Seasonal Sensitivity of Reco from Aquatic Ecosystem to Meteorological and Physicochemical Water Parameters

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Abstract. Ecosystem respiration (Reco) is the main contributor to carbon emissions from different types of aquatic ecosystems. For a better understanding of CO_2 emissions from the water-atmosphere interface of rivers and to evaluate the influence of meteorological factors and water quality parameters on Reco, in-situ measurements were carried out in Dambovița River in the winter season when temperatures were up to freezing point as well as in the summer period, which is the most dynamic in terms of CO_2 exchange. Reco during the monitoring period ranged from 4.56 to 40.5 $gm^{-2}h^{-1}$. The statistical analysis of the data set showed that among the meteorological parameters, temperatures explain most temporal variability of CO_2 fluxes. By scaling the importance of the water quality parameters, the precision of the permutations indicated the pH as the most influential parameter in the analysis of the dependent factors. The analysed data indicates that aquatic ecosystems are highly sensitive to changes in the current context of climate change, which implies that these ecosystems can easily turn into important sources of carbon in the atmosphere.

1 Introduction

Aquatic ecosystems provide one of the best natural environments for long-term carbon sequestration and storage, but they are also natural sources of greenhouse gases (GHGs) in the atmosphere, mostly through Reco process [1]. It is well recognised that rivers and streams contribute significantly to the global carbon cycle. Rivers have a significant role in controlling the transport of continental carbon to the ocean [2]. In addition, carbon in rivers

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is transformed and can either be temporarily stored through photosynthesis and sedimentation or released through biological respiration. Therefore, river CO_2 emissions are crucial for understanding the land-water exchange of carbon with the atmosphere [3] as well as determining how much terrestrial carbon is lost in the aquatic network or exported to coastal areas.

Reco in aquatic ecosystems is influenced by several environmental factors, including meteorological parameters, as well as soil and water physical-chemical parameters [4]. The water surface temperature, air temperature, the type of vegetation, and the chemical and physical properties of the water all impact CO_2 emissions at the water-atmosphere interface [5]. Quantifying the response of different types of aquatic ecosystems to seasonal variations of environmental factors is a crucial issue in the context of climate change [6]. Knowing the interactive effects of the factors that determine greenhouse gas emissions is a prerequisite to be able to manage different types of aquatic ecosystems in a way that minimizes greenhouse gas emissions and to forecast the long-term effects of changes future climate on greenhouse gas emissions [7, 8].

The production of CO_2 depends on the interaction between several environmental factors, the type of vegetation, the weather conditions, but also on the water quality parameters. The most significant factor in understanding and predicting the effects of climate change is how ecosystem processes respond to temperature [9]. According to previous studies, temperature affects the metabolic rates of heterotrophic processes that release carbon into the atmosphere, which could have a significant impact on the decomposition of organic matter [10, 11].

CO_2 is naturally captured from the atmosphere through biological, chemical, or physical processes. Temperature, humidity [12], the physical properties of the water, and chemical properties like pH, salinity, or nutrients all have a direct impact on CO_2 emission rates and are used to predict how long the water and sediment layer's biological and microbiological growth season may last [13].

The prime objective of this paper is to evaluate the temporal distribution of CO_2 emissions from the study area according to seasonal dynamics, comparing the values monitored in the warm season with those in the cold season. The second objective is to highlight the dependence of Reco values on the main meteorological parameters and water quality parameters, the selected data set being statistically analysed in comparison with the measurements recorded in the corresponding season.

2 Materials and Methods

To quantify Reco and to determine how environmental factors affect the seasonal dynamics of this CO_2 exchange in aquatic ecosystems, closed chamber measurements were used to perform an analysis at the water-air interface of the Dambovița river, located near the city of Bucharest, in the Southeast of Romania.

Field measurements were performed using conventional methods to ascertain each variable's evolution in order to evaluate the parameters on which Reco depends. The air temperature (T_{air}), precipitation (PP), and wind speed are the meteorological parameters that are classified as factors that significantly influence or even regulate CO_2 exchanges at the water-air interface [14]. The Baneasa Meteorological Station, which is the closest to the case study area, made available the average daily values for the air temperature at 2 metres and the wind speed at 2 metres. The daily precipitation values are satellite data, and their resolution is a global grid of 0.1° x 0.1° latitude/longitude (approximately 10 km^2). For a better highlighting of the influence of precipitation on CO_2 emissions, it was studied whether their effect is accentuated over time, and, thus, the Reco correlation with cumulative precipitation over 3 days was applied.

