An Environmental Cost Value Model Based on Dynamic Neural Network Prediction

Yaxin Tan¹, Jiankai Zuo² and Jiatong Chen³*
¹,²,³ Shenyang Aerospace University, Shenyang, Liaoning, 110136, China
*Corresponding author’s e-mail: sau_cjthb@foxmail.com

Abstract. Ecological environment, which human beings depend on for survival, constantly provides us with various benefits. The exploitation and use of land by human beings will cause damage to the ecological environment. More seriously, the loss caused by environmental damage is often not concluded in the cost. Therefore, it is necessary to establish a complete environmental cost assessment model. By analyzing the value of ecosystem service and combining with previous studies, we proposed a new model—“DIP-PRSC model”—for evaluating the environmental costs of land projects. This model creatively divides environmental costs into fixed costs and floating costs. We use 16 indicators to measure the cost of each part of the model. We applied the model to the construction of the Rondônia highway in the Brazilian to verify the validity of the model, using NAR neural network to predict the cost of each part of the DIP model, and put the predicted cost into the DIP model to calculate the total cost. The results show that the environmental cost of the land project will continue to rise in the next eight years.

1. Introduction
Many scholars have already evaluated the cost of ecosystem services: Costanza et al. combine ecology and economics to make a more reasonable assessment of ecosystem values. Xie Gaodi et al. used the Costanza model to evaluate the value of ecosystem services using the equivalent factor method. However, these studies only focused on the environmental costs of occupying land, and did not consider factors such as the pollution of the building itself and time value.

With reference to the MA evaluation framework and previous studies, we propose a new ecosystem service cost assessment model based on the actual situation and call it the “DIP-PRSC” model. The main components of the model are as follows (where “D”, “I”, “P” refer to direct value, indirect value and potential value respectively; “P”, “R”, “S” and “C” separately refer to provisioning value, regulating value, supporting value and cultural value).

2. Model establishment
In the process of establishing the DIP-PRSC model, we considered various factors. According to the different construction stages of land projects, we divide the cost into fixed cost and floating cost. The fixed cost refers to the value created by the ecosystem corresponding to the land being reclaimed; the floating cost is the cost of the completed building's impact on the surrounding environment.
2.1. Direct value

- Agricultural production

\[ C = \frac{1}{7} \sum_{i=1}^{7} m_{i} p_{i} q_{i} \]

where \( C \) is the agricultural production value provided by the ecosystem (US$/hm^2), \( i \) stands for crop type, \( p_{i} \) represents the national average price of the \( i \) grain (US$/kg), \( q_{i} \) represents the yield per unit area (kg/hm^2) of grain type \( i \), and \( m_{i} \) is the planting area (hm^2) of grain type \( i \).

- Photosynthesis

\[ C = 1.2 p_{o} q_{o} \]

where \( p_{o} \) is the price of oxygen in dollars per kilogram (US$/kg), and \( q_{o} \) represents the net productivity of vegetation per unit area (kg/hm^2).

- The value of water resources

\[ C = p_{w} q_{w} M \]

where \( p_{w} \) is the national average water price (US$/m^3), and \( q_{w} \) is the ecosystem water storage per unit area of land (m^3).

- NPP increase

\[ C = p_{p} (q_{g} - q_{r}) \]

where \( p_{p} \) represents the national average price of an organism, \( q_{g} \) represents the total organic production of vegetation, and \( q_{r} \) represents the respiratory consumption of organic matter.

The total cost generated by the above four indicators is given by the following function:

\[ C_{d} = C_{a} + C_{p} + C_{w} + C_{npp} \]

where \( C_{d} \) stands for direct cost, \( C_{a} \) represents the value cost of agricultural production, \( C_{p} \) stands for photosynthetic value cost, \( C_{w} \) represents the cost of water resource value, and \( C_{npp} \) represents an increase in the corresponding value cost of NPP.

2.2. Indirect value

- Regulating value

Since the cost corresponding to the adjustment value is difficult to be quantified, we use the equivalent factor method for calculation here:

\[ C = V_{e} M + V_{e} M \]
$V_{cli}$ represents the equivalent factor of climate regulation, and $V_{cle}$ stands for the equivalent factor of the purified environment.

- Supporting value
  
  Supporting value includes energy supply and nutrient cycling. The supporting value cost is given by the following formula:

  $$C = M \left( \sum_{i=1}^{n} p_{enei} q_{enei} + \sum_{j=1}^{n} p_{nuti} q_{nuti} \right)$$  

  $p_{enei}$ represents the national average price of energy type $i$ (US $/kg)$, $q_{enei}$ indicates the type $i$ energy source's unit area yield (kg/hm$^2$), $p_{nuti}$ represents the national average price of the $i$ nutrient (US $/kg$), $q_{nuti}$ represents the cycling amount per unit area (kg/hm$^2$) of nutrient $i$.

  $$C_i = C_{cli} + C_{cle} + C_{ene} + C_{nut}$$  

  $C_i$ stands for indirect value, $C_{cli}$ stands for climate regulatory value, $C_{cle}$ stands for clean environmental value, $C_{ene}$ represents the value of energy supply, and $C_{nut}$ represents nutrient cycling value.

2.3. Potential value

Potential value refers to the undiscovered and unexploited value in the ecological environment. From an economic point of view, money has time value. The environmental cost needs to be multiplied by a time factor to represent its time value. This factor is the compounding final value coefficient, which is calculated as follows:

$$CF_{i,n} = (1 + i)^n$$  

$i$ is the interest rate, and $n$ is the number of years.

