Trend Analysis of Water Quality Parameters of Surma River, Bangladesh

Tajmunnaher¹, Mohammod Aktarul Islam Chowdhury², Shakib Bhuiyan³

¹Associate Professor, Department of Civil and Environmental Engineering, Shahjalal University of Science and Technology (SUST), Sylhet, Bangladesh

²Professor, Department of Civil and Environmental Engineering, Shahjalal University of Science and Technology (SUST), Sylhet, Bangladesh

³Research Student, Department of Civil and Environmental Engineering, Shahjalal University of Science and Technology

(SUST), Sylhet, Bangladesh

Corresponding Author: moon_cee@yahoo.com

Abstract— This study analyzes trends water quality of the Surma River in Sylhet, Bangladesh focuses to physico-chemical parameters, including temperature, pH, dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD), total solids (TS), total dissolved solids (TDS), and suspended solids (SS) during the rainy and winter seasons from 2010 to 2013. The findings revealed that temperature, pH, TS, and TDS of the Surma River exhibited variations within the prescribed standards. However, the average values of BOD, COD, and SS surpassed the established limits, while DO levels were consistently below the permissible threshold. Employing Principal Component Analysis (PCA), 18 significant variables were identified, showing a mix of linear, quadratic, and cubic trends across the seasons. From trend analysis it is found that three variables follow linear trend, five variables follow quadratic trend and ten variables follow cubic trend successively. These insights into the trends of Surma River's physico-chemical parameters contribute to understanding its behavior, aiding in effective monitoring and management strategies.

Index Terms—Adjusted R squared value, Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Cubic Trend, Dissolved Oxygen (DO), Linear Trend, PCA (Principal Component Analysis), pH, Quadratic Trend, Rainy Season, Surma, Suspended Solids (SS), Temperature, Total Solids (TS), Total Dissolved Solids (TDS), Water Quality Parameters and Winter Season.

1. Introduction

Rivers are essential for the survival and wellbeing of ecosystems and humans because they provide water supplies. Therefore, river water quality is a crucial factor that needs to be maintained and watched over (Othman et al., 2012). Integral to both ecosystems and human lives, water is the foundation of terrestrial life (Sahoo, 2014; Aziz, 1975).

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This paper available online at <u>www.ijprse.com</u> ISSN (Online): 2582-7898; SJIF: 5.59 Freshwater is in great demand due to population growth and industrial development, which has put an enormous demand on this resource (Ramakrishnaiah, C. R., Sadashivaiah, C., & Ranganna, G., 2009). The quality of stream water, characterized by its physical, chemical, and biological parameters, exhibits notable temporal and spatial variability owing to diverse land cover and human conditioning (Loukas & Vasiliades, 2010; Singh, K. P., Malik, A., & Sinha, S., 2005). This variability complicates the identification of pollution sources and the development of effective control strategies (Massoud, M. A., Scrimshaw, M. D., & Lester, J. N., 2006; Sigua, G. C., & Tweedale, W. A., 2003). Given rivers' crucial role in sustaining agriculture, industry, and domestic requirements, maintaining their water quality stands as a paramount necessity (Chen, Y. D., Zhang, D., Sun, Y., Liu, X., & Wang, L., 2003).

The integration of multivariate statistical ways such as Principal Component Analysis (PCA) and Factor Analysis (FA) has become instrumental in the comprehensive assessment and opration of water resources. These techniques aid in identifying pollution sources and trends (Helena, B., Pardo, R., Vega, M., Barrado, E., Fernández, J. M., & Fernández, L., 2000; Lee, J. H., & Bang, K. W., 2000; Adams, B., Papa, L., Parker, A., & Voulvoulis, N., 2001; Wunderlin, D. A., Diaz, M. P., Ame, M. V., Pesce, S. F., Hued, A. C., & Bistoni, M. A., 2001; Reghunath, R., Murthy, T. R. S., & Raghavan, B. R., 2002). These statistical tools enable the explanation of temporal and spatial variations in water quality, aiding in effective monitoring and management of aquatic ecosystems (Singh, K. P., Malik, A., Mohan, D., & Sinha, S., 2004).