Physicochemical water parameters were measured using a calibrated Eureka Manta 2 multiparameter water quality probe. For validation, the water temperature and pH were determined in-situ, simultaneously, with the same multiparametric measuring instrument, Lutron PH222. To determine the concentration distribution of each measured parameter, two series of recordings were performed at the same plot. Variables including pH (with an accuracy of ±0.1), chlorophyll, salinity (with an accuracy of 0.1‰), dissolved oxygen (HDO) concentration (with an accuracy of ±0.1 mg/L), potential oxidation-reduction (ORP), conductivity, turbidity, water temperature (with a precision of ±0.01°C) and total dissolved solids (TSD) were collected in-situ simultaneously with CO_2 emission measurements. The concentration of chromophoric dissolved organic matter (CDOM) was also measured using the same probe and used as a proxy for dissolved organic matter in the water column.

Fig. 1. Spatial representation of the measurement plots in Dambovița river

A statistical analysis software called Statistical Product and Service Solutions (SPSS) 29.0 was used for the entire factorial analysis process. The Pearson analysis was considered important for the examination of the impact of climatic parameters on Reco variability. The correlation coefficient calculation is significant for identifying the strong correlations between carbon dioxide emissions and certain variables or the relationships of uncertainty between them, with the aim of excluding those with weak correlation. Also, simple, and multiple regression analysis were used to test and validate Reco models appropriate to the study area.

3 Results

In the following figure is represented the evolution of Reco during the selected seasons. To better highlight the temporal distribution of CO_2 emissions, the seasonal dynamics of Reco for the study area was analysed.

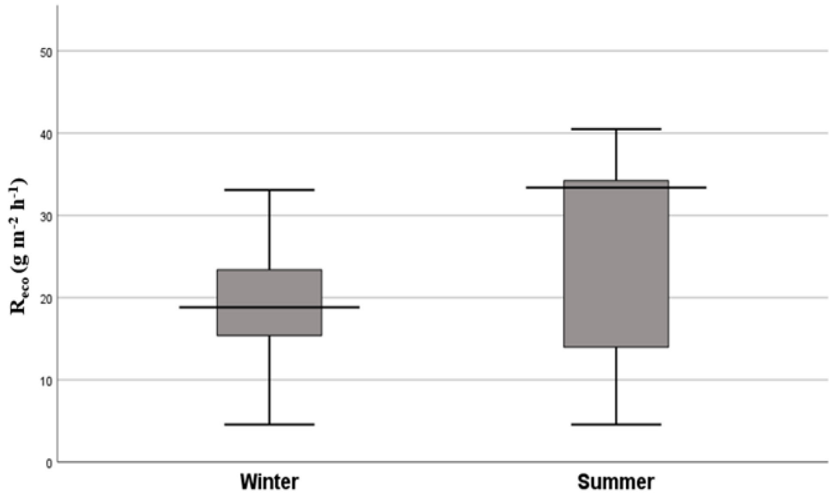

Fig. 2. Distribution of Reco values in winter season and in summer season

From the graphic above (Figure 2) it can be observed that, during the study period, the range of Reco varied between 4.56 $gm^{-2}h^{-1}$ and 33.08 $gm^{-2}h^{-1}$ in winter, with a three-months average of 14.41 $gm^{-2}h^{-1}$, and between 19.39 $gm^{-2}h^{-1}$ and 40.50 $gm^{-2}h^{-1}$ in summer. The comparison of Reco values displayed distinct seasonal patterns that peaked in summer with an average of 31.56 $gm^{-2}h^{-1}$.

Figures 3 and 4 show the results of the Reco values measured both in the cold season when the temperatures were low, up to the freezing point, and the accumulated precipitation was quantitatively more significant, as well as the Reco results measured in the warm season when the temperatures were continuously increasing, and cumulative precipitation was low.

As shown in Figure 3, the Reco values recorded during the winter season do not follow a similar trend to those of the meteorological parameters, but the climatic conditions in which the extreme values were recorded were highlighted. The highest Reco values were recorded under conditions where air temperature anomalies were up to 14°C for the cold season, which, along with the delayed effect of cumulative precipitation, resulted in a substantial rise in CO_2 emission values for the same day.

