Fingerprinting of Phosphorus in river sediments using the structural equation modeling

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Abstract

Phosphorus (P) is transported into the water resources mainly due to soil erosion. Accumulation of P in water bodies leads to the subsequent eutrophication phenomenon. Using the structural equation modeling, this study investigated the relative contribution of different P-producing sources in the Pasikhan river watershed, south of the Caspian Sea, Northern Iran. For this purpose, 79 surface soil samples and 14 suspended sediments were taken from the potential P sources and the river. These sources included undisturbed and degraded rangelands, forests, rice fields, tea gardens, and gullies. Phosphorus transfer is mainly associated with the movement of clay particles. Therefore, clay was used as an intermediary parameter to make the modeling more reliable. The implemented structural equations in PLS software were used for modeling purposes. The overall model fitting index (goodness of fit,GOF=0.591) showed the model's strong forecasting capability. The results of the T-values test also showed that undisturbed rangelands (T-values=1.67) and forests (T-values=1.31) have no significant effect on the river's P content. Degraded rangelands, gullies, rice fields, and tea gardens significantly contribute to P in the river sediments. In particular, the highest contribution was related to degraded rangelands (intensity of the effect=0.63) and gullies (intensity of the effect=0.47). Finally, the results showed that gullies' contribution was 28.26% to the P production in river sediments, while the other sources had a relatively equal contribution (degraded rangelands=27.5%; tea gardens=23.9%; rice fields=20.3%). Overall, the results confirmed that structural equation modeling is a robust and efficient approach to identifying P sources.

1. Introduction

Population growth, industry developments, agricultural activities, and urbanization have led to severe soil erosion and subsequent water pollution in rivers, lakes, and reservoirs (Varol et al., 2013; Zeinalzadeh and Rezaei, 2017; Wen et al., 2019; Ebrahimi et al., 2022a,b). Among the most critical consequences of soil erosion, one can point to soil fertility reduction and the unfavorable transfer of nutrients and organic matter (e.g., N, P, K, and sediments) to the surface waters (Troeh Frederick et al., 2003). In most cases, erosion is considered only in terms of the quantitative soil mass loss in the eroded area (Xingchang et al., 2004; Singh et al., 2008), which is not all that matters. Phosphorus and nitrogen are the two primary nutrients that behave differently in soils during water erosion. Due to the high surface area and adsorption capacity of clay particles, P firmly attaches to the soil particles and moves with them during the erosion process, much more than the soluble form (Hatch et al., 1999). Therefore, the primary mechanism of P loss is in particulate form (with suspended sediment), the values of which fluctuate widely (Hatch et al., 1999; Asadi, 2016). The P attached to the surface of the clay particles gradually separates from it and runs into the water in a soluble form (Shoja et al., 2017; Zhou et al., 2020). During surface runoff in cultivated lands, 80% of P losses are in the form of sediment-bound particles (Sharpley et al., 1992). While in runoff that flows through grasslands and meadows, uncultivated soils, and forests, less sediment is transferred, and most downstream P is soluble in water (Sharpley et al., 2003).

Lagoon ecosystems are particularly important among water resource systems and cover about six percent of the planet. They are among the richest natural ecosystems with many ecological and environmental functions. Due to its remarkable ability to reproduce, Anzali Lagoon, located in northern Iran on the southern shore of the Caspian Sea, is an outstanding international lagoon with a prominent role in ecology, economy, and environment. It is vital to the survival of many plants and animals and is also an essential dwelling for birds, reptiles, amphibians, fishes, and invertebrates. Anzali Lagoon was registered in the list of lagoons of the Ramsar Convention in 1975 (Ramsar convention Bureau, 1975). Birdlife International, a global partnership of non-governmental organizations, has also identified this lagoon as an exceptional bird habitat (Evans, 1994).

Meanwhile, the practical function of the lagoons in removing nutrients is one of their unique features. In this regard, studies on the Anzali lagoon have also proved its influential role as an intermediate filter of nutrients between the rivers entering the lagoon and the Caspian Sea. In recent years, unfortunately, due to the excessive entry of nutrients from urban, agricultural, and industrial effluents, the main functions of this lagoon have been seriously endangered, and it demands serious attention and better management. This lagoon is included in the list of Montreux (JICA, 2012) due to its current status.

Eutrophication is a serious threat to lakes and surface waters, mainly due to the pollution induced by human activities. Therefore, one of the leading factors in the deterioration of surface water's quality is the occurrence of nutritionism due to the entry of nutrients, mainly nitrate and phosphate, into water resources. In other words, erosion in upstream lands, the entry of various elements and particles into the river, and finally, accumulation in water reserves such as lagoons is the leading cause of eutrophication. Phosphorus is considered a significant limiting factor in the eutrophication of water bodies (Smith et al., 2017; Ni et al., 2019; Moyle and Boyle, 2021). Asadi (2016) examined the sediment, P, and organic matter of the Pasikhan River. This researcher stated that 245.3 tons of P enter the Anzali lagoon annually through the Pasikhan river. He also stated that in wet seasons only 20% of the total P is soluble. However, in dry seasons this contribution reaches 50%, which indicates the significant share of clay particle bonded P.

It is imperative to identify the prominent locations of P origin to take controlling and protective actions to maintain and rehabilitate lagoons, especially the Anzali lagoon. Although many methods have been exploited to identify the origin of sediments, none targeted the nutrients such as P, to the authors' knowledge. This research used the structural equation modeling method to trace P for the first time. Therefore, this study aimed to investigate the method of structural equation modeling based on partial least squares in determining the sources of P production in the watershed.

2. Materials And Methods

2.1. Study Region

The study was carried out in the Mobarakabad sub-watershed of the Pasikhan river watershed (Fig. 1). Pasikhan watershed is the most important river with the highest discharge and sediment load entering to Anzali lagoon. Mobarakabad sub-watershed is located at 347639 to 353603 meters east longitude and 4090746 to 4098907 meters north latitude. The area of this sub-watershed is 111.5 square kilometers, and its average slope is 37.6%. In particular, 45% of the sub-watershed has more than 60% slope, and the river length is 17.93 km (Ebrahimi et al., 2022a,b). The soil moisture regime of this region is Udic, and its thermal regime is Mesic. The Gravelius coefficient of the sub-watershed is 1.2. According to the Chao and California methods, its concentration time is 41.36 and 40.46 minutes, respectively. Mean annual rainfall and evapotranspiration are 1163 and 872 mm, respectively. The geology of this area dates back to the Paleozoic and Jurassic eras. The primary use in this sub-watershed is in the form of forests (61.01%) and rangelands (29.56%) (Table 1). The rangelands are located in the upper and high mountains (south of the watershed), while the rice fields are in the lowlands (the north part) (Fig. 2).

