term) ; b1..........b9: Long-term dynamics (Parameter to be estimated over the long term); εt: error term (this error term captures measurement errors in the data and sample fluctuations); p: the shift operator ; i: Number of offset periods.

3. Results

3.1. Variations in temperature, rainfall, relative humidity and wind speed around Lake Kivu

According to the graph below and after linear adjustment, it can be seen that only the mean annual temperature changed, but not significantly, between 1981 and 2023, with a slight increase of 1.13°C in the Lake Kivu catchment area, rising from 18.04°C in 1981 to 19.17 in August 2023 (R2=0.633). All the other climatic variables were not evaluated during the period of our research because their coefficients of determination are almost zero. This is the case, for example, for relative humidity, which fell from 79.22% in

1981 to 78.82% in August 2023, with a coefficient of determination R2 of 0.0403, and rainfall, which did not show any significant variations (R2 = 0.0361) ; the highest rainfall was in 2020, with 2,320.3 mm, whereas 1992 was characterised by a large drop (729.4 mm). And wind speed over the period 1981 -2023 after linear adjustment (R2= 0.2742) falls from 2.92 in 1981 to 2.08 in August 2023.

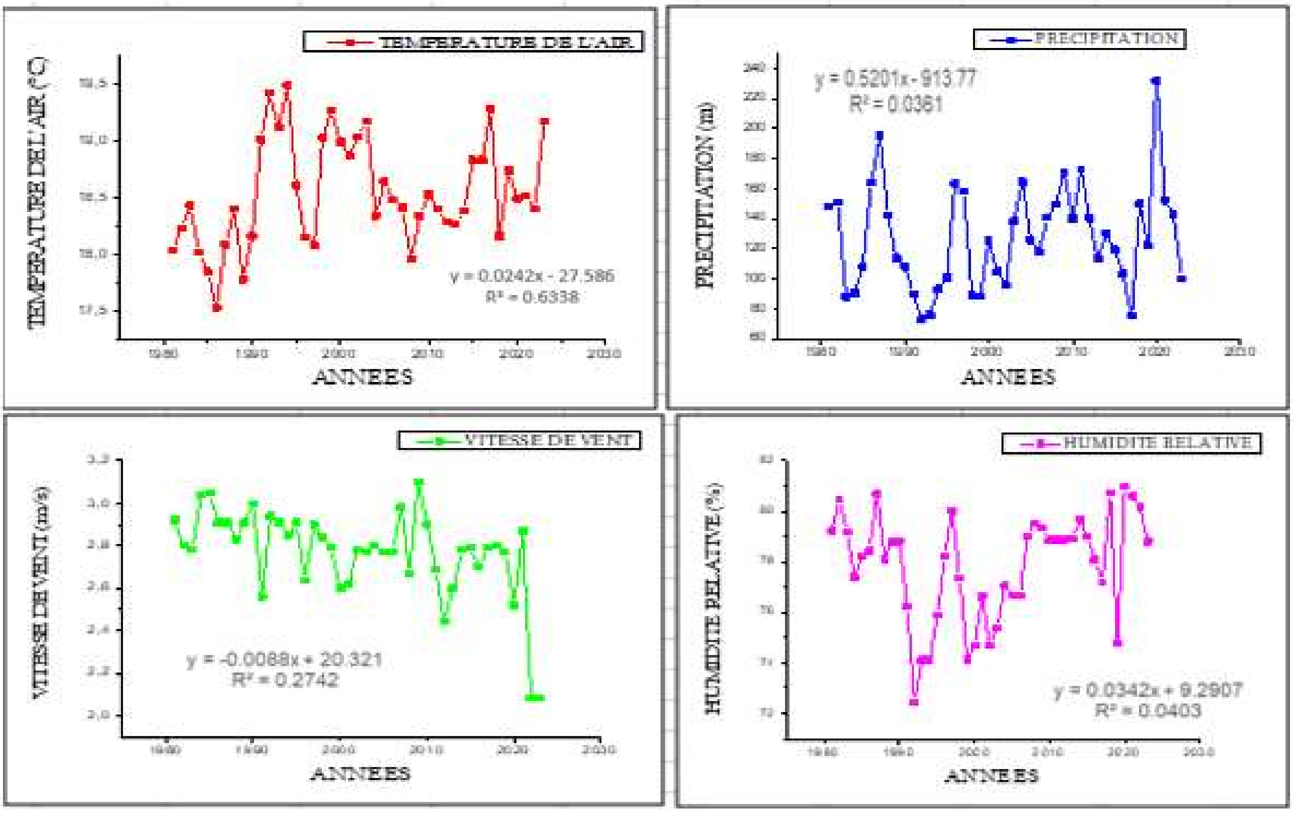


Figure 1 : Variations in climatic variables around Lake Kivu : (a) temperature variation between 1981 and 2023, (b) rainfall variation between 1981 and 2033, (c) annual variations at Lwiro between 1973 and 2012 and (d) wind speed variability over the period 1981-2023.

3.2. Stationarity test

Before processing a time series, its stochastic characteristics (its expectation and variance) need to be studied (Boubonnais, 2018). With regard to the dynamics of the variables studied, the Augmented Dickey-Fuller tests (1981) enabled us to check the order of integration of the different variables.

Table 1: Variable stationarity test

