A modified habitat quality model to incorporate the effects of ecological restoration

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Abstract
Ecosystem restoration has the potential to improve the ecological environment, increase ecosystem service delivery capability, and promote biodiversity conservation. Although habitat quality (HQ) is being widely used as a metric for large-scale biodiversity conservation, it is poorly understood and measured in areas with significant vegetation restoration (VR). This study proposes a modified approach based on the InVEST-HQ module by coupling Normalized Difference Vegetation Index to measure the HQ in the Yellow River Basin (YRB) with extensive VR in recent decades. The results show that the VR area with significant increases in both Leaf Area Index and net primary production accounts for 29.7% of the total area of the YRB. The original and modified modules were compared. Based on the InVEST-HQ module, the results show that HQ has a tendency for very small changes in the years 2000, 2010, and 2020, with first a small increase and then a small decrease; however, HQ based on the modified method has a significantly increasing trend, which is consistent with the ecological restoration status of the study area and the trend of key ecosystem parameters. The modified method effectively expresses HQ changes with VR, making it more appropriate for usage in areas where nature conservation and ecosystem restoration are important management actions, allowing for realistic decision-making and data support for regional biodiversity conservation and habitat management.

1. Introduction

Ecological restoration is becoming a prominent issue of worldwide concern. Policies and strategies from global to regional scales, such as the UN Decade on Ecosystem Restoration (Fischer et al 2021) and China’s Grain to Green Program (GFGP) (Wu et al 2019), have been proposed or implemented to restore degraded lands. Ecological restoration influences carbon storage (Lu et al 2018), water management (Zhao et al 2021), and biodiversity conservation (Crouzeilles et al 2017) along with habitat recovery over time (Chase et al 2020). However, empirical studies on the relationship between ecological restoration and habitat quality (HQ) are still relatively scarce.

HQ is the ability of ecosystems to supply essential goods and services for both individuals and groups (Hall et al 1997, Goldstein et al 2012), which was developed based on extensive research on the relationship between wildlife and habitat (Hall et al 1997). HQ is often used as proxy for biodiversity (Baral et al 2014) to reflect regional ecosystem service levels and ecological security (Bai et al 2019, Zhang et al 2022). Nevertheless, HQ is influenced by human activities and climate change; and HQ degradation also negatively affects human well-being (Ando et al 1998, Chaplin-Kramer et al 2015, Haddad et al 2015). Ecosystem restoration has been shown to positively affect ecosystem health and HQ (Liao et al 2018, Yan et al 2018), however, more effort is needed...
to quantify the relationship between HQ and ecological restoration.

Depending on the disciplinary context and data requirements, two types of HQ quantification approaches are available. One is based on classical ecology to quantify habitat suitability using wildlife population size as an indicator estimated from *in situ* population monitoring or species distribution models for small-scale ecological niche theory-based investigations (Bean et al 2014, Bailey and King 2019, Alaniz et al 2021, Michalko and Birkhofer 2021, Shaw et al 2021). The alternative is based on macroecology or geography, using natural capital or spatio-temporal conservation measures as the starting point to cost-effectively evaluate HQ by readily available and spatially explicit indicators for broad biodiversity conservation (Terrado et al 2016, Vallecillo et al 2016, Berta et al 2020, Akbari et al 2021). Model development has provided an easy-to-apply research methodology for HQ assessment (Seoane et al 2006, Dong et al 2013, Ding et al 2015). Along this line, the HQ module of the InVEST (InVEST-HQ) is one of the most widely used tools globally (Polasky et al 2011, Yan et al 2017). The spatialized HQ derived from the InVEST-HQ model is a proxy for biodiversity at landscape scale, considering the habitat's proximity to human-dominated land use and the severity of disturbance generated by that land use (Sharp et al 2020) with the assumption that Land Use/Land Cover (LULC) with higher HQ is relatively intact and capable of maintaining higher levels of biodiversity (Baral et al 2014).