Overall, 93 samples were collected, including 14 sediment samples and 79 soil samples from sediment-producing sources (Fig. 3). These resources include gully (25 samples), degraded rangelands (23 samples), undisturbed rangelands (11 samples), forests (8 samples), rice fields (7 samples), and tea gardens (5 samples). The number of samples taken from each potential sediment source was based on field surveys, soil erosion features, and aerial imagery and was not proportional to the land area. There existed minimal signs of soil erosion under the forests. Therefore, only a few samples were taken from this land use. The depth of soil sampling was 0–2 cm from the surface. The subsurface soil samples were collected just from river and gully banks. Sediment samples were collected from deposited mud from previous floods trapped between the rocks and ditches at the watershed outlet.

Table 1
Land use percentage in the studied basin

Land use	%	Land use	%
Forest	61.01	Rural	1.45
Disturbed Rangelands	24.2	River	1.22
Undisturbed Rangelands	5.36	Other	0.54
Tea Garden	3.69	Gully	0.30
Rice Field	2.23		

The Hydrometric method was used to measure the soil particle size distribution (particles smaller than 2 mm) (Gee and Dani, 2002). Organic carbon content was measured through Walkey and Black method (Walkey and Black, 1934), to measure phosphatase enzyme in samples, a method exploited by Tabatabai et al. (Tabatabai et al., 1994) was used. Available P was measured by the Olsen method at a wavelength of 880 nm by a spectrophotometer (Olsen, 1954). All measurements were carried out in three replicates.

2.2. Modeling

In general, the analysis using the Partial Least Square (PLS) method comprises three stages: measurement model, structural model, and general model. Model variables are divided into two categories: implicit and explicit. Implicit variables are used at different levels. The measurement model takes care of each dimension's parameters along with that dimension. The relationships between the parameters and dimensions are analyzed in this stage. The structural model considers all the structures proposed in the research. The degree of correlation between these structures and their relationships are considered in this section. The general model, which includes both the measurement and structural model, completes the fitting evaluation in a comprehensive model by confirming its fit (Kline, 2015). The modeling process is shown in Fig. 4.

2.3. Cronbach's alpha and composite reliability

In this section, Cronbach's alpha and combined reliability are evaluated and represented in Table 2. In order to calculate the reliability, the combined reliability criterion is used, which has advantages over the traditional approaches such as Cronbach's alpha. The optimum limit for composite reliability is considered a value greater than or equal to 0.7 (Nanley, 1978), as shown in Table 2. Considering the reported values for Cronbach's alpha and composite reliability, it can be inferred that the model has a good level of reliability.

2.4. The Sobel test

The Sobel test for inferring the indirect effect coefficient of $a \times b$ is based on the same inference theory used for the direct effect. In general, in the Sobel test, the normal estimation can be used to evaluate the significance of the relationship. By estimating the standard error of the indirect effect, the null hypothesis can be tested against the alternative (opposite) hypothesis. The Z-Value can be obtained using the following equation:

$$Z - value = \frac{a \times b}{\sqrt{(b^2 \times s_a^2) + (a^2 \times s_b^2) + (s_a^2 + s_b^2)}}$$

1

Where

a: Multivariate regression coefficient of the path between the independent and mediation variables (clay)

b: The path coefficient between the mediating and the dependent variable

S_a: Standard error of the independent and mediation variable path

S_b: Standard error of mediation and dependent variable path

Table 2
Reliability coefficients for variables

Sources	Composite reliability	Cronbach's alpha
Optimum Limit	0.70 ≤	0.60 ≤
Undisturbed Rangelands	0.92	0.89
Degraded Rangelands	0.93	0.90
Forest	0.87	0.80
Tea Garden	0.91	0.86
Rice Field	0.91	0.89
Gully	0.89	0.85

2.5. VAF index

According to Baron and Kenny's definition in 1986, mediation is a variable that takes the effect of an independent variable on a dependent variable upon itself entirely or partially. Variance Accounted For (VAF) is the ratio of indirect effect to total effect (Eq. 2):

$$VAF = \frac{(a \times b)}{(a \times b) + c}$$

2

In the above equation, c is called the direct path or direct effect, the nominator (a × b) is the indirect path or indirect effect, and the denominator is the total path or total effect.

If the indirect path is significant, both a and b and their product can be inferred to be significant, so the VAF can be evaluated. The variable has no mediation effect if its VAF value is less than 0.2, it has a partial mediating effect if the VAF lies between 0.2 and 0.8, and if it is more than 0.8, it has a full mediation effect.

2.6. Evaluation of Parameters Weight Factor

Weight factors resulting from model execution are represented in Table 3. In this table, clay is considered a mediation parameter. Therefore, the weight factor is not calculated for the clay. The weights are calculated by evaluating the correlation of indices of a structure with their parent structure, and the appropriate value is equal to or greater than 0.4 (Hulland, 1999). Kline (2015) also stated that the weight factor is a value between zero and one. If the weight factor for a parameter is less than 0.3, it has a weak correlation with the structure and is dismissed. The weight factor between 0.3 and 0.6 is acceptable and is considered desirable if it is greater than 0.6. Results represented in Table 3 indicate that P and phosphatase have the highest weight factor in each source of P production.

Table 3
Weight factor coefficients of the studied parameters in different sources of phosphorus production

Sources	Parameter	Weight factor	Sources	Parameter	Weight factor
Undisturbed Rangelands	Clay		Tea Garden	Clay	
	OC	0.73		OC	0.77
	P	0.88		P	0.86
	Ca + Mg	0.81		Ca + Mg	0.89
	Phosphatase	0.85		Phosphatase	0.90
Degraded Rangelands	Clay		Rice Field	Clay	
	OC	0.76		OC	0.82
	P	0.85		P	0.81
	Ca + Mg	0.85		Ca + Mg	0.67
	Phosphatase	0.87		Phosphatase	0.75
Forest	Clay		Gully	Clay	
	OC	0.83		OC	0.84
	P	0.80		P	0.87
	Ca + Mg	0.75		Ca + Mg	0.85
	Phosphatase	0.91		Phosphatase	0.88

Two validity matrices of Latent variable correlation and the Fornell-Larcker criterion (1981) are used to examine the discriminant validity of the measurement model (Table 4). Fornell and Larker (1981) stated that discriminant validity is acceptable when the amount of average variance extracted (AVE) for each structure is greater than the shared variance between that structure and other structures (i.e., the square of correlation coefficients of structures) in the model. Accordingly, the acceptable divergent validity of a measurement model implies that a structure in the model interacts more with its characteristics than with other structures. The Latent variable correlations section in the output file in Smart PLS software is used in this study. For the matrix's main diagonal, the square of the AVE is used.