Multivariate statistical techniques have been extensively applied to characterize and evaluate surface and freshwater quality, supporting temporal and spatial variations influenced by natural and anthropogenic factors, particularly seasonality (Singh et al., 2004, 2005; Shrestha et al., 2007). Specifically, PCA has been widely used in evaluating water quality monitoring stations and assessing long-term hydrochemical data of shallow water bodies (Ouyang, 2006; Medina-Gomez & Herrera-Silverira, 2003; Solidoro et.al., 2004; Parinet et al., 2004). Furthermore, water quality modeling using hydrochemical data, multiple linear regression, structural equation modeling, predictability and trend analysis have provided significant tools for water quality management (Attah et al., 2012; Chenini et al., 2009; Fang et al., 2016; Singh et al., 2004; Su et al., 2011; Prasad et al., 2013; Seth et al., 2013).

The objective of this study is to conduct trend analysis using statistical methods, particularly PCA, to evaluate the Surma River's physico-chemical parameters. The selected parameters, based on data availability and applicability to assessing the river's condition, will provide insights into the trends and potential pollution sources impacting the Surma River. This analysis aims to aid policymakers in documenting necessary remedial actions to prevent adverse effects on water quality and ensure the sustainability of this vital resource.

2. Materials and Method

A. Description of Study Area

Sylhet, a major city in northeastern Bangladesh, is situated along the Surma River, surrounded by the Jaintia, Khasia, and Tripura hills (Sylhet City Corporation, 2014). The Surma River, originating from the Barak River in India's Shillong and Meghalaya hills, bifurcates at Amalshid in Sylhet, with the northwest branch becoming the Surma River. The Surma River traverses through various regions, including Zakiganj, Golabganj, Fenchuganj, Balaganj, Rajnagar, Maulvibazar, and Nabiganj before merging with the Kushiyara River (Surma Meghna river System, 2015). The Surma River, integral to Sylhet's landscape, serves multiple purposes such as irrigation, domestic water supply, and industrial use (Surma Meghna river System, 2015). It has an average width of 830 feet and reaches depths of up to 33 feet during the rainy season. This river, crucial for the livelihoods and economy of Sylhet, ultimately merges with the Kushiyara River to form the Meghna River, which flows into the Bay of Bengal. The Surma River's course, including the presence of the Fenchuganj Fertilizer Factory, significantly impacts the local ecosystem and economy (Kushiyara River, 2014).

B. Sampling and Analysis

The characteristics of the water quality were divided into two groups in distinct times of year (winter and rainy season). The first 20 to 30 centimeters of the water column were used to gather water samples. Using a pre-sterilized two-liter plastic bottle, each site was repeatedly washed with water from those sites and tested for certain physical and chemical water quality parameters that are necessary for this study. The study was conducted along the Surma River from upstream to downstream during two seasons: the rainy season (June-July) and the winter season (November-December). For the years 2010, 2011, 2012, and 2013, correspondingly, water samples were gathered throughout the rivers during both seasons. The average data is used for correlation analysis, and data for the years 2005–2009 and 2014 were collected from the DoE, BWDB, and CEE department's earlier research projects. For statistical analysis, seasonal data spanning the last ten years is employed. Water samples were taken at different locations along the Surma River, and normal laboratory procedures were followed to analyze the water's physical and chemical characteristics (APHA-AWWA-WPCF, 1998).