Identification	Modèle	ADF	Valeur critique	Probabilité	Processus	Ordre de différence ou intégration	Ordre de polynôme
D(BC)	3	-6.264413	-1.945199	0.0000	DS	I(1)	
COND	2	-9.590148	-2.896346	0.0000	DS	I(0)	
D.O	2	-3.591000	-2.896346	0.0079	DS	I(0)	
pH	2	-6.006990	-2.896346	0.0000	DS	I(0)	
PMM	2	-7.228934	-2.896346	0.0000	DS	I(0)	
SE	1	-5.606789	-3.464198	0.0001	TS		0
TA	2	-5.186462	-2.896779	0.0000	DS	I(0)	
D(TE)	3	-6.097679	-1.951000	0.0000	DS	I(1)	
Turb.	1	-7.520303	-3.464198	0.0000	TS		0

An initial look at the series graphs (Table 1) suggests that most of the variables (Conductivity, Dissolved Oxygen, Hydrogen Potential, Precipitation, Secchi and Turbidity) were stationary at level and others (Carbon

Biomass and Water Temperature) were stationary at the filter in first difference. This justifies the use of the ARDL method (Autoregressive Staged Retardation Model) of Pesaran et al. (2001).

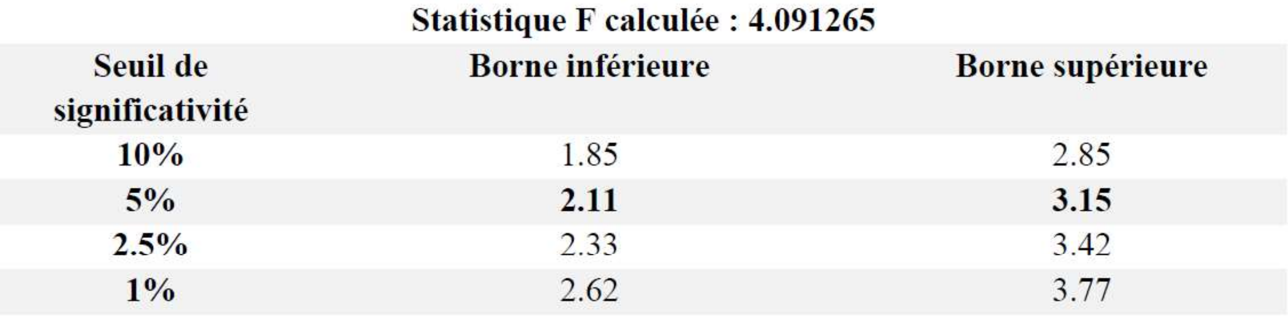
In addition, the variables Carbon biomass, Conductivity, Dissolved oxygen, Hydrogen potential, Precipitation, Atmospheric temperature and Water temperature followed the DS (Differency stationary) process which is a random non-stationary process whereas the Secchi and Turbidity variables followed the TS process which represents a deterministic non-stationarity. The statistics calculated are Student's t at 5%.

3.3. Pesaran boundary cointegration test

Following the automatic procedure in Eviews 12, the Pesaran et al (2001) cointegration test requires the ARDL model to be estimated first. The test statistic, Fisher's F-value, is then compared with critical values (establishing thresholds) as follows :

- ✓ If the calculated F-value is greater than the upper limit : cointegration exists ;
- ✓ If F-calculated is less than the lower bound : cointegration does not exist ;
- ✓ If the lower bound is lower and F-Fisher is lower than the upper bound: no conclusion.