Moreover, based on the Latent matrix table (Table 4), it is understood that the correlation of each structure with its constituents is more than that of other structures. As a result, the discriminant validity of the model is confirmed. As inferred from the results, the appropriateness of the convergent validity criterion is confirmed.

Table 4
Fornell-Larcker and Latent matrix of sources

Fornell-Larcker matrix						
Sources	Undisturbed Rangelands	Degraded Rangelands	Forest	Tea Garden	Rice Field	Gully
Undisturbed Rangelands	0.81					
Degraded Rangelands	0.74	0.87				
Forest	0.69	0.63	0.84			
Tea Garden	0.68	0.76	0.65	0.82		
Rice Field	0.55	0.44	0.66	0.60	0.90	
Gully	0.53	0.43	0.47	0.73	0.62	0.85
Latent matrix						
Sources	Undisturbed Rangelands	Degraded Rangelands	Forest	Tea Garden	Rice Field	Gully
Undisturbed Rangelands	1.00					
Degraded Rangelands	0.74	1.00				
Forest	0.69	0.63	1.00			
Tea Garden	0.68	0.76	0.65	1.00		
Rice Field	0.55	0.44	0.66	0.60	1.00	
Gully	0.53	0.43	0.47	0.73	0.62	1.00

2.7. Convergent validity and discriminant validity

Table 5 represents the output results of the model for AVE. Convergent validity is another criterion for fitting measurement models in the structural equation modeling method. Fornell and Larcker (1981) proposed using the AVE as a measure of convergent validity. The desirable range of AVE is equal to and higher than 0.5. As can be seen, the results of all the studied parameters indicate the appropriateness of the convergent validity criterion, AVE.

2.8. Evaluation of the Structural Model

After measuring the validity and reliability of the measurement model, the structural model is examined through the relationships between the independent variables. In addition, in this study, the most widely used criteria have been used to evaluate the structural model. These criteria include the coefficient of significance (T-values), the coefficient of determination (R^2), and the goodness of prediction coefficient (Q^2).

Table 5
Average variance extracted coefficients for each variable

Sources	AVE
Optimum limit	≥0.5
Undisturbed Rangelands	0.65
Degraded Rangelands	0.75
Forest	0.71
Tea Garden	0.68
Rice Field	0.81
Gully	0.72

2.9. Coefficient of significance (T-values)

The first and fundamental criterion to measure the relationship between parameters in the model (structural part) is the coefficients of significance, T-values. If the absolute value of these numbers is more than or equal to 1.96, it indicates the correctness of the structure's relationship. It thus confirms the research hypotheses at the 95% confidence level. Figure 5 shows the evaluation of T-values of different resources on P sediments. This figure shows that undisturbed rangelands and forests do not significantly affect P sediments.

2.10. Coefficient of determination (R^2)

One of the main advantages of the PLS method is the ability to reduce errors in measurement models or increase the variance between structures and indices. The essential point here is that the value of R^2 is calculated only for the dependent structures of the model, whereas in the case of independent structures, it is considered zero. The R^2 value is in the range of zero to one and indicates three levels of the fit of the structural model: weak (0-0.19), medium (0.19–0.33), and strong (0.33–0.67) (Hair et al., 2021; Salimi and Nazarian, 2022). Table 6 represents the R^2 value for each variable. It can be observed that the amount of R^2 for all parameters is at a moderate to strong level, except for the clay- undisturbed rangelands relationship.

Table 6

R^2 index coefficient of model's endogenous variables and Q^2 index coefficient

Endogenous variables	R^2	Sources	Q^2
Clay- Undisturbed Rangelands	0.17	Undisturbed Rangelands	0.839
Clay-Degraded Rangelands	0.45	Degraded Rangelands	0.521
Clay-Forest	0.36	Forest	0.458
Clay-Tea Garden	0.54	Tea Garden	0.744
Clay-Rice Field	0.63	Rice Field	0.388
Clay-Gully	0.71	Gully	0.354
P Sediment	0.65		
Q^2 (= 1-SSE/SSO)			

2.11. *Q^2 index*

This criterion, introduced by Geysers (1974), determines the model's predictive power. They believed that models with an acceptable structural fit should be able to predict the characteristics of the endogenous structures of the model. Accordingly, if in a model, the relationships between structures are properly defined, the structures will be able to have a sufficient impact on each other's characteristics, and thus the hypotheses are correctly confirmed. Three ranges of 0-0.02, 0.02–0.15, and 0.15–0.35 for the Q^2 value of an endogenous structure correspond to its weak, medium, and strong forecasting capability, respectively (Chin, 1998; Salimi and Nazarian, 2022). Suppose the value of Q^2 for an endogenous structure is zero or less. In that case, it indicates that the relationship between the other structures of the model and that specific endogenous structure is not well explained. As a result, the model needs to be modified. This criterion generally shows the model's predictive power .based on three intensities: weak, medium, and strong. Table 6 represents the results of the Q^2 index. According to Table 6, the model has outstanding predictive power because the Q^2 index of structures has a magnitude greater than 0.35.

PLS software was used to perform Structural Equation Modeling (SEM). Due to the insufficient quality of the PLS visualized output, Microsoft PowerPoint was used to reproduce the graphs according to the values and paths.

3. Results And Discussion

3.1. The inclusivity of the model

One of the issues associated with PLS was the lack of a general criterion for fitting the general model (the general model includes both the measurement and structural model sections). Many efforts were made to address this issue. Only Tenenhaus et al. (2004) proposed a general criterion called GOF (Goodness of

Fit) which can be considered a reliable indicator of the overall model fit. According to their studies, GOF can be calculated using Eq. 3. According to Wetzels et al. (2009), the values obtained by this formula can be divided into three levels weak, medium and strong, with three corresponding ranges: ≤0.25, 0.25–3.25, and 0.36-1. Eq. 3 shows the formula for calculating the model's overall fit in the PLS method.

$$\text{GOF}= \sqrt{\overline{communalities} \times \bar{R}^2} \tag{3}$$

In the above formula, $\overline{communalities}$ is an indicator for each structure's shared average used to evaluate the fit of the measurement part of the model. This criterion is used to evaluate the quality of measurement models and shows the variability of the indicators (questions) explained by the related structure. $\bar{R}^2$ is the average value of R^2 of the model's endogenous structures, which is used to examine the fit of the structural part of the model (Hair et al., 2021). Thus, the process through which the GOF for the research model was calculated is as follows. It should be noted that only the shared values of the first-order hidden variables should be included in the calculation of communalities. The values of $\bar{R}^2$ related to all the model's dependent variables should be considered to calculate $\bar{R}^2$, both first and second-order. Table 7 represents the results of communalities and $\bar{R}^2$ for mediation variables. Given that the GOF is 0.591, the model's overall fit is considered "very strong" according to Wetzels et al. (2009) and Salimi and Nazarian (2022).