C. Methodology of trend analysis

The study conducted various statistical analyses using different software to achieve its objectives effectively. Principal Component Analysis (PCA) was employed to extract important parameters for trend analysis, aiming to reduce the dimensionality of the dataset (Wunderlin et al., 2001; Jianqin et al., 2010). Furthermore, due to the limited four years of collected data (2010-2013) for both the rainy and winter seasons, additional data from 2005 to 2009 and 2014 were obtained from secondary sources to enhance the analysis (Ramakrishnaiah et al., 2009). PCA, an extensively used multivariate statistical technique, transforms the dataset into a new set of orthogonal variables known as principal components (PCs), arranged in decreasing order of importance (Wunderlin et al., 2001; Jiangin et al., 2010). It is worth noting that the origin of PCA can be traced back to historical figures such as Pearson (1901) or even Cauchy (1829), but its modern instantiation was formalized by Hotelling (1933) (Grattan-Guinness 1997; Stewart 1993; Boyer and Merzbach, 1989). PCA aims to extract important information from the data and express it as a set of new orthogonal variables called principal components (Wunderlin et al., 2001). The Scree Plot, a graphical tool developed by R. B. Cattell in 1966, was utilized to visually identify the appropriate number of principal components to retain, assisting in the determination of significant components (Jianqin et al., 2010). The scree plot displays eigenvalues associated with a component or factor in descending order versus the number of the component or factor (Jianqin et al., 2010). The ideal pattern in a scree plot is a steep curve followed by a bend and then a flat or horizontal line, indicating the number of important components to retain (Jianqin et al., 2010). Finally, curve fitting, based on the principle of least squares, was employed for trend analysis to establish mathematical relationships between dependent and independent variables (Wunderlin et al., 2001). This method provides a unique curve of best fit to the given data points, offering valuable insights into the trends of water quality parameters in the Surma River (Sahoo, 2014; Ramakrishnaiah et al., 2009). There are various types of curves that are used to describe the given data in the study as: Straight line: [y] t=a+bt, Quadratic line: y t=a+bt+ct^2 and Cubic line: y t=a+bt+ct^2+dt^3

3. Results and discussion

A. Extraction of WQP's and Fitting trend of important variables extracted from PCA

From total variance explained by PCA, it is found that nearly 95% variance explained by the first six component. But from the scree plot, first two component is sufficient to explain total

variation that is shown in table 1.

The component matrix indicates the correlation of each variable with each component. From the table 1 it is found that the most important variables using their high loadings (≥ 0.70) that is, highly correlated variables associated with component 1 and component 2. The results shown in table 1 indicate total 18 variables are highly correlated with component 1 and 2 that is contains high loadings. Those variables are shown in table 2.

Water quality parameters	Component		
	1	2	
Temperature of the Surma river in winter season	0.174	0.497	
pH of the Surma river in winter season	0.339	- 0.064	
DO of the Surma river in winter season	- 0.731	- 0.350	
BOD of the Surma river in winter season	0.620	0.008	
COD of the Surma river in winter season	0.259	0.612	
TS of the Surma river in winter season	0.907	0.342	
TDS of the Surma river in winter season	0.924	0.281	
SS of the Surma river in winter season	0.348	0.604	
Temperature of the Surma river in rainy season	0.605	0.012	
pH of the Surma river in rainy season	0.743	0.390	
DO of the Surma river in rainy season	- 0.134	- 0.066	
BOD of the Surma river in rainy season	0.862	- 0.101	
COD of the Surma river in rainy season	0.962	0.139	
TS of the Surma river in rainy season	0.961	0.198	
TDS of the Surma river in rainy season	0.891	0.230	
SS of the Surma river in rainy season	0.087	- 0.083	

Table.1. Component Loadings of different variables of the Surma
Diver

Using PCA-extracted variables, we fit trend lines (linear, quadratic, cubic) over time to find the best-fitting trend for each variable. Linear, quadratic, and cubic trends are chosen as they are widely used for data fitting. Trends are compared using Adjusted R-squared, a more reliable measure than R-squared. Adjusted R-squared considers sample size and variables, making it preferable. It's an unbiased estimate of explained variance. Adjusted R-squared is typically slightly smaller than R-squared, indicating goodness of fit. However, it can be zero or negative if the model lacks informative variables or the sample size is too small. This process ensures robust trend selection for each water quality variable.

Table.2. Water quality parameters extracted form Principal Component Analysis (PCA)

Surma River							
Rainy	Rainy season		er season				
1	pН	6	DO				
2	BOD	7	TS				
3	COD	8	TDS				
4	TS						
5	TDS						

B. Fitting trend line for pH of the Surma River in rainy season

For the selection of trend line for pH of the Surma River in rainy season linear, quadratic and cubic trend lines are analyzed. These three trend lines are selected because these are the basic trend lines among all others. For trend analysis used notations in tables are abbreviated as: R = Absolute value of Correlation Coefficient, R2 = Proportion of variation that is explained by model, Adjusted R2 = R square value adjusted for the number of variables in the regression model, df = Degree of Freedom, t = Computed test statistics and F = F statistics.