Table 2 : Pesaran cointegration test



Statistique F calculée : 4.091265

Seuil de significativité	Borne inférieure	Borne supérieure
10%	1.85	2.85
5%	**2.11**	**3.15**
2.5%	2.33	3.42
1%	2.62	3.77

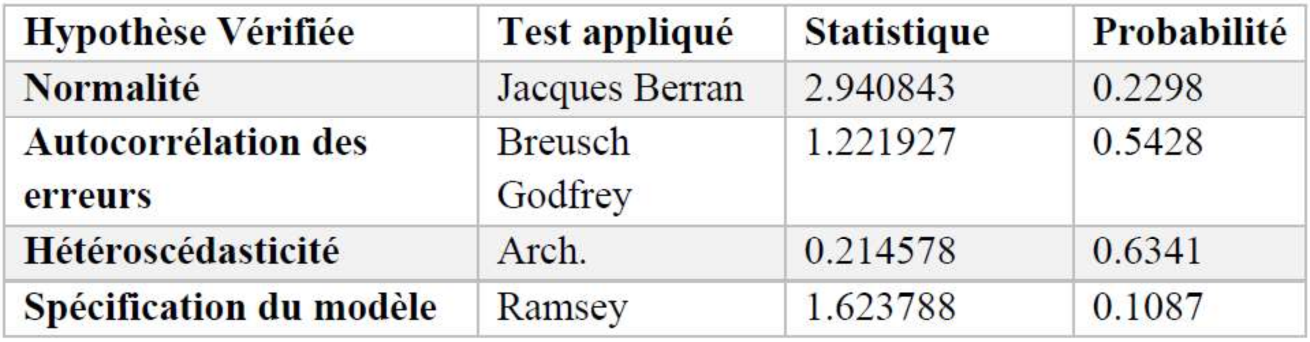
Table 2 presents the estimates of the cointegration procedure and shows that the value of the Fisher statistic (F=4.091265) is greater than Pesaran's upper bound (2.11) at the 5% threshold. This result leads us to reject the hypothesis of the absence of a cointegrating relationship between the variables.

It reveals that there is cointegration between the endogenous variable, in this case Carbon Biomass, and the exogenous variables in the study (Conductivity, Dissolved Oxygen, pH, Precipitation, Secchi, Air Temperature, Water Temperature and Turbidity). These results imply that long-term equilibrium relationships can be deduced from our estimates. Long-term effects between endogenous and exogenous variables can therefore be calculated.

3.4. Validation tests and model specification

After long-term model estimation, we used Jacques Berran's Normality, Breusch Godfrey's error autocorrelation, Arch's heteroscedasticity and Cusum's model specification tests to specify and validate our model.

Table 3: Validation tests and model specification



Hypothèse Vérifiée	Test appliqué	Statistique	Probabilité
Normalité	Jacques Berran	2.940843	0.2298
Autocorrélation des erreurs	Breusch Godfrey	1.221927	0.5428
Hétéroscédasticité	Arch.	0.214578	0.6341
Spécification du modèle	Ramsey	1.623788	0.1087

Table 3: shows the various residual tests for validating the model before its protocol (interpretation). The Jarque Berra probability (Prob. 0.2298) remains above the 5% margin of error, and the errors are normally distributed (follow the normal distribution). Furthermore, Breusch Godfrey's error autocorrelation test shows that the errors (Prob. 0.5428) are not strongly correlated, as the probability associated with the chi-

square statistic remains above the 5% threshold for false rejection. Mutatis mutandis for the Fisher statistic. For its part, the heteroskedasticity test (Prob. 0.5428) shows homoskedastic errors for a probability of 5%. Finally, the Ramsey Reset test concludes in favor of the model specification, with both the Student and Fisher probabilities above the standard significance level for the model under study (Prob. 0.1087 and 0.2345).