The data for the InVEST-HQ model is comparatively easy to obtain, making it an effective tool, with proven reliability (Terrado et al 2016), for studying HQ in areas lacking species distribution data (Polasky et al 2011). HQ has been used to reflect the ecosystem response to land-use change (Polasky et al 2011, Baral et al 2014, Wu et al 2014, Terrado et al 2016, Yan et al 2017, Xu et al 2019), represent regional ecological networks (Gao et al 2017) and ecological security patterns (Wang and Cheng 2022, Zhang et al 2022), as well as conduct trade-off analysis among multi-ecosystem services (Xu et al 2020). However, uncertainty in HQ assessment and implementation can result when data is sparse or due to the subjective assignment of parameters (Berta et al 2020).

Studies have been developed to reduce uncertainty by improving parameter acquisition methods (Berta et al 2020, Akbari et al 2021) and constructing composite indicator framework (Gong et al 2019). Existing advances and improvements have mostly focused on the negative effects of threat factors, ignoring the positive effects of ecological restoration on HQ, and lacking effective quantification of differences in HQ due to the inherent geographic diversity and multifunctionality of ecosystems.

Therefore, using the vegetation restoration (VR) areas in the Yellow River Basin (YRB) as the study area, a modified model for terrestrial HQ evaluation coupling Normalized Difference Vegetation Index (NDVI) and a degradation map from InVEST-HQ module, was proposed to determine the spatio-temporal variation of modified habitat quality (MHQ) at the landscape scale. The objectives of this study were to (a) improve the InVEST-HQ module’s indicator parameters so that it can better reflect changes in HQ caused by ecosystem improvement itself or by ecosystem restoration projects, and (b) quantitatively assess the spatial and temporal changes in HQ in the VR areas in the YRB using the original and modified methods to reveal the differences and implications.

2. Methods

2.1. Study area

The YRB, which stretches across Central and Northern China's arid and semi-arid regions between 96°E–119°E and 32°N–42°N, is the cradle of Chinese civilization, with the Yellow River, at 5464 km in length, the second-longest river in Asia and the sixth longest in the world. With a drainage area of ~795,000 km² (figure 1), the Yellow River has the world’s highest level of sediment discharge. The mean annual precipitation ranges from 123 mm to 1021 mm and the annual mean temperature varies between ~4 °C and 14 °C. The YRB’s total water resources account for only 2% of China’s total water resources, yet it provides water for 15% of agricultural irrigation and 12% of China’s population.

Before 2000, millennia of intensive human-nature interrelations in the YRB led to continued ecosystem degradation and threatened biodiversity (Wohlfart et al 2016). In response, a variety of ecosystem conservation and restoration initiatives for statewide environmental protection were initiated in the YRB, such as GFGP in the middle of the YRB since 1999. This has led to a dramatic decrease in sediment discharge and load (Liu et al 2020). The ecological conservation and high-quality development of the YRB has been a national-level strategy in China.

2.2. Data

LULC, net primary production (NPP), Leaf Area Index (LAI), NDVI, and road data were all derived from publically available datasets (table 1). These data were resampled at a spatial resolution of 300 m and the Krasovsky_1940_Albers spatial reference system. Due to the data shortage, road data in 2009 was used as the input of the HQ module for HQ in 2010. Despite this, having three different periods of threat data improved the limitations and uncertainties (Berta et al 2020) associated with missing time series data.
Table 1. Data list and sources.

| Data       | Temporal resolution | Spatial resolution | Source                                                                 |
|------------|---------------------|--------------------|------------------------------------------------------------------------|
| LULC       | 2000, 2010, and 2020| 300 m              | ESA CCI LC products ([http://maps.elie.ucl.ac.be/CCI/viewer/download.php](http://maps.elie.ucl.ac.be/CCI/viewer/download.php)) |
| NPP        | Annual              | 1 km               | MOD17A3H, Google Earth Engine platform ([https://code.earthengine.google.com/](https://code.earthengine.google.com/)) |
| LAI        | 8-day               | 500 m              | MOD15A2H, Google Earth Engine platform ([https://code.earthengine.google.com/](https://code.earthengine.google.com/)) |
| NDVI       | 16-day              | 1 km               | MOD13A2H, Google Earth Engine platform ([https://code.earthengine.google.com/](https://code.earthengine.google.com/)) |
| Road       | 2000, 2009, 2020    | Vector data (shp)  | Geographic data platform of Peking University ([https://geodata.pku.edu.cn/](https://geodata.pku.edu.cn/)) and Open Street Map ([https://osm2pgsql.org/](https://osm2pgsql.org/)) |