As indicated in Figure 4, the trend of Reco's evolution throughout the summer season fluctuated during the monitoring period in relation to the evolution of the main meteorological parameters analysed. The peak point of the Reco values was recorded in Tair conditions above 20°C and in the presence of cumulative precipitation of up to 5.4 mm/day. The next section presents a statistical analysis of the values obtained during the two monitored seasons.

The Pearson product correlation between Reco and T_{air} was found to be positive and statistically significant with r=0.695 ($p<0.01$). To determine how well T_{air} can predict Reco values, a bivariate regression was applied. A scatterplot showed that the relationship between Reco and T_{air} was positive and linear and did not reveal any bivariate outliers. The regression equation for predicting the Reco from T_{air} was $y=11.46+0.82x$. The r^2 for this equation was 0.483 which indicates that 48.3% of the variance in Reco was predictable from the level of T_{air}. This is a moderately strong relationship [15]. The bootstrapped 95% confidence interval for the slope to predict Reco from T_{air} ranges from 0.530 to 1.113, thus, for each unit of increase of T_{air}, Reco increases by about 0.5 to 1 point.

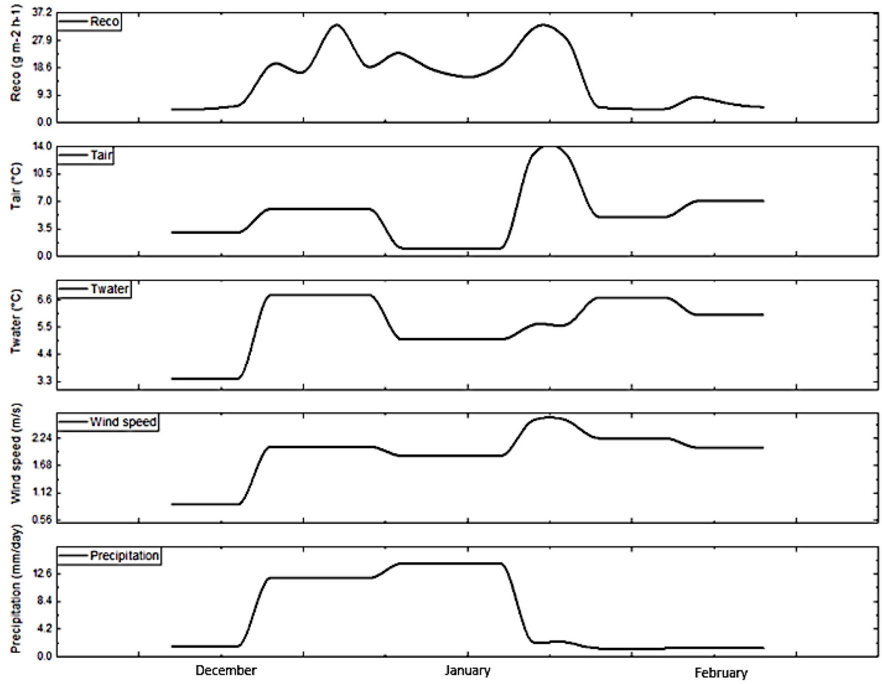

Fig. 3. The evolution of Reco and meteorological parameters in winter season

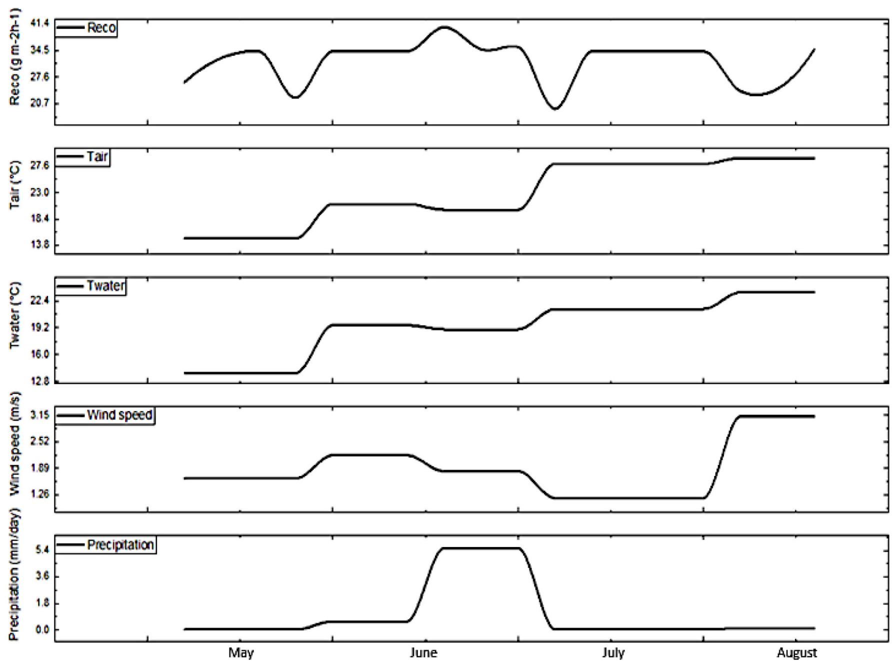

Fig. 4. The evolution of Reco and meteorological parameters in summer season

Table 1. Correlation matrix showing Pearson's r for Reco and meteorologic parameters.

Pearson Correlation	Reco	T_{air}	T_{water}	Wind speed	Cumulative PP
Reco	1				
T_{air}	**.695***	1			
T_{water}	**.711***	**.965***	1		
Wind	.113	.114	.111	1	
Cumulative PP	-.077	-.582	-.483	.054	1

*. Correlation is significant at the 0.01 level (2-tailed).
PP – precipitations
Tair – air temperature
Twater– water temperature

Among the meteorological parameters studied, the highest Pearson product coefficient of r=0.711 ($p<0.01$) was found between Reco and T_{water}. This correlation is positive and statistically significant. A regression was also performed to observe how well the T_{water} could predict the level of Reco The regression equation is $y=8.77+1.14x$, where $r^2=0.505$ which indicates that 50.5% of the variance in Reco was predictable from level of T_{water} The bootstrapped 95% confidence interval for the slope to predict Reco from T_{water}, range from 0.752 to 1.52, thus, for each one unit of increase of T_{water}, Reco increases by about 0.8 to 1.5 points.