3.5. Model stability

To check the stability of our model, we adopted the CUSUM test (Fig. 2), based on the cumulative sum of the square of the recursive residuals, with a null hypothesis of stability of the relationship between two straight lines representing the bounds of the interval. We can say that our estimated model is stable, given that the coefficients were stable during the period under study, as the curve snaked through the corridor using the Cusum test. In short, the results of the various diagnostic tests have led to the statistical validation of our ARDL models.

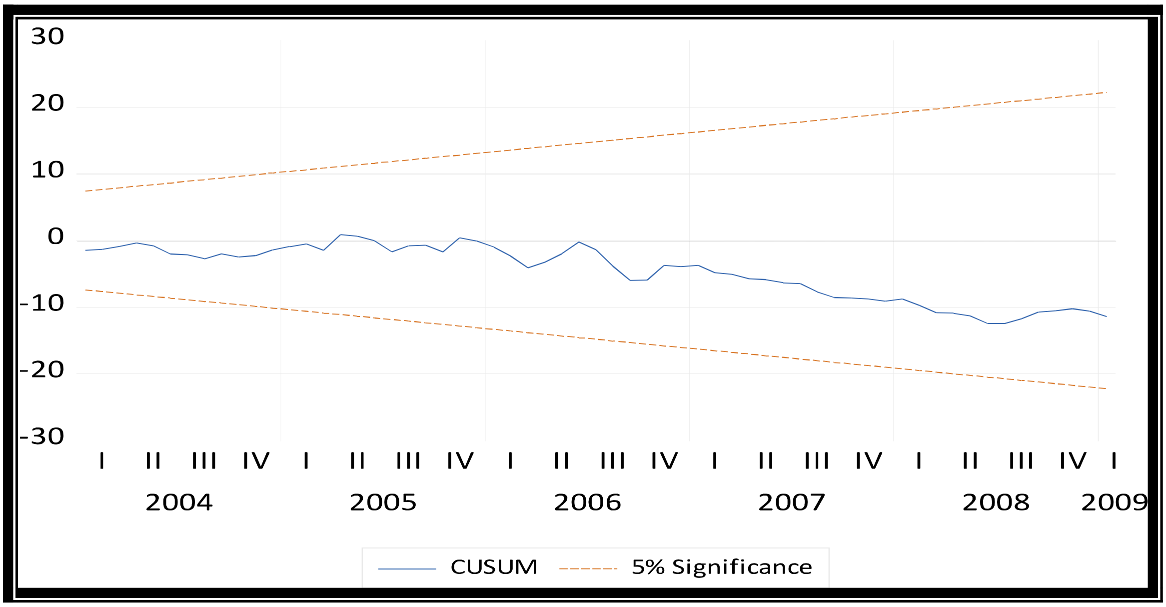


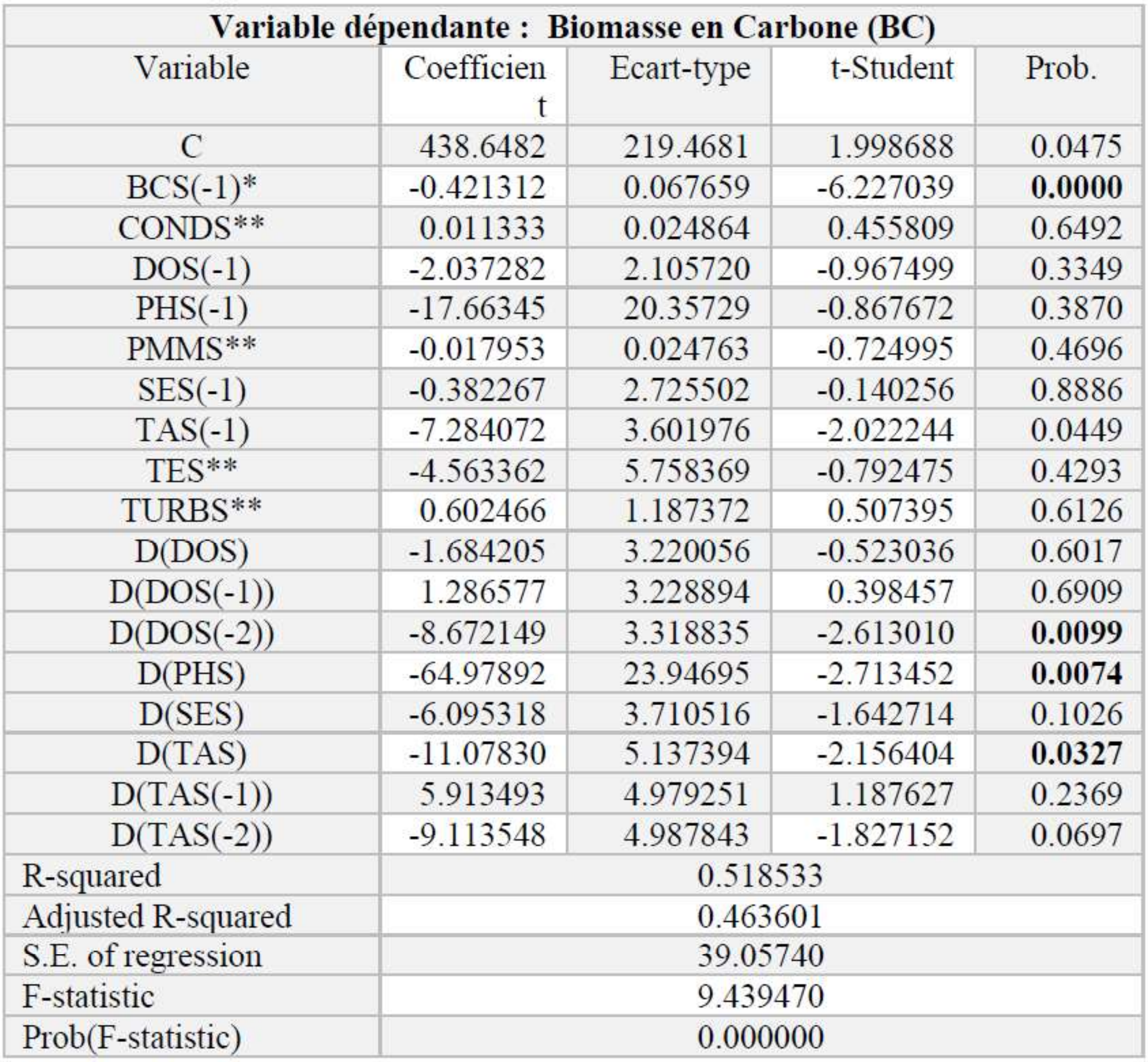
Figure 2: Model stability test

3.6. Long-term model estimation

The result obtained for the estimation of the long-term dynamics of the model (Table 4), in a long maturity, shows that Carbon Biomass is negatively and significantly impacted by its own one-period lagged past (Prob. 0.0000) and by air temperature, dissolved oxygen and pH instantaneously, given that the