Figure 6 shows the results of the relationships between structures (sources of P production) and mediation variables (clay) on sediment P. The reason for using clay as mediation is that, in most cases, elements attached to clay separate from the soil and enter the river. As shown in Fig. 6, undisturbed rangelands and forest resources had no significant effect on sediment P. The four sources of gully, degraded rangelands, and agricultural lands, including rice fields and tea gardens, determine the amount of P in sediments. Sediment P is observed at the level of one percent under the influence of four sources: Gully (T-value = 4.26), degraded rangelands (T-value = 2.59), rice field (T-value = 8.14), and tea gardens (T-value = 4.29). The most effective variable is degraded rangelands (0.63) and gully (0.47).

Table 7

Values of communalities and R^2 in order to calculate the overall model fit index (GOF)

Sources	Communalities	$\overline{R^2}$
Optimum limit	≤ 0.50	≤ 0.33
Clay- Undisturbed Rangelands	0.65	0.17
Clay-Degraded Rangelands	0.75	0.45
Clay-Forest	0.71	0.36
Clay-Tea Garden	0.68	0.54
Clay-Rice Field	0.81	0.63
Clay-Gully	0.72	0.71
P Sediment	0.57	0.65
GOF$= \sqrt{0.698 \times 0.501} = 0.591$		

The greater effect intensity of degraded rangelands compared to forests and agricultural lands can be attributed to several factors. Excessive livestock grazing and poor vegetation of the studied rangelands are among the issues observed during the field studies. Excessive grazing in rangelands reduces vegetation cover and compacts the soil surface, exposing the soil to raindrops and resulting in more runoff and surface soil loss. In addition, livestock weight pressure on the soil surface leads to the destruction of granular soil structure (Bayat et al., 2017) and a subsequent release of P. It is also observed that the effect of paddy origin in P production (0.36) is higher than in tea gardens (0.26). The amount of runoff P in agricultural lands is affected by using P-enriched fertilizer. Also, due to tillage operations in agricultural lands, soil porosity is high, runoff penetrates the soil, and further loss of P is prevented. Also, the residual straw in the agricultural lands after the harvest is effective in the amount of element loss. It reduces the release of elements compared to degraded rangelands and mud. Examining P-producing sources based on the mediation index (clay) also confirms that the two sources of rangelands and forest have no role in the P of sediments.

Figure 7 shows the results of the relative contribution of four sources: gully, degraded rangelands, rice fields, and tea gardens. As can be seen, these four sources have a relatively equal share, yet gully is relatively more important than the other three sources. Most of the disturbed gullies and degraded rangelands in this sub-watershed are located in parts with a steep slope; hence, the erosion process is intensified and increases the rate of P outflow from these sources.

At high slopes, the surface flows velocity and erosion intensity increase which can be attributed to the decrease in permeability and increase in the runoff volume (Ekwu and Harrilal, 2010). In sloping rangelands, changing the land use to dry farming due to reduced vegetation and soil resistance leads to the intensification of water erosion (Peng and Wang, 2012). Rangeland ecosystems are affected by climate change, human activities, and management strategies. The results of previous studies indicate that excessive and continuous grazing and consumption of vegetation by livestock reduces soil surface cover and carbon in the soil and increases flow velocity, compaction level, and density, leading to the increased rate of permanent soil erosion and degradation (Marcos et al., 2003; Reeisi et al., 2005).

4. Conclusion

This study investigated the contribution of different production sources of Phosphorous in the river sediments. The structural equation modeling method in PLS software was used to determine the relative contribution of each resource. This study showed that the two sources of undisturbed rangelands and forests do not play an essential role in supplying P out of the Mobarakabad watershed. Phosphorus transfer and its outflow from the watershed are mainly related to four sources: gully, degraded rangelands, rice fields, and tea gardens. Field surveys and aerial photographs have also confirmed that erosion is high in the gullies, causing soil particles to flow out of the watershed. Severe surface erosion is also occurring in the degraded rangelands, which causes the release of particles and P. Therefore, the relative contribution of locations where the erosion rate was high was significant in supplying P to the river sediments. The results showed that the agricultural sector (rice fields and tea gardens) also significantly impacted the outflow of P from the watershed. In these lands, a large amount of phosphate fertilizers are used annually without soil and plant analysis, often much more than the plant needs. Excessive phosphate fertilizers leave the land and enter rivers and water sources due to soil erosion. The modeling results showed that tea gardens are more critical than rice fields in P outflow from the watershed. The tea gardens in this watershed are located mainly on hills and areas with very steep slopes. Due to the high slope of tea lands and heavy rainfall in the region, erosion is high in the lands under tea cultivation, and nutrients such as P are easily transported downstream along with soil particles by runoff. Rice fields are located in the flat section in the studied area, and P is removed from them through surface runoff.

In general, P-producing resources can be divided into two groups for management. The first group consists of degraded rangelands and gullies, where P is mainly a part of their constituent minerals, and erosion and sediment transport are very high. The second group is agricultural lands, where the P is supplied through human activities (fertilization). The type of management strategy that should be taken in each group is different. In the first group, there is a need for physical measures such as tree planting, rangeland management, livestock grazing control, protection of the gully wall, etc. However, in the second group, it is possible to prevent the excessive use of fertilizer by raising farmers' knowledge and awareness about fertilizers. In general, the results of this study showed that structural equation modeling is a very promising approach through which sensitive and critical information about the watershed can be obtained. It helps improve the situation of the watershed more efficiently in terms of time and cost.

Statements And Declarations

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Ethical Approval

The authors have considered the subject of plagiarism, and this article is without problem.

Competing Interests

None.

Availability of data and materials

Yes

Author Contribution Statements

Eisa Ebrahimi and Hossein Asadi: Conceived the presented idea.

Eisa Ebrahimi, Hossein Asadi, and Mohammad Rahmani: Developed the theoretical framework

Eisa Ebrahimi, Hossein Asadi, and Hossein Bayat: Developed the theory and performed the computations.

