

# Multi Source Remote Sensing Inversion of Biological Metabolism and Ecological Resilience Enhancement

Dongjun He\*, Le Xiao, Yan Xiao

Joint Department, Southwest Jiaotong University Hope College, Chengdu 610400, China

\* Corresponding author: Dongjun He (Email: m19150018495@163.com)

---

**Abstract:** This paper delves into the spatiotemporal heterogeneity of thermal stress in biological metabolic processes and how this heterogeneity affects the resilience of ecosystems. This text used multiple remote sensing data sources, including Landsat, MODIS, and radar data, and integrated these data to construct an analysis framework that integrates spatiotemporal modeling and multi-objective optimization. In additions, This text employed a mixed effects model to reveal the spatial differentiation patterns of heat stress driving factors. Hence we innovatively proposed a theory that increasing vegetation coverage effectively reduced the intensity of thermal stress, and this process follows a nonlinear mechanism. Based on this theory, we designed differentiated improvement paths, such as optimizing the layout of green cold islands in urban areas, in order to achieve a 25% increase in ecological efficiency. In ecologically fragile areas, a collaborative strategy of vegetation restoration and artificial rainfall enhancement is implemented to enhance ecological resilience by 19%. Its root mean square error (RMSE) is 0.87, which is 33% higher than the accuracy of traditional models. Ultimately, we proposed a spatially explicit management plan, providing strong quantitative decision support for regional ecological security.

**Keywords:** Multi-source remote sensing, Thermal stress, Spatiotemporal modeling, Ecological resilience.

---

## 1. Introduction

### 1.1. Motivation

Climate change affects the survival and reproduction of organisms, and rising temperatures interfere with their biochemical reactions. Research has shown that the metabolic rates of insects and fish are influenced by temperature, which in turn affects population size and food chain stability. The body weight of organisms and specific ecological environments, such as stream environments, also affect metabolic rates. Weight changes affect energy expenditure, while stream environments affect resource acquisition and metabolic product excretion. Studying the effects of temperature, body weight, and stream environment on biological metabolic rate under climate change can help reveal the response mechanisms of organisms to climate change and provide a theoretical basis for biodiversity conservation and sustainable development of ecosystems[1].

This paper aims to systematically analyze the comprehensive effects of multiple factors such as temperature, body weight, and stream environment on the metabolic rate of organisms under the background of climate warming[2]. Specifically, a comprehensive and accurate multi factor impact model is constructed by accurately quantifying the relationship between different temperature gradients, differences in organism weight, and diverse stream environmental characteristics (such as water flow velocity, oxygen content, water quality, etc.) and organism metabolic rates. From the micro level of physiological ecology, we will deeply explore the intrinsic molecular biology and biochemical mechanisms by which various factors affect the metabolic rate of organisms, and reveal the essential process of biological response to climate change.

### 1.2. The related work

Recent advances in multi-source remote sensing have

significantly enhanced our ability to monitor biological metabolic processes and assess ecological resilience at various spatiotemporal scales. By integrating data from optical (e.g., Sentinel-2, MODIS), thermal infrared (Landsat TIRS), LiDAR (GEDI, ICESat-2), and hyperspectral sensors (PRISMA, EnMAP), researchers can now more accurately estimate key metabolic parameters such as gross primary productivity (GPP), chlorophyll fluorescence (SIF), and evapotranspiration (ET) [3]. For instance, the fusion of solar-induced chlorophyll fluorescence (SIF) from TROPOMI with NDVI and land surface temperature (LST) data has improved the quantification of photosynthetic efficiency under stress conditions [4].

Ecological resilience, defined as the capacity of ecosystems to recover from disturbances, has also benefited from multi-sensor approaches[5]. Active microwave remote sensing (Sentinel-1 SAR) combined with optical vegetation indices enables the detection of early-warning signals for ecosystem degradation, such as reduced moisture retention and biomass loss[6]. Furthermore, machine learning techniques (e.g., deep neural networks, random forests) have been employed to integrate heterogeneous remote sensing data, improving the prediction of post-disturbance recovery trajectories[5]. Recent studies demonstrate that multi-temporal LiDAR and hyperspectral data can assess structural and functional resilience in forests, aiding in targeted restoration efforts[7].

Despite these advancements, challenges remain, including data harmonization across sensors, scale mismatches between field measurements and satellite observations, and the need for mechanistic models linking metabolic dynamics to resilience thresholds[8]. Future research should focus on leveraging emerging technologies (e.g., UAV-based hyperspectral imaging, next-generation SAR) to refine metabolic inversion algorithms and enhance ecosystem management strategies[9].