Regarding the correlation of the Pearson product of Reco with the wind speed, this was positive, but statistically insignificant, where the value of r=0.113 ($p>0.05$). Also, a bivariate regression was performed for this parameter, where the equation has $y=18.41+2.28x$ and $r^2=0.013$. The correlation of the Pearson product between Reco and the cumulative precipitation over 3 days did not prove to be statistically significant either, with r=-0.077 ($p>0.05$). The regression equation for this relationship is $y=23.42-0.18x$, with $r^2=0.006$.

For a more precise explanation of the CO_2 emissions from the water-air interface, the values of the water quality parameters were assessed. Thus, statistical analysis was applied through the correlation of the Pearson product and to the interpretation of the result obtained through metrics of variable importance.

Following the Pearson product correlation analysis, only the water quality parameters that presented statistically significant correlations ($p<0.01$) were selected and their influence on Reco was evaluated from a statistical point of view. Thus, the correlation between Reco and pH is negative and statistically significant, with r=0.762, ($p<0.01$). The regression equation for Reco prediction from pH is $y=283.7-35.5x$, $r^2=0.581$, which means that 58.1% of the Reco variation was predictable from pH values. This is a strong relationship [15]. Also, the correlation of the Pearson product between Reco and ORP is positive and statistically significant, where r=0.722, ($p<0.01$). The linear regression equation is $y=15.86+0.07x$, r^2 for this equation is 0.522, meaning that 52.2% of the Reco variation was predictable from the ORP values. The Pearson product of the correlation between Reco and HDO (mg/l) is positive and statistically significant, with r=0.719, ($p<0.01$). The linear regression equation is $y=8.87+3.04x$, where $r^2=0.517$, meaning that 51.7% of the Reco variations were predictable from the HDO values (mg/l). This is also a strong relationship [15].

Tabel 2. The regression coefficients of the relationship between Reco and the physicochemical parameters.