Hossein Asadi, Eisa Ebrahimi, and Hossein Bayat: Verified the analytical methods

Eisa Ebrahimi and Mohammad Rahmani: Carried out the experiments

All authors discussed the results and contributed to the final manuscript

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Figures

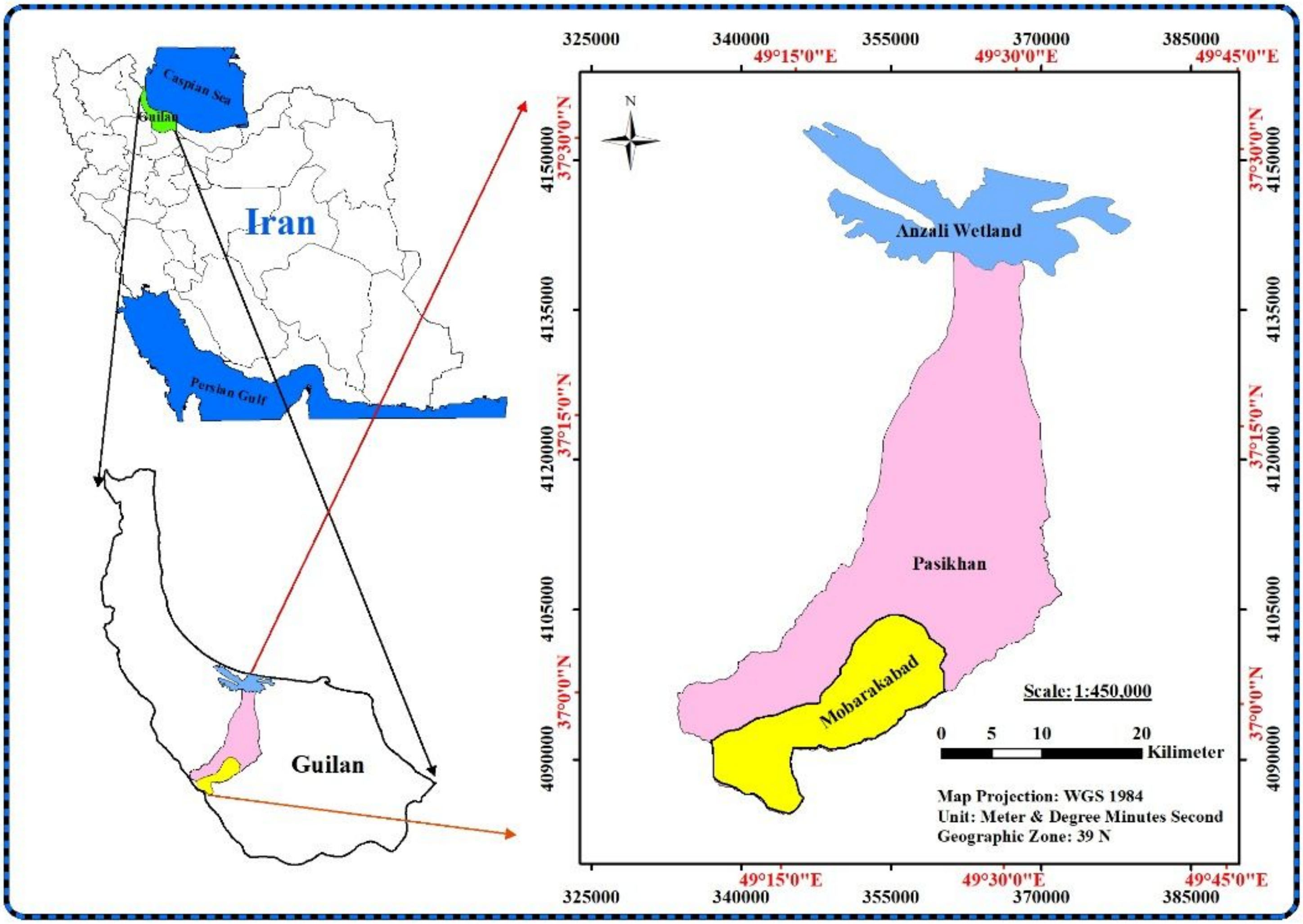

Figure 1

Location of the studied watershed

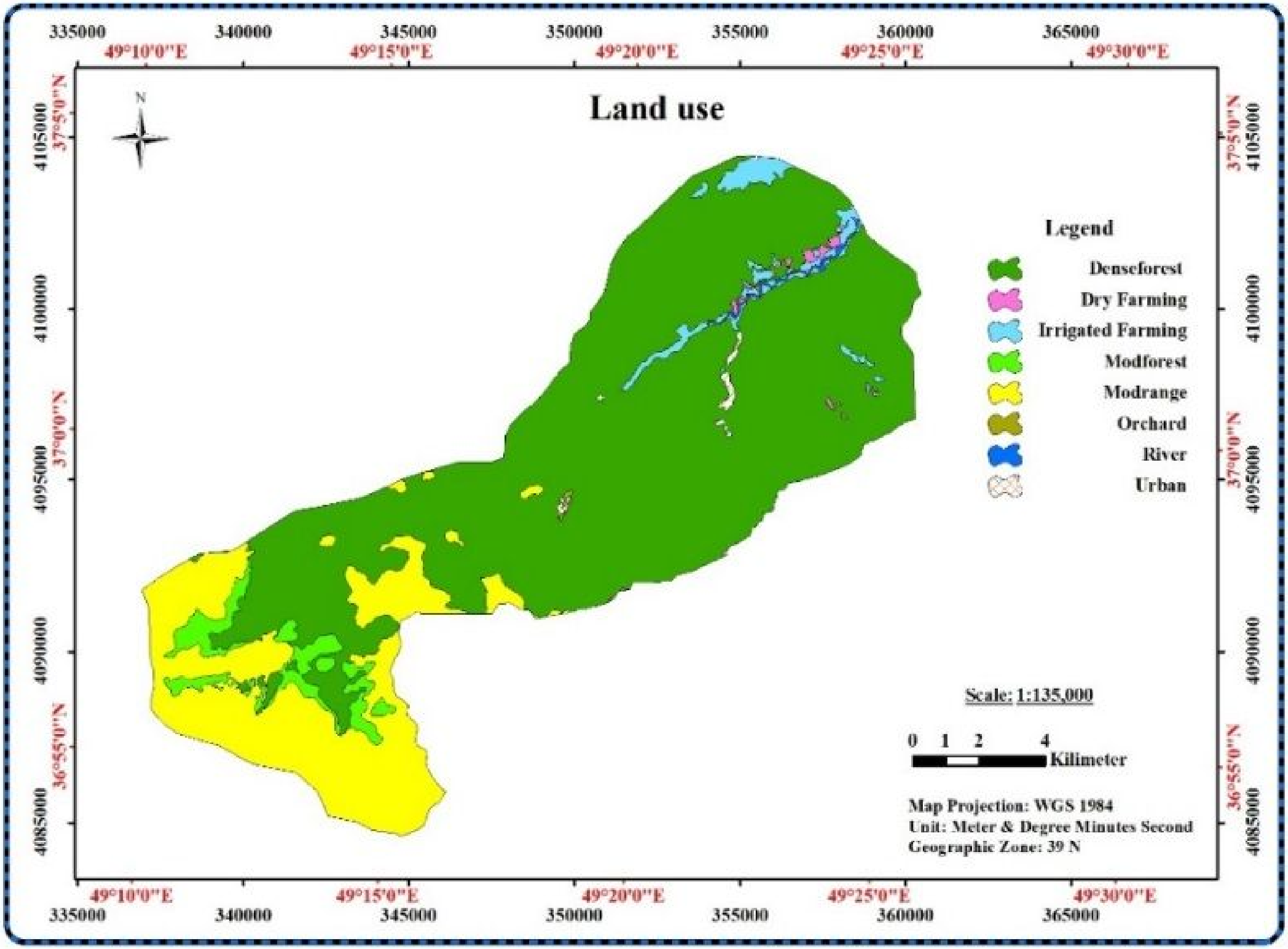

Figure 2

Land use map of the studied area

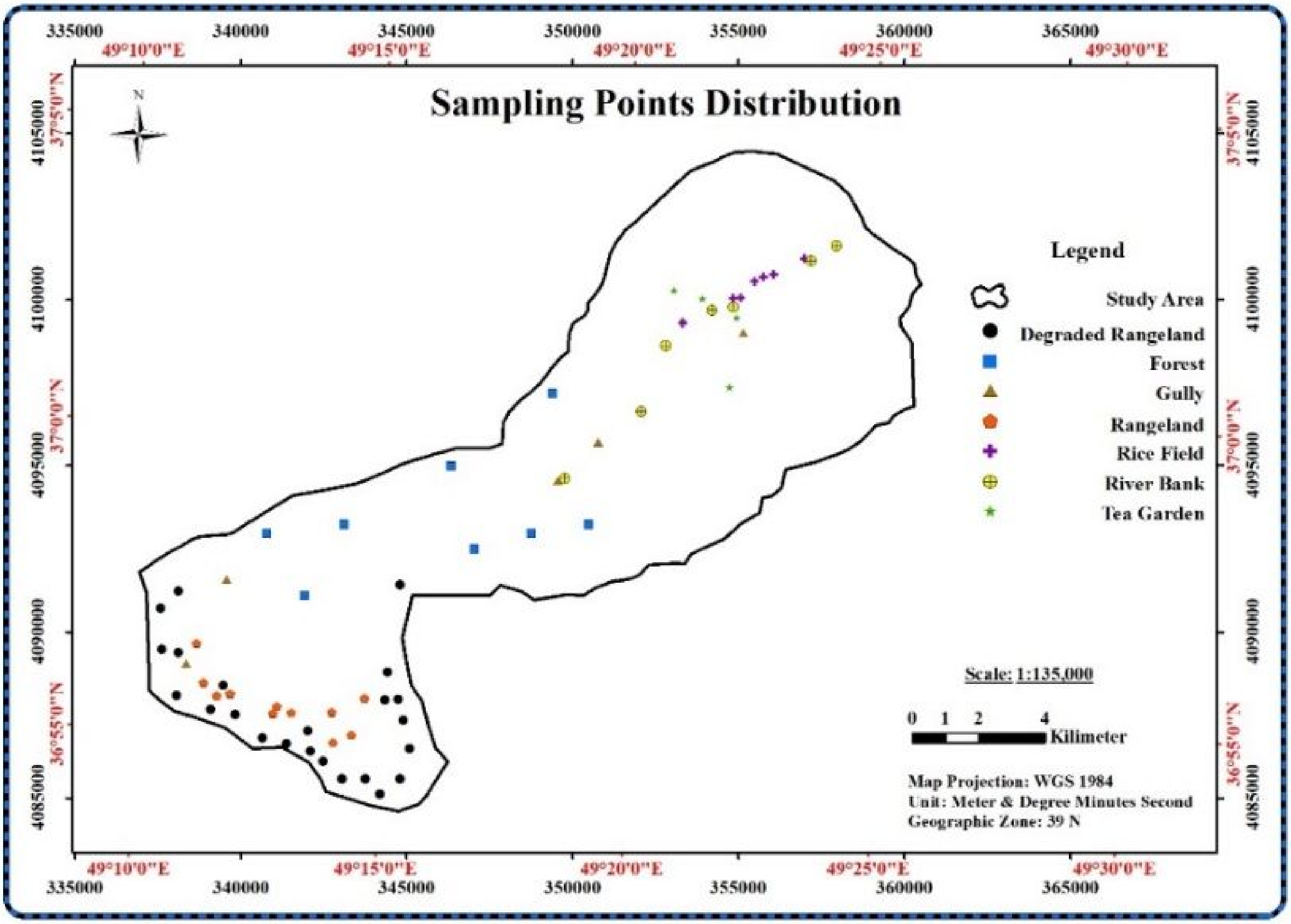