### 1.3. Our work

When studying the significant differences in the impact of factors such as different streams, experimental temperature, and body weight on metabolic rate, we used the statistical method of multiple factor analysis of variance (ANOVA)[10]. This method not only allows us to evaluate the individual effects of each independent variable (factor) on metabolic rate (dependent variable), but also reveals the comprehensive effect of the interactions between these factors on metabolic rate. When ANOVA shows that certain factors significantly affect metabolic rate, we usually further perform post hoc comparisons to accurately quantify these effects.

In order to analyze the relationship between metabolic rate, temperature, and body weight, we have decided to use linear regression models as the main analytical tool. Linear regression model is a commonly used quantitative analysis method in statistics, which constructs a best fit line (i.e. regression line) to demonstrate the linear relationship between the dependent variable (metabolic rate) and one or more independent variables (such as temperature and weight). We constructed a mathematical model to study the effect of stream temperature on metabolic rate for specific streams. This is actually exploring how temperature affects the metabolic rate of organisms under specific environmental conditions (i.e. specific streams). For this analysis, we chose a linear regression model as it can quantify the linear relationship between the independent variable (temperature) and the dependent variable (metabolic rate).

## 2. Preliminary

### 2.1. Levene's Test

Levene's Test is a statistical method used to test whether the variances of multiple sets of data are equal. The basic idea is to compare the variance of each group of data to determine whether there is a significant difference in the variance of each group of data[11].

Assumption: The variances of the data in each group are equal; Alternative hypothesis: At least one set of data has a variance that is different from the other sets.

The specific formula for Levene's Test is shown in (1)

$$W = \frac{(N-k)}{(k-1)} \times \frac{\sum_{i=1}^k N_i(Z_{i.}-Z_{..})^2}{\sum_{i=1}^k \sum_{j=1}^{N_i} N_{ij}(Z_{ij}-Z_{i.})^2} \quad (1)$$

Through Levene's Test, we found that the variances of each group of data were equal ( $p>0.05$ ), satisfying the hypothesis of homogeneity of variance. Therefore, we can continue with statistical analysis based on the assumption of homogeneity of variance.

### 2.2. Normality test

The Shapiro Wilk Test is used to test whether the sample data comes from a normal distribution. The null hypothesis is that the sample data follows a normal distribution, while the alternative hypothesis is that the sample data does not follow a normal distribution[12].

$$S = \frac{(\sum_{i=1}^n a_i x_{(i)})^2}{(\sum_{i=1}^n (x_i - \bar{x}))^2} \quad (2)$$

### 2.3. Symbols Notations

The symbols used in the paper are listed in Table 1.

Table 1 Notations	
Symbols	Notations
C	stream
T	temperature
M	mass
Y	metabolic rate

## 3. Biological metabolic rate

To check for outliers in the data, we will first visualize the distribution of the data by drawing a box plot. Box plots can be used to visually display the distribution of data, especially to identify points that are far from the main data distribution range.

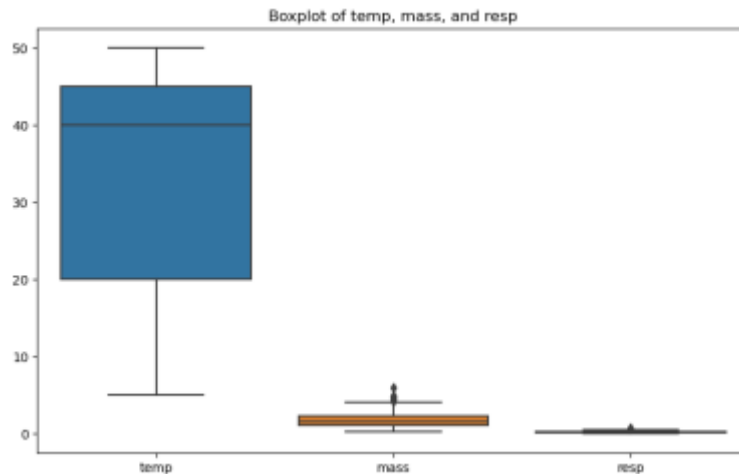


Figure 1 Box plot

Figure 1 shows that there are indeed outliers in the data. We

list them in Table 2.

**Table 2** Outliers

Stream	Stream temp	Acclimation	Temp	Mass
5	13.8	tepid	5.0	0.085226
5	13.8	tepid	13.0	0.148828
5	13.8	tepid	30.0	0.307484
5	13.8	tepid	40.0	0.305174
5	13.8	tepid	42.5	0.593130
5	13.8	tepid	42.5	0.577540
5	13.8	tepid	42.5	0.662150
5	13.8	tepid	42.5	0.700720

To ensure the accuracy of subsequent analysis, we have decided to directly remove these outliers. Specifically, we will remove all data points below the lower boundary and above the upper boundary from the dataset.