probability associated with Student's T statistic (respectively 0.0327, 0.0099 and 0.0074) is below the 5% margin of error. Thus, any 1°C increase in air temperature translates into a 11.07830 mg C/L decrease in Biomass, all other things being equal. Similarly, a one-unit increase in pH negatively impacts 64.97892 mg C/L of biomass.

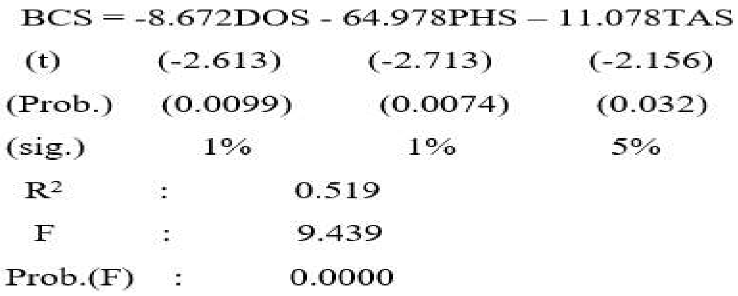
On the other hand, the other synchronous explanatory variables (Conductivity, Precipitation, Secchi, Water Temperature and Turbidity) have coefficients that are statistically null because they have probabilities greater than 5%. They therefore have no effect on carbon biomass. It should be noted that 51.9% of biomass is explained by the explanatory variables included in the synchronous and lagged models, with an adjusted (corrected) determination coefficient of 46.3%. Finally, Fisher's F probability (0.000000), being below the 5% margin of error, shows that the model is globally and statistically significant.

Table 4: Long-term model estimation.