The following is the environmental cost model considering the value of time:

$$DIP = CF_{i,n} (C_d + C_i + C_p + F_f)$$  

3. Cost Prediction Application Based on NAR Neural Network

we will conduct a cost analysis for a city road construction project in the Brazilian rainforest of Rondônia. According to NASA's Terra satellite and vegetation index data based on MODIS, we mapped vegetation cover over 3 periods in the Brazilian rainforest state of Rondônia using remote sensing data.
Since Rondônia is mostly a tropical rainforest region, we believe that in such ecological environment, climate regulation, nutrient cycling, energy supply and environmental purification account for a major part of the environmental cost.

We use the DIP model to predict the cost of urban road construction in Rondonia to verify the validity of the model. Since the DIP model requires data for each cost indicator, the indicator needs to be predicted. Most of these indicators are related to time, and the prediction of each indicator is a time series prediction problem. Therefore, we use the NAR neural network suitable for time series prediction problems. The figure represents the NAR neural network topology.

The NAR neural network is a dynamic neural network, which is characterized by the fact that the network output value at time \( t \) depends on several orders of known data before time \( t \), so it can better reflect the variation of the predicted value with respect to time. Time series prediction problems can be mainly divided into three categories: 1 with \( y \) without \( x \); 2 with no \( y \) with \( x \); 3 with \( y \) with \( x \). The main research problems of NAR neural network belong to the first type of problem, so the network input and output relationship is as follows:

\[
y(t) = f(y(t-1), y(t-2), \ldots, y(t-n))
\]

(11)

In the above formula, \( y(t) \) represents the value at the time of the predicted index \( t \). When predicting the value at time \( t-1 \), it is necessary to input the predicted value at time \( t \) as an input value into the network for prediction.

We use the NAR neural network to predict each cost indicator in the DIP model for the next eight years and substitute the predicted value into the DIP model.

| year | Predictive value (billions of dollars) |
|------|--------------------------------------|
| 2019 | 5.83                                 |
| 2020 | 6.36                                 |
| 2021 | 6.92                                 |
| 2022 | 7.24                                 |
| 2023 | 8.01                                 |
| 2024 | 8.15                                 |
| 2025 | 8.47                                 |
| 2026 | 8.94                                 |
Figure 4. Land cost forecast  
Figure 5. Climate adjustment cost forecast  
Figure 6. Nutrient cycle cost forecast  
Figure 7. Energy supply costs forecast  

Figure 8. NAR network training error  
Figure 9. NAR error autocorrelation map

It can be seen from the NAR neural network error autocorrelation graph that the network can show that the autocorrelation error at time interval 0 exceeds the confidence interval, and the rest of the time does not exceed the confidence interval, so the prediction result is reliable. In the next five years, the environmental costs of the city's highway projects are still rising, basically in line with objective facts. At the same time, the increase in cost also indicates that the project should pay attention to reducing the damage to the ecological environment during the construction process.
4. Conclusions
This paper divides the environmental cost into fixed cost and floating cost, further refines the fixed cost into direct value, indirect value and potential value, and considers the time factor, thus establishing the ecosystem service cost model. Applying the model to the environmental cost prediction of urban road construction in Rondônia, Brazil, the NAR neural network is used to predict the environmental costs in the DIP model, and the predicted values are substituted into the DIP model to obtain the total cost forecast. The results show that the environmental cost of road construction in Rondonia will continue to rise.

Acknowledgments
This research was supported by 2018 National College Students’ Innovation and Entrepreneurship Training Program (project number: 201810143087) and 2019 Liaoning Provincial College Students’ Innovation and Entrepreneurship Training Program (project number: 201910143479)

References
[1] Erik Gómez-Baggethun, Rudolf de Groot, Pedro L. Lomas. The history of ecosystem services in economic theory and practice: From early notions to markets and payment schemes [J]. ECOLOGICAL ECONOMICS, 2010, 69: 1209-1218
[2] Huang Jianfeng, LU Wencong. Time series prediction of meteorological elements and rainbow option valuation based on wavelet-NAR neural network [J]. Systems Engineering - Theory & Practice, 2016, 36(05): 1146-1155.
[3] Li Jienan, Wang Ning, Mei Yadong, Zhao Xianjin. Application and Test of NAR Neural Network——Taking Urban Residents’ Water Demand Quota as an Example[J]. Journal of Irrigation and Drainage, 2017, 36(11): 122-128.
[4] WANG Nan, HOU Tieshan. Research on RMB Exchange Rate Forecasting Based on NARX Network[J]. Journal of Northeastern University (Social Science), 2015, 17(01): 32-37.
[5] Xie Gaodi, Zhang Caixia, Zhang Leiming, etc. Based on unit area value Improvement of the Value Method of Ecosystem Service Based on Equivalent Factor [J]. JOURNAL OF NATURAL RESOURCES, 2015, 30: 1243-1254
[6] Qing Yanga, Gengyuan Liu, Marco Casazzac, etc. Development of a new framework for non-monetary accounting on ecosystem services valuation [J]. Ecosystem Services, 2018, 34: 37-54.
[7] Marina Kohler, Caroline Devaux, Karl Grigulis b, etc. Plant functional assemblages as indicators of the resilience of grassland ecosystem service provision [J]. Ecological Indicators, 2017, 73: 118-127.
[8] Ana Stritiha, Peter Bebib, Adrienne Grêt-Regamey. Quantifying uncertainties in earth observation-based ecosystem service assessments [J]. Environmental Modelling & Software, 2019, 111: 300-310.
[9] Victor Platon, Simona Frone, Andreea Constantinescu, Victor Platon, Simona Frone, Andreea Constantinescu [J]. Procedia Economics and Finance, 2015, 22: 45-54.