Table 2. Land cover classification system.

| Land cover code | Land cover name        | ESA Land cover code |
|-----------------|------------------------|---------------------|
| 1               | Cropland               | 10, 20, 30, 40      |
| 2               | Forest land            | 50, 60, 70, 80, 90  |
| 3               | Shrubland              | 100, 110, 120       |
| 4               | Grassland              | 130                 |
| 5               | Unused land            | 140, 150, 160, 170, 180 |
| 6               | Urban areas            | 190                 |
| 7               | Bare areas             | 200                 |
| 8               | Water bodies           | 210                 |
| 9               | Permanent snow and ice | 220                 |

LAI and NDVI were synthesized into annual scale using the Maximum Value Composite approach. The ESA CCI LC products were defined using Land Cover Classification System developed by the United Nations Food and Agriculture Organization, which includes 22 land cover classifications ([Lamarche et al 2017](https://www.fao.org)). The landcover data were reclassified into 9 types for this study (table 2).

2.3. Operational flow
This study includes three parts: (a) identification of the VR areas. Mann-Kendall (MK) test and Sen-Slope method were used to obtain the trend of NPP and LAI in the YRB from 2000 to 2020, for extracting the vegetation improvement area and overlaying the two trend results with the natural vegetation areas to obtain the VR areas; (b) HQ assessment based on the InVEST-HQ method. The HQ in the YRB and VR areas was assessed in 2000, 2010, and 2020 based on the InVEST-HQ model for the degradation maps and HQ maps for each period. (c) MHQ assessment based on the modified method. The MHQ based on the modified method for the three periods in the YRB and VR areas were calculated using the half-saturation function of the InVEST-HQ model, which was combined with the degradation maps and NDVI (figure 2).

2.3.1. Identification of vegetation restoration areas
Identification of the VR areas in the YRB based on the consideration of ecosystem structure and function was the priority in this study. LAI ([Asner et al 2003](https://www.asnerlab.com)) and NPP ([Costanza et al 1998](https://www.environmental-sciences.org)) were used to express the changes of ecosystem structure and function, respectively. LAI is defined as the one half the total green leaf area per unit of horizontal ground surface area ([Chen and Black 1992](https://www.sciencedirect.com)) and is used to quantify the amount of leaf area in an ecosystem, primarily for vegetation change monitoring, climate change...
analysis, and process analysis of photosynthesis and precipitation (Asner et al 2003, Baret et al 2013, Fang et al 2019). NPP, defined as the net amount of organic matter fixed by plants through photosynthesis, is the difference between gross primary productivity and autotrophic respiration, which represents the net carbon flow from the atmosphere to the terrestrial ecosystems (Gang et al 2018), connecting to vegetation activity, biogeochemical cycling, and ecosystem functions and services (Costanza et al 1998, ITO 2011), and can be used to efficiently evaluate terrestrial ecosystems’ carbon budgets (Zhao and Running 2010).

Two steps were taken to identify the VR areas:

(a) The MK test method was utilized to determine the significance of LAI and NPP in the YRB on the annual scale. The time series was labeled \( x_i \) with \( i = 2000, 2001, 2002, \ldots, 2020 \), the Z test statistic is defined as:

\[
Z = \begin{cases} 
\frac{S-1}{\sqrt{\text{var}(S)}}, & S > 0 \\
0, & S = 0 \\
\frac{S+1}{\sqrt{\text{var}(S)}}, & S < 0 
\end{cases}
\]

(1)

\[ S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sgn}(x_j - x_i) \]

(2)

\[
\text{sgn}(x_j - x_i) = \begin{cases} 
1, & x_j - x_i > 0 \\
0, & x_j - x_i = 0 \\
-1, & x_j - x_i < 0 
\end{cases}
\]