Table.3. Output of fitting linear trend line

	(a) Model Summary										
	P	R Square	Adjusted Square	R	Std. Estimate	Error	of	the			
F	0.863	0.745	0.713		0.134						

(b) ANOVA										
	Sum of Squares	df	Mean Square	F	Sig.					
Regression	1				-					
Regression	0.494	3	0.165	13.958	0.004					
Residual	0.071	6	0.012							
Total	0.565	9								

(c) Coefficients											
	Unstandardized		Standardized								
	Coefficients		Coefficients								
		Std.									
	В	Error	Beta	t	Sig.						
Time	0.396	0.158	4.792	2.509	0.046						



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2	Time **	-0.075	0.033	-10.187	-2.291	0.062						
3	Time **	0.005	0.002	6.462	2.410	0.053						
	Constant	5.960	0.211		28.278	0.000						
	Table.4. Output of fitting quadratic trend line											
	(a) Mad	ol Summon										

	(a) Woder Summary										
ſ		R	Adjusted R		Std.	Error	of	the			
	R	Square	Square		Estimate						
	0.868	0.753	0.683		0.141						

(b) ANOVA											
	Sum of		Mean								
	Squares	df	Square	F	Sig.						
Regression	0.425	2	0.213	10.692	0.007						
Residual	0.139	7	0.020								
Total	0.565	9									

(c) Coefficients										
	Unstand	lardize	Standardized							
	d Coefficie	ents	Coefficients							
		Std.								
	В	Error	Beta	t	Sig.					
Time	0.038	0.0	0.460	0.54	0.60					
	0.058	69	0.400	9	0					
Time ** 2	0.003	0.0	0.413	0.49	0.63					
	0.005	06	0.415	4	7					
(Constant)	6.364	0.1		38.3	0.00					
	0.304	66		65	0					

Table.5.	Output	of fitting	cubic	trend line

(a) Model Summary										
	R	Adjusted	R		Std.	Error	of	the		
R	Square	Square		Es	stimat	e				
0.935	0.875	0.812		0.109						

(b) ANOVA						
	Sum o	of		Mean		
	Squares		df	Square	F	Sig.
Regressi on	0.494		3	0.165	13.95 8	0.004
Residual	0.071		6	0.012		
Total	0.565		9			

(c) Coef	ficients				
	Unstandardized		Standardized		
	Coefficients		Coefficients		
		Std.			
	В	Error	Beta	t	Sig.
Time	0.396	0.158	4.792	2.509	0.046
Time ** 2	-0.075	0.033	-10.187	-2.291	0.062
Time ** 3	0.005	0.002	6.462	2.410	0.053
Constant	5.960	0.211		28.278	0.000

From the above analysis of linear, quadratic and cubic trend it is found that adjusted R squared values are 0.71, 0.68 and 0.81 respectively, and considering the maximum adjusted R squared value the cubic model is selected as the trend line and the equation coefficients are constant (5.960), time (0.396), time**2 (-0.075) and time**3 (0.005). The figure of all models and the selected model coefficients values are shown in figure 1 and table 6.

Therefore, the fitted cubic model for pH of the Surma River in rainy season is as the equation: Yt = 5.960 + 0.396t - 0.075t2 + 0.005 t3.

C. Fitting trend line for BOD of the Surma River in rainy season

To choose the best trend line for BOD of the Surma River in rainy season linear, quadratic and cubic trend lines are examined. From the analysis it is found that adjusted R squared values are 0.69, 0.72 and 0.71 respectively, and considering the maximum adjusted R squared value the quadratic model is selected as the trend line and the equation coefficients are constant (3.319), time (-0.064) and time**2 (0.031). The figure of all models and the selected model coefficients values are shown in figure 2 and table 7.

Accordingly, the fitted quadratic model for BOD of the Surma River in rainy season is as equation: Yt = 3.319 - 0.064t + 0.031t2.