Variable dépendante : Biomasse en Carbone (BC)				
Variable	Coefficient	Ecart-type	t-Student	Prob.
C	438.6482	219.4681	1.998688	0.0475
BCS(-1)*	-0.421312	0.067659	-6.227039	**0.0000**
CONDS**	0.011333	0.024864	0.455809	0.6492
DOS(-1)	-2.037282	2.105720	-0.967499	0.3349
PHS(-1)	-17.66345	20.35729	-0.867672	0.3870
PMMS**	-0.017953	0.024763	-0.724995	0.4696
SES(-1)	-0.382267	2.725502	-0.140256	0.8886
TAS(-1)	-7.284072	3.601976	-2.022244	0.0449
TES**	-4.563362	5.758369	-0.792475	0.4293
TURBS**	0.602466	1.187372	0.507395	0.6126
D(DOS)	-1.684205	3.220056	-0.523036	0.6017
D(DOS(-1))	1.286577	3.228894	0.398457	0.6909
D(DOS(-2))	-8.672149	3.318835	-2.613010	**0.0099**
D(PHS)	-64.97892	23.94695	-2.713452	**0.0074**
D(SES)	-6.095318	3.710516	-1.642714	0.1026
D(TAS)	-11.07830	5.137394	-2.156404	**0.0327**
D(TAS(-1))	5.913493	4.979251	1.187627	0.2369
D(TAS(-2))	-9.113548	4.987843	-1.827152	0.0697
R-squared	0.518533			
Adjusted R-squared	0.463601			
S.E. of regression	39.05740			
F-statistic	9.439470			
Prob(F-statistic)	0.000000			

Algebraically, the validated model looks like this :



$$BCS = -8.672DOS - 64.978PHS - 11.078TAS$$

(t)	(-2.613)	(-2.713)	(-2.156)
(Prob.)	(0.0099)	(0.0074)	(0.032)
(sig.)	1%	1%	5%

R^2 : 0.519
F : 9.439
Prob.(F) : 0.0000

4. Discussions

This study has determined the influence of climate variability on the carbon biomass of Lake Kivu.

The results indicate that atmospheric temperature negatively and significantly influences the carbon biomass of Lake Kivu. On the other hand, the other explanatory variables (Conductivity, precipitation, Secchi depth, Water temperature and Turbidity) synchronous have statistically zero coefficients because they have probabilities greater than 5%. They therefore have no effect on the carbon biomass.

The effectiveness of climate change and variability around Lake Kivu has been verified from time series of climate data of more than 3 decades with an increase in air temperature of 1.57°C in Kamembe for the period from 1971 to 2013 (Akokwa, 2017). At the regional scale, high temperatures show a significant warming trend in the large lakes of the Eastern region (Edmond et al. 1993). Around Lake Tanganyika, another large lake in the region, historical data predict an increase in air temperature of 1.3°C for a period of 80 years (Hulme et al. 2001). This contributes to overheating surface waters, increasing thermal stability and reducing productivity. A regional decrease in wind speed contributed to reduced mixing, thereby decreasing the upwelling and entrainment of nutrients from deep waters to surface waters (Molsa et al., 1999).

Thus, our results are consistent with those found by O'Reilly et al, 2003 who show that global warming decreases the productivity of Lake Tanganyika. The same author indicates that carbon isotope records in sediment cores suggest that primary productivity may have decreased by about 20%. This implies a decrease of about 30% in fish yields. Similarly, in the Taihu Lake basin in China, Xiaohua 2010 shows a general trend of climate change between 1991 and 2000 with an increase in the annual mean temperature of 0.4°C air. The composition of phytoplankton changed at the same time, going from a dominance of diatoms to a dominance of cyanobacteria.

In general, Litchman et al. 2012, shows that phytoplankton can respond to environmental variations in three ways: (I) thanks to their phenotypic plasticity, organisms are able to persist in the environment, (II) the limits of their phenotypic plasticity being reached, some species not adapted to the new conditions are replaced by others better adapted, (III) species can adapt thanks to the selection of new genotypes through processes such as mutations.

5. Conclusion

It is important to conclude that climate variability has a negative effect on the Carbon Biomass carried by phytoplankton. These effects are functions of spatial distribution and anthropogenic activities. To do this, the adoption of policies for adaptation to the effects of climate change are measures proposed by this study for the sustainable management of fishery resources in Lake Kivu.

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