(3)

The variance expression of statistic \( S \) is:

\[
\text{var}(S) = \frac{n(n-1)(2n+5)}{18} - \sum_{i=1}^{n-1} t_i(i-1)(2i+5)
\]

(4)

The expression of the Theil-Sen slope test method:

\[
\beta = \text{Median} \left( \frac{x_j - x_i}{j - i} \right)
\]

(5)

where \( x_i \) and \( x_j \) are the corresponding values of the \( i \)th and \( j \)th years of time series, respectively, \( 2000 \leq i < j \leq 2020 \), sgn is the sign function, and Median represents the median of the sequence. The parameter \( \beta \) indicates the slope of the sequence’s trend. The statistic \( Z \) is ranging from minus infinity to plus infinity. Here, the method used for the MK trend test was as follows: null hypothesis: \( \beta = 0 \), at a given significance level of 0.05, when \( |Z| > 1.96 \), the trend of the time series was significant. When \( |Z| > 2.58 \), the significance test of 0.01 was passed.

(b) As this study is oriented toward VR, several decisions were made in the principle of LULC selection. We started by removing urban areas due to a lack of vegetation regeneration. Further, we removed four land cover types in 2020—cropland, water, bare land, and ice—based on the removal of urban areas in the previous step by considering the human disturbances and lack of vegetation cover.

2.3.2. The InVEST-habitat quality model

The HQ was assessed by the InVEST-HQ (3.8.0) model (Sharp et al 2020), a function of the suitability of individual patches and degradation caused by the spatial sources of disturbance across the landscape. The degradation \( (D_{ij}) \) ranges 0–1 and was quantified by: (a) the relative effect of each threat \( (w_i) \), (b) the effect of the threat over space \( (i_{xy}) \), and (c) the relative sensitivity of each habitat type to each threat \( (S_{ji}) \):
Table 3. The threat factor properties and the sensitivity of habitat types to each threat factor.

| The properties of threats | Threats | Habitat suitability | Construction land | Road |
|---------------------------|---------|---------------------|-------------------|------|
| Sensitivity of different land cover types | Weight | 1 | 0.6 |
| Maximum distance of influence (km) | — | 10 | 2 |
| Cropland | 0.5 | 0.5 | 0.2 |
| Forest | 1 | 0.8 | 0.4 |
| Shrub | 0.6 | 0.6 | 0.7 |
| Grassland | 0.7 | 0.7 | 0.6 |
| Unused land | 0.1 | 0.1 | 0.3 |
| Urban | 0 | 0 | 0 |
| Bare land | 0 | 0 | 0 |
| Water | 0.9 | 0.9 | 0.5 |
| Ice | 0.1 | 0 | 0 |

\[
D_{ij} = \sum_{r=1}^{r_{max}} \sum_{y=1}^{y_{max}} \left( \frac{w_r}{\sum_{r=1}^{r_{max}} w_r} \right) r_{xy} D_{ij} / d_{ij} 
\]

2.3.3. The modification of the InVEST-habitat quality model

The InVEST-HQ model assumes that each habitat type has a single habitat suitability value, yet a single parameter cannot reflect the habitat suitability variability in the same habitat type in such a complex environment like the YRB and the improved vegetation conditions. Although the InVEST-HQ approach can describe changes in HQ as a result of the land cover change, this may not be the case for ecosystem improvement without a land cover change (Lee and Carroll 2018). As a result, the habitat suitability was replaced with NDVI, a temporally dynamic, geographically heterogeneous vegetation index, which was combined with the habitat degradation map produced from the InVEST-HQ model to obtain MHQ.