Figure 3

Sampling locations in the area

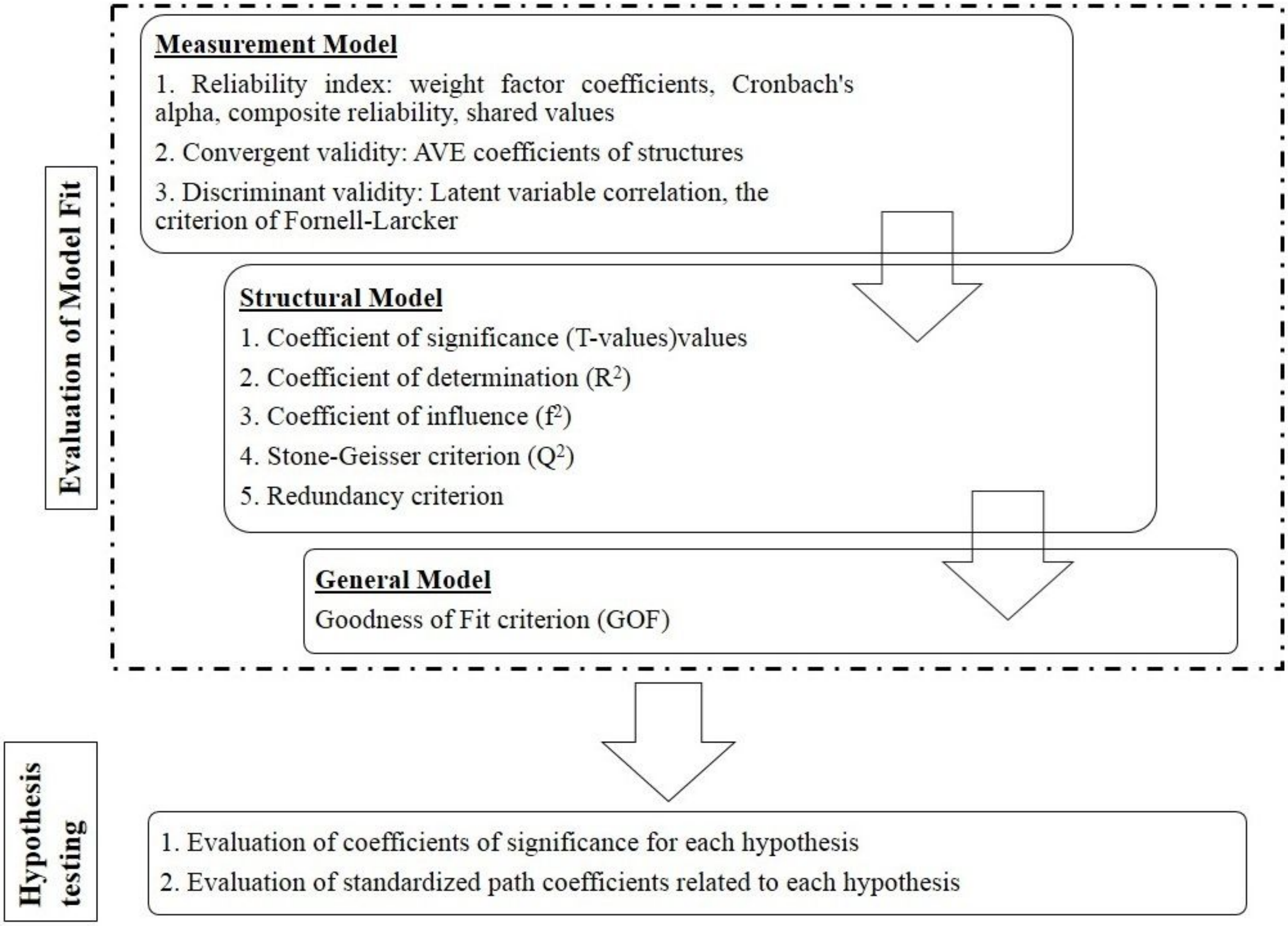

Figure 4

The process of evaluation and confirmation of the fitted model

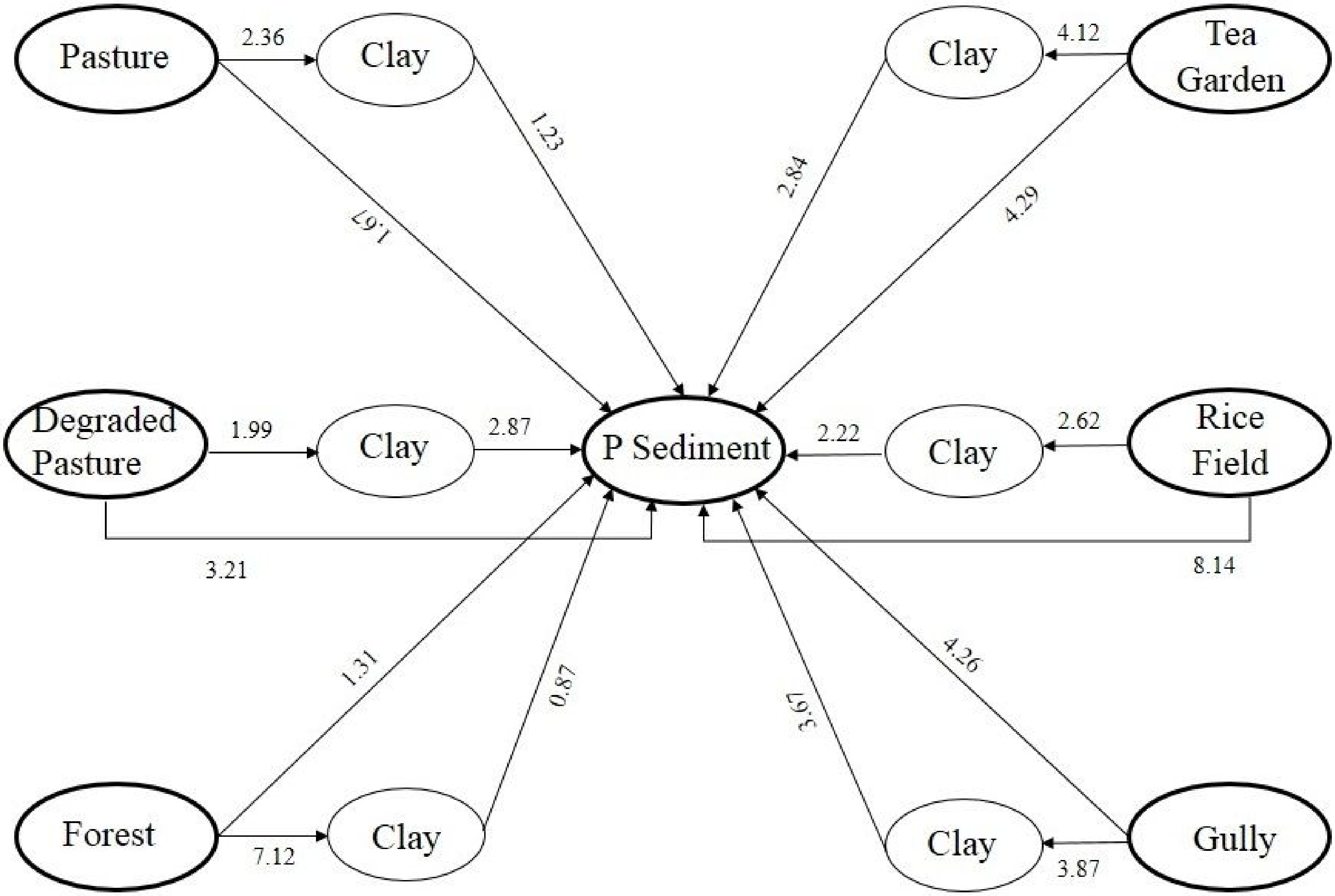

Figure 5

T value of various components of the designed model