D. Fitting trend line for COD of the Surma River in rainy season

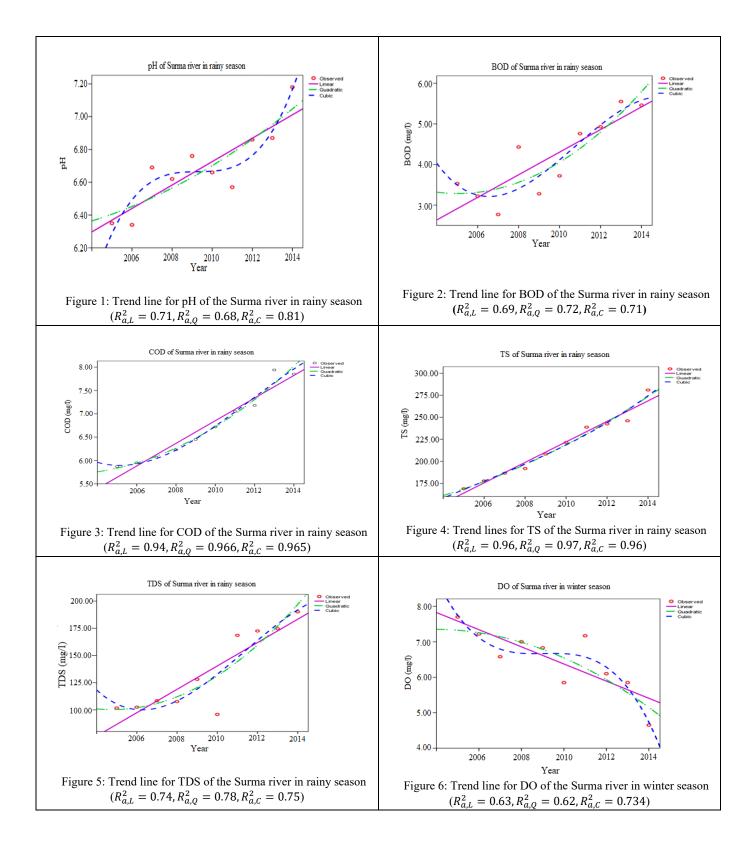
For the selection of trend line for COD of the Surma River in rainy season linear, quadratic and cubic trend lines are analyzed. From the analysis it is found that adjusted R squared values are 0.94, 0.966 and 0.965 respectively, and considering the maximum adjusted R squared value the quadratic model is selected as the trend line and the equation coefficients are constant (5.757), time (0.062) and time**2 (0.016). The figure of all models and the selected model coefficients values are shown in figure 3 and table 8.

Thus, the fitted quadratic model for COD of the Surma River in rainy season is as equation: Yt = 5.757 + 0.062t + 0.016t2.

E. Fitting trend line for TS of the Surma River in rainy season

TS of the Surma River in rainy season is analyzed for linear, quadratic and cubic trend lines to choose best one. From the study it is observed that adjusted R squared values are 0.96, 0.97 and 0.96 respectively, and considering the maximum adjusted R squared value the quadratic model is selected as the trend line and the equation coefficients are constant (161.248), time (7.158) and time**2 (0.407).

The figure of all models and the selected model coefficients values are shown in figure 4 and table 9. Hence the fitted quadratic model for TS of the Surma River in rainy season is as equation: Yt = 161.248 + 7.158t + 0.407t2.



F. Fitting trend line for TDS of the Surma River in rainy season

For the selection of trend line for TDS of the Surma river in rainy season linear, quadratic and cubic trend line is analyzed. From the analysis it is noticed that adjusted R squared values are 0.74, 0.78 and 0.75 respectively, and seeing the maximum adjusted R squared value the quadratic model is picked as the trend line and the equation coefficients are constant (100.916), time (-1.772) and time**2 (1.138). The figure of all models and the selected model coefficients values are cited in figure 5 and table 10. Therefore the fitted quadratic model for TDS of the Surma river in rainy season is exhibited as equation: Yt = 100.916 - 1.772t + 1.138t2

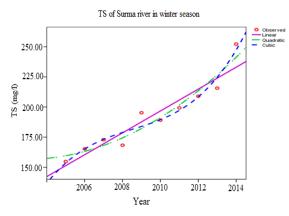
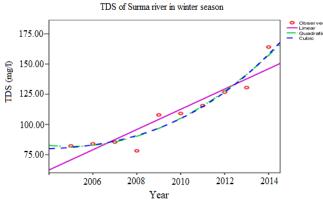
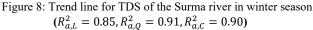