In this study, NDVI was used as a proxy for habitat suitability based on the following considerations. Firstly, research has shown that NDVI can effectively represent the spatio-temporal evolution of green space (Cao et al 2018). It is one of the key parameters for expressing ecosystem conditions and status over a wide range of spatial and temporal scales (Huang et al 2017, Migliavacca et al 2021). Secondly, NDVI is a more accurate and detailed expression of spatial and temporal heterogeneity of habitats than habitat types, and heterogeneous systems outperform homogeneous systems in terms of diversification impacts (Oehri et al 2020), particularly in agricultural landscapes (Plath et al 2021). Habitat heterogeneity is an essential determinant of species diversity (Farwell et al 2020), which can provide multiple ecosystem services and buffer uncertainty (Knoke et al 2016). Thirdly, the estimation of the NDVI method is constant and is between near-infrared and infrared bands, with values in terrestrial surface ranges from 0 to 1, which is consistent with the setting of the half-saturation function in the method. Furthermore, the constant estimation approach allows for the comparison of HQ assessment results inside the study area as well as with the HQ index outside the study area. Although some other indicators such as NPP and LAI can also

\[
i_{xy} = 1 - \left( \frac{d_{xy}}{d_{i_{max}}} \right) \]  

\[
i_{xy} = \exp \left( -\frac{2.99}{d_{i_{max}}} d_{xy} \right) \]  

where the \(d_{xy}\) is the distance of cell \(x\) from the threat \(y\), and the \(d_{i_{max}}\) is the maximum effective distance of the threat \(r\).

HQ score \(Q_{ij}\) was then calculated using the suitability \(H_j\) of individual habitat patches and the cumulative degradation caused by sources of threat (equation (6)):

\[
Q_{ij} = H_j \left( 1 - \left( \frac{D_{ij}}{D_{ij} + K^2} \right) \right). \]  

The scaling parameters \(K\) and \(Z = 2.5\) are adjusted by the user, however, the value for parameter \(K\) is commonly set equal to half of the maximum degradation score in the habitat degradation map. The default value for this option is 0.5 (Sharp et al 2020).

The threat factor properties and the sensitivities of the habitat types to each threat (table 3) were value-assigned based on the existing literature (Li et al 2018, Zhang et al 2020, Ding et al 2021, Song et al 2021, Tang et al 2021, Yang et al 2021, Yohannes et al 2021, Wu et al 2021a). In this study, the decay types of Construction land and Road are exponential and linear, respectively.
reflect ecosystem features to some extent, in reality, these indicators often require reprocessing of data, such as normalization, which increases the uncertainty of the results. The satellite-acquired NDVI has been considered a potential biodiversity characterization indicator at a large scale (Pettorelli et al 2005, 2011, Barela et al 2020), and studies have investigated the correlation between NDVI and species (Shen et al 2013, St-Louis et al 2014, Onyia et al 2018) and the application for HQ prediction (Weber et al 2018, Salata et al 2020).

The following is the modified function:

\[ MQ_{ij} = NDVI_j \times \left( 1 - \frac{D_{ij}^2}{D_{ij}^2 + k^2} \right) \]  

(10)

where the \( MQ_{ij} \) is the MHQ value, NDVI\(_j\) is the value of NDVI of cell \( j \).

### 3. Results

#### 3.1. Vegetation restoration area in the YRB

**3.1.1. Trend of LAI in the YRB**

Results show that LAI in the YRB has been steadily increasing over the last two decades (figure 3(a); \( R^2 = 0.86 \)). Even though the values vary between years (solid line in figure 3(a)), the overall increase is approximately 59%, from 1.584 m\(^2\) m\(^{-2}\) in 2000 to 2.459 m\(^2\) m\(^{-2}\) in 2020. Areas with a growing tendency of LAI in the YRB are concentrated in the middle and upper reaches, notably in the middle reaches (figure 3(b)), accounting for approximately 59.16% of the total area. The major decreasing tendency areas are generally concentrated in the peri-urban zones and some areas in the river source, covering 1.32% of the total area.

**3.1.2. Trend of NPP in the YRB**

The results indicate that the NPP in the YRB is growing overall from 2000 to 2020, with a 56% rise from 0.203 kgC m\(^{-2}\) in 2000 to 0.316 kgC m\(^{-2}\) in 2020 (figure 8(a)). The areas in the YRB with an increasing trend of NPP, according to the geographical distribution results of the MK test, are primarily concentrated in the middle reaches, where the areas with a significant increasing trend account for 81.80% of the total area. Areas with a significant decreasing trend, covering 0.31% of the YRB, are primarily found in and around cities, as well as parts of the source area and upper reaches (figure 4(b)).