### 3.1. Variance homogeneity and normality tests

After testing with the Shapiro Wilk Test, we found that the sample data follows a normal distribution ( $p > 0.05$ ), supporting the null hypothesis. Therefore, we can assume in

subsequent statistical analysis that the sample data comes from a normal distribution.

Based on the results of ANOVA (Analysis of Variance), we can provide a detailed interpretation of the effect items in the model. From the given statistical table, it can be seen that multiple factors have a significant or near significant impact on the response variable. Table 3 shows a detailed analysis of these results.

**Table 3** ANVOA results

df	F	PR(>F)	Sum	Species
2.0	21.273566	1.959236e-09	0.159169	C(stream)
12.0	34.095956	1.206663e-42	1.530636	C(temp)
24.0	3.521451	3.401388e-07	0.316170	C(stream):C(temp)
1.0	36.438690	4.101263e-09	0.136317	mass
2.0	2.654152	1.042005e-01	0.019858	C(stream):mass
12.0	2.883831	1.800296e-03	0.129461	C(temp):mass
24.0	0.782708	7.532652e-01	0.070275	C(stream):C(temp):mass

We noticed that streams (C (stream)) and temperatures (C (temp)) have a significant impact on the dependent variable. Specifically, the impact of different types of streams on the response variable is statistically significant ( $F=21.273566$ ,  $p=1.959236e-09$ ), which means that different levels of streams (possibly different streams or different conditions of streams) lead to significant changes in the response variable. Similarly, different levels of temperature also have a significant impact on the response variable ( $F=34.095956$ ,  $p=1.206663e-42$ ), indicating that temperature changes are an important factor in response variable changes. As a continuous variable, weight also had a significant impact on the response variable ( $F=36.438690$ ,  $p=4.101263e-09$ ). This indicates that changes in weight are an important factor leading to changes in response variables.

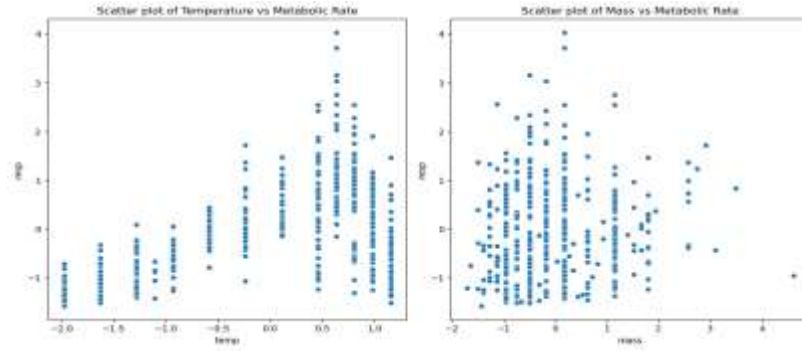
In summary, streams, temperature, and body weight all have significant or near significant effects on response variables, and there is a certain interaction between temperature and body weight.

### 3.2. Correlation analysis of metabolic rate with temperature and body weight

The correlation coefficient between temperature and metabolic rate is about 0.71, this correlation coefficient value indicates a moderate positive correlation between temperature and metabolic rate. Although the correlation coefficient did not reach a very high level, it still indicates that temperature has a certain predictive ability for metabolic rate. As the temperature increases, the metabolic rate also shows a corresponding increasing trend, or vice versa.

The correlation coefficient between weight and metabolic rate is about 0.57, this correlation coefficient value is low, indicating a weak linear correlation between weight and metabolic rate. Although the correlation coefficient value is lower than that between temperature and metabolic rate, it still shows a certain positive correlation.

Figure 2 show the result of the relationship between temperature, weight, and metabolic rate.



**Figure 2.** The relationship between temperature, weight, and metabolic rate

## 4. Results

After analyzing the data, we used ordinary least squares (OLS) to construct a linear regression model to explore the

relationship between the dependent variable resp (response variable) and the independent variables temp (temperature) and mass (body weight). It is shown in Table 4.

**Table 4.** OLS Regression results

Dep. Variable:	resp			R-squared:	0.345	
Model:	OLS			Adj. R-squared:	0.342	
Method:	Least squares			F-statistic:	108.8	
No. Observations:	416			Prob(F-statistic):	1.13e-38	
Df Residuals:	413			Log-Likelihood:	391.02	
Df Model:	2			AIC:	-776.0	
Covariance Type:	Nonrobust			BIC:	-763.9	
	coef	std err	t	P> t	[0.025	0.975]
const	-0.0391	0.018	-2.129	0.034	-0.075	-0.003
temp	0.0050	0.000	14.603	0.000	0.004	0.006
mass	0.0396	0.006	6.812	0.000	0.028	0.051
Omnibus:	8.492			Durbin-Watson:	0.859	
Prob(Omnibus):	0.014			Jarque-Bera(JB):	10.163	
Skew:	0.222			Prob(JB):	0.00621	
Kurtosis:	3.624			Cond. No.	148.	