Dependent Variable: Reco	Unstandardized Coefficients		Standardized Coefficients
	B	Std. Error	Pearson Correlation
pH	-35.501	5.097	**-0.762***
ORP	0.074	0.012	**0.722***
Chlorophyll	6.551	1.45	0.607
HDO %	0.328	0.077	0.585
CDOM	39.568	7.259	0.678
Turbidity	0.09	0.033	0.415
Salinity	-143.52	31.064	-0.615
TSD	-0.108	0.024	-0.610
HDO mg/l	3.036	0.496	**0.719***

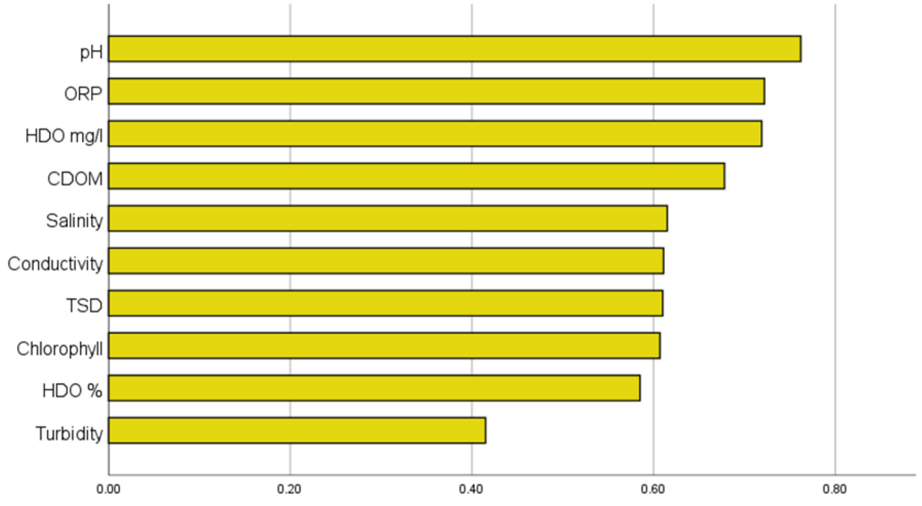

Fig. 5. The scalar importance of water quality parameters

The ranking of water quality parameters according to their influence on the Reco variation is shown in Figure 5. The main parameter that has a dominant importance in the statistical relationship between Reco and water quality parameters is pH. Also, ORP, HDO (mg/l) and CDOM seem to be some of the dominant parameters in the production of CO_2 emissions in the study area. Salinity, conductivity, TSD and chlorophyll were also highlighted as having an increased influence on Reco variation, while turbidity had the lowest statistical influence.

4 Conclusions

Through the analysis of the main hydro-meteorological and physicochemical parameters of respiration rates in the aquatic ecosystem formed by the Dambovita River, the temporal variation of Reco at the water-air interface and its relationship was evaluated with the main meteorological factors, including air temperature, precipitation, wind speed, but also with water quality parameters. It was found that absolute respiration rates are more sensitive to temperature factors than to the direct effects of non-temperature parameters measured in situ. However, the temperature sensitivity of emissions from the water-air interface tends to be more important to change in non-temperature factors and, thus, to influence the way Reco fluctuates over time. The statistical analysis highlighted a significant correlation ($p<0.01$) of Reco with T_{air} and T_{water} of 0.695 and 0.965, respectively. It was observed that the influence of the wind speed on the Reco values is not significant in any of the monitored seasons, not being a decisive parameter in this case. Cumulative precipitation over 3 days and wind speed are two other meteorological variables that were statistically analysed in correlation with Reco, but they did not show a decisive influence on the evolution and distribution of Reco.

Regarding the influence of the physicochemical parameters, the Reco variation from the water surface proved to be strongly dependent on the pH values measured in-situ, both with the digital multiparameter and with the Manta 2 multiparameter probe. In the study area, the correlations were negative and statistically significant, the Pearson product having the highest value of $r=-0.762$ ($p<0.01$). Of all the water quality parameters, measured in-situ with the Manta 2 multiparametric probe, only pH, ORP and HDO showed statistically significant correlations ($p<0.01$). Thus, by scaling the importance of the water quality parameters, the precision of the permutations indicated the pH as the most influential parameter in the analysis of the dependent factors.

This study suggests that warming temperatures may be more important than water quality parameters, but that it influences them indirectly and functions as a driver of changes in the carbon balance of aquatic ecosystems in the future. Therefore, to estimate emissions from global streams, both the influence of meteorological parameters and water quality parameters should be included.

Acknowledgments

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