**3.1.3. Vegetation restoration areas**

The overlapping part of areas with significant increases in both LAI and NPP accounted for 53.7% of the entire area as shown in figure 5(a). It is mostly found in the middle reaches. The VR areas identified are primarily found in the YRB’s north-central and northern upper reaches, accounting for 29.7% of the total area (figure 5(b)).

#### 3.2. Habitat quality revealed by original and modified InVEST-HQ module

**3.2.1. Spatial and temporal variation of habitat quality index based on the original and modified InVEST-HQ module**

The distribution pattern of the HQ displayed considerable regional variances, as illustrated in figure 6. The woodlands in the mountainous areas have the highest HQ value, followed by areas of natural vegetation in the middle and upper reaches. In the northern midstream, HQ values are lower in urban regions and bare land areas, but greater in arable areas in the plains of the middle and lower reaches. The average HQ values were 0.616, 0.617, and 0.613 in 2000, 2010, and 2020, respectively.

In the YRB, the average MHQ values were 0.509, 0.577, and 0.638 in 2000, 2010, and 2020, respectively (figure 6). The overall average MHQ values in the YRB showed a considerable increasing tendency. The higher MHQ areas are consistent with the InVEST-HQ model’s results and are primarily found in mountainous areas with high vegetation coverage. The results demonstrate that the modified method allows for more heterogeneous and dynamic mapping and assessment of HQ.

In 2000, 2010, and 2020, based on the InVEST-HQ model, the average HQ values in the VR areas were 0.716, 0.729, and 0.734, respectively. They exhibited a rather small trend of improvement across these three periods, as can be observed in figure 7. And the MHQ values in the VR areas in 2000, 2010, and 2020 were 0.444, 0.530, and 0.615, respectively, with a significantly increasing trend.

**3.2.2. Comparative analysis of the habitat quality results**

We can draw three points from figure 8. Firstly, the results of HQ evaluated based on the InVEST-HQ model show a flat change over time, while the results evaluated from the modified method reveal a considerable increasing trend over time. Secondly, we can see that the results for the YRB, based on the InVEST-HQ model, show a flatter trend, with a slight increase followed by a decrease, whereas the HQ in the VR areas shows a slight increase, but the increase is not significant, and the HQ in the VR areas is significantly higher than that in the YRB as a whole. As a result, we cannot help but suspect that the InVEST-HQ model’s results do not accurately represent habitat changes in VR areas, owing to its LULC parameterization, which ignores intra-class heterogeneity and changes in habitat restoration. Thirdly, the MHQ values are increasing, both in the YRB and in the VR areas, which is...
Figure 3. Trend of annual LAI in the YRB.

Figure 4. Trend of annual NPP in the YRB.

Figure 5. Overlayed areas of significant LAI and NPP increasing areas (a) and vegetation restoration areas (b) in the YRB.
consistent with the practice of implementing ecological restoration projects in this region. The results of the modified model reveal that the gap between the MHQ in the VR areas and the YRB has been decreasing over time, from 0.065 in 2000 to 0.047 in 2010 to 0.023 in 2020, indicating that the VR level has improved significantly.

4. Discussion

4.1. Applicability of the InVEST-HQ model
The InVEST-HQ model broadens the perspective of biodiversity conservation from critical, endangered species conservation to general biodiversity conservation by protecting the habitat conditions of wildlife especially in areas where species monitoring data is lacking (Yan et al 2018, Zhang et al 2020). The findings are spatially explicit for characterizing regional biodiversity and ecological functioning hotspots (Bai et al 2019, Gomes et al 2021, Zhang et al 2022). Although it has been demonstrated that the InVEST-HQ model results and actual biodiversity data have a strong connection (Terrado et al 2016), there is also a consensus among scholars that the results are heavily dependent on LULC type and the model parameters rely on the subjectivity of expert knowledge (Yang 2021, Wu et al 2021b). Most existing studies focus on habitat degradation such as the selection of threat factors and the improvement of relevant parameters (Tang et al 2020, Akbari et al 2021). However, ignoring habitat suitability leads to results that are insensitive to changes in habitat types and the complexity of the habitats (Zhu et al 2020).