Figure 7: Trend line for TS of the Surma river in winter season $(R_{a,L}^2 = 0.884, R_{a,Q}^2 = 0.91, R_{a,C}^2 = 0.93)$





G. Fitting trend line for DO of the Surma River in winter season

DO of the Surma River in winter season is explored for linear, quadratic and cubic trend lines for the selection of best trend line. From the investigation it is observed that adjusted R squared values are 0.629, 0.620 and 0.734 respectively, and considering the maximum adjusted R squared value the cubic model is chosen as the trend line and the equation coefficients are constant (8.780), time (-1.271), time**2 (0.253) and time**3 (-0.017). The figure of all models and the selected

model coefficients values are illustrated in figure 6 and table 11. Thus the fitted cubic model for DO of the Surma river in winter season is as equation: Yt = 8.780 - 1.271t + 0.253t2 - 0.017 t3

H. Fitting trend line for TS of the Surma River in winter season

To choose best trend line for TS of the Surma River in winter season linear, quadratic and cubic trend line are analyzed. From the analysis it is found that adjusted R squared values are 0.884, 0.91 and 0.93 respectively, and considering the maximum adjusted R squared value the cubic model is selected as the trend line and the equation coefficients are constant (136.749), time (19.807), time**2 (-3.278) and time**3 (0.240). The figure of all models and the selected model coefficients values are shown in figure 7 and table 12. So the fitted cubic model for TS of the Surma River in winter season is as equation: Yt = 136.749 + 19.807t - 3.278t2 + 0.240t3

I. Fitting trend line for TDS of the Surma river in winter season

For the choice of trend line for TDS of the Surma river in winter season linear, quadratic and cubic trend lines are evaluated and it is found that adjusted R squared values are 0.85, 0.91 and 0.90 respectively. The quadratic model is selected as the trend line considering the maximum adjusted R squared value and the equation coefficients are constant (82.773), time (-1.84) and time**2 (0.928). The figure of all models and the selected model coefficients values are shown in figure 8 and table 13. Therefore the fitted quadratic model for TDS of the Surma river in winter season is as equation: Yt = 82.773 - 1.840t + 0.928t2

Table.14. Trends of WQP's of the Surma Rivers extracted by PCA important for both seasons

Serial No	WQP's selected for forecasting	Rainy Season	Winter Season
1	TS of Surma river	Quadratic (increasing)	Cubic (overall increasing)
2	TDS of Surma river	Quadratic (increasing)	Quadratic (increasing)

Table.15. Trends of WQP's of the Surma River extracted by PCA important for only one season

Serial No	WQP's selected for forecasting	Rainy Season	Winter Season
1	DO of Surma river	-	Cubic (overall decreasing)
2	pH of Surma river	Cubic (overall increasing)	-
3	BOD of Surma river	Quadratic (increasing)	-
4	COD of Surma river	Quadratic (increasing)	-



From table 14 & 15 it is shown that quadratic trend is followed by TDS of the Surma River in winter season, BOD of the Surma River in rainy season, COD of the Surma River in rainy season, TS of the Surma River in rainy season and TDS of the Surma River in rainy season. Cubic Trend Model is followed by DO of the Surma River in winter season, TS of the Surma River in winter season, pH of the Surma River in rainy season.

4. Conclusion

The analysis of trends in water quality parameters of the Surma River reveals significant insights into its environmental dynamics. The study found that the river does not follow a linear trend, with certain parameters showing quadratic and cubic trends over the years. Specifically, during the winter season, Total Dissolved Solids (TDS) exhibited a quadratic trend, while Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Total Solids (TS), and Total Dissolved Solids (TDS) displayed quadratic trends in the rainy season. Additionally, Dissolved Oxygen (DO) and Total Solids (TS) followed cubic trends in the winter season, while pH exhibited a cubic trend during the rainy season. These trends indicate various factors affecting the Surma River's water quality. The increasing trends in parameters such as BOD, COD, Total Solids, Total Dissolved Solids, and Suspended Solids suggest a deterioration in water quality, likely due to anthropogenic activities, industrial discharge, and runoff from agricultural and residential areas. The higher temperatures in the river water during the rainy season can be attributed to upstream influences and changes in effluents from different sources. In light of these findings, it is crucial to implement effective measures to mitigate pollution and preserve the Surma River's ecosystem.

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