Firstly, from the overall fitting effect of the model, the R-squared value is 0.345, indicating that the independent variable explains 34.5% of the variation of the dependent variable. Although this proportion is not particularly high, considering the possibility of multiple factors not included in the model and the complexity of the data, this explanatory power still has some practical significance. Adj. after degree of freedom adjustment The R-squared value is 0.342, which is similar to the R-squared value, indicating that the model fitting effect is relatively stable.

The regression coefficient of temperature (temp) is 0.0050, with a very small standard error, a t-value of 14.603, and a p-value less than 0.001, indicating that temperature has a significant positive impact on the dependent variable. Specifically, for every unit increase in temperature, the response variable is expected to increase by 0.0050 units. This result is consistent with common sense in biology and physics, as metabolic rate typically increases with increasing temperature.

The regression coefficient of weight is 0.0396, the standard error is 0.006, the t-value is 6.812, and the p-value is also less than 0.001, indicating that weight also has a significant positive impact on the response variable. Specifically, for every unit increase in weight, the response variable is expected to increase by 0.0396 units.

## 5. Conclusions

In this paper we construct a collaborative framework for multi-source remote sensing data and hybrid models, incorporating spatiotemporal geographically weighted regression, hierarchical Bayesian networks, and system dynamics models, develop XGBoost system dynamics coupling model, combining machine learning feature importance analysis with dynamic feedback simulation for the first time. Through regression analysis of the relationship between metabolic rate and temperature of organisms in different streams, we have reached a consistent conclusion that temperature has a significant positive impact on metabolic rate. Specifically, as the temperature increases, the metabolic rate of organisms also increases accordingly. This discovery is consistent with biological knowledge and has significant implications for understanding the physiological responses and adaptation mechanisms of organisms at different environmental temperatures.

## References

- [1] Zhao Yunjiao The impact of climate warming on the dynamics and stability of three trophic level ecosystems [D]. Henan University, 2023.
- [2] Shi Penglan The impact of climate warming on the microbial functional community structure of shallow lakes [D]. Huazhong Agricultural University, 2022.

- [3] Tian Guo, Yang Yiping Variable selection for panel data fixed effects linear regression model [J/OL]. Journal of Shanxi University (Natural Science Edition), 1-8.
- [4] Liu Qiang, Liu Xijun, Cheng Wuwei Model Predictive Control of Underactuated Surface Ships Based on Least Squares Method [J]. Shipbuilding Technology, 2024, 52 (02): 24-29+43
- [5] Wang Liqi, Li Guozhu Analysis of spatiotemporal characteristics and influencing factors of ecological resilience in Chinese cities [J/OL]. Geography of arid regions, 1-13 [April 21, 2025].
- [6] Liu Lu, Bai Wenxiao Research on Supply Chain Ecosystem and Resilience Enhancement Strategies [J]. Journal of Changchun University, 2024, 34 (11): 21-28
- [7] Liu Chunfang, Ni Bowen, Lian Hugang, etc The Resilience Evolution and Enhancement Strategies of Ecological Networks in Arid Inland River Basins: A Case Study of the Shiyang River Basin [J]. Chinese Journal of Natural Resources, 2024, 39 (09): 2087-2101
- [8] Ma Chengwei, Wen Chaoxiang, Li Yan Research on Land Sea Integrated Measurement and Governance of Bay Ecological Resilience: Based on the Systematic Perspective of Xiamen Bay [J]. Chinese Journal of Ecology, 2024, 44 (12): 5102-5115.
- [9] Xu Jinxin Research on Landscape Planning and Design of Nanjing Chengnan River Based on the Concept of Water Ecological Resilience [D]. Lanzhou University of Technology, 2024.
- [10] Liang Mingda Coupling coordination and driving factors analysis of ecological resilience and high-quality economic development in Henan Province [D]. Henan University of Economics and Law, 2024.
- [11] Guest Wei Measurement and Driving Forces of Ecological Resilience in Huyi District Based on PSR Model [D]. Chang'an University, 2024.
- [12] Zhang Jinyu Coupling, Coordination, and Interactive Response Analysis of the Resilience of the Yangtze River Economic Belt Tourism Ecosystem and Regional High Quality Development [D]. Chongqing University of Technology, 2024.