In this study, the HQ based on InVEST-HQ shows minor changes, particularly in the VR areas (figure 7), which is in contrast to the existing vegetation change trend. The primary reason is that the model is essentially focused on assessing the risk of habitat degradation as a result of human disturbance. Each habitat type in the InVEST-HQ model corresponds to a single habitat suitability index, and the equation (9) shows that the HQ scores for each habitat type are driven by a single feature of habitat degradation. This could explain why the majority of the evaluation results were trending downward (Kija et al 2020, Li et al 2021).
Furthermore, the results in this study indicated that the InVEST-HQ method is suitable for static assessment, that is, HQ assessment under conditions where the dynamic characteristics of ecosystems are not taken into account. It is mainly because the habitat suitability assignments in the model based on habitat types have low sensitivity to ecosystem changes. As a result, the method cannot effectively express changes in HQ for situations where ecological restoration is prevalent across habitat types, resulting in more reliable model results in the assessment of areas without ecological restoration (Terrado et al 2016). However, it can bring about an underestimation of the changes in HQ in areas with a significant ecological restoration as shown by the results of this study (figures 6–8). Therefore, the improvement of the HQ assessment methods is still a critical task as the world has already stepped into the UN Decade of Ecosystem Restoration with more restoration actions on the ground globally (Fischer et al 2021). The modified model in this paper provides an alternative approach to support this critical task.

4.2. Advantages and limitations of the modified model, and future directions

By coupling habitat degradation and NDVI, the MHQ effectively reflects both the changes in HQ brought about by VR and the impacts of human disturbances in the InVEST-HQ model. With the success of the GFGP on the Loess Plateau in the middle reaches of the YRB since 1999 (Feng et al 2016), the vegetation cover has been improved from 31.6% in 1999 to 59.6% in 2013 (Chen et al 2015) with a total afforestation area of $4.793 \times 10^3$ km$^2$ (33.4%
is converted from farmland and 62.7% from afforestation of barren land) by 2014 (Wu et al. 2019), enhancing the ecosystem services and carrying capacity (Liang et al. 2019, Lü et al. 2021). This tendency is consistent with the changes of LAI and NPP in the identification of VR areas in this study. And the MHQ changes demonstrated the improvement of the ecosystems in this area.

Our study demonstrated the necessity and effectiveness of modifying the model of HQ assessment for VR areas in the YRB. There are evidences that revegetation improves biodiversity (Bennett et al. 2022, Romanelli et al. 2022) and in situ investigations in YRB also show that revegetation enhances plant biodiversity (Liu et al. 2015, Wang et al. 2019), however, it is difficult to prove our results using species abundance data at such a large scale. Species data are crucial for biodiversity conservation (Vallecillo et al. 2016), and combining the two approaches can better enhance biodiversity conservation efforts. Furthermore, predictions on the future change trends of HQ under the influence of multiple drivers will provide longer-term perspectives for decision-making on biodiversity conservation, habitat management, and regional sustainable development. This can be addressed in future research with the support of dependable methods.

5. Conclusions

We proposed a modified method based on the InVEST-HQ model in the present paper to better describe the changes in HQ in the VR areas in the YRB by coupling the effects of habitat degradation and vegetation factors (NDVI). The results showed that both LAI and NPP were significantly improved in the VR areas, but the results of the InVEST-HQ model were unable to properly describe the HQ changes influenced by the VR. Based on the modified model, the HQ results showed significant improvement in the expression of spatial and temporal heterogeneity, especially in the areas with VR. This study reveals that HQ assessment and mapping methods are necessary to incorporate the effects of ecological restoration along with the factors driving land degradation. This is a timely research campaign because more and more restoration actions will be implemented globally as we have already in the Decade of Ecosystem Restoration promoted by the United Nations.

Data availability statement

No new data were created or analysed in this study.

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