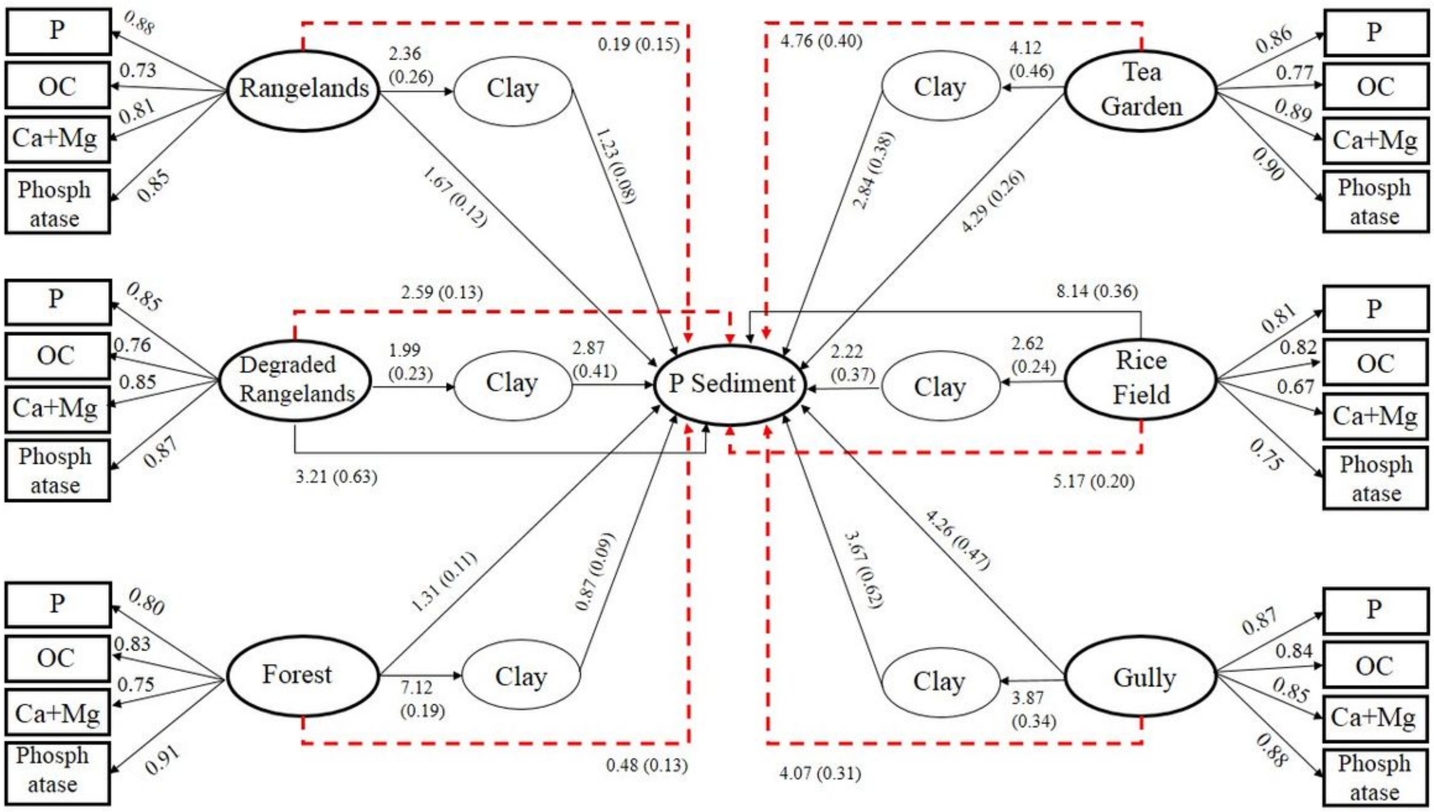

Figure 6

Relationship between structures and mediation variables with sediment phosphorus

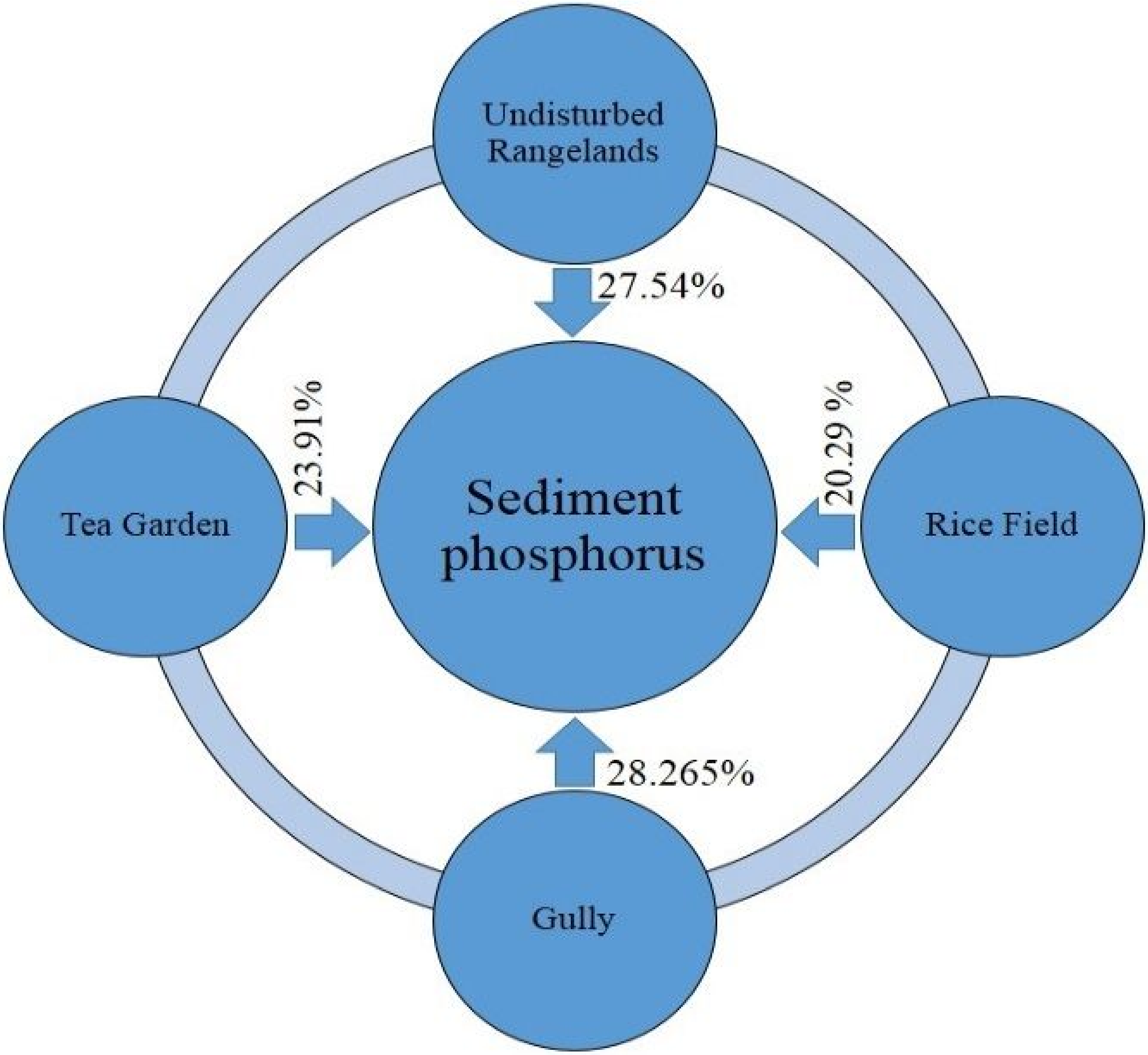

Figure 7

The relative share of each Phosphorus producing source