Analyzing the interactions among multiple ecosystem services in a rural mining region in Central Appalachians

Vincenzo Cribari, Michael P. Strager, Davide Geneletti and Charles Yuill

ABSTRACT
This study analyzed the interactions among a set of ecosystem services (ES) and derived ES bundles in the Headwaters of Coal River West Virginia (WV), in the Central Appalachians, an area historically characterized by surface mining and coal extraction. ES were modeled using the InVEST system, while a custom model was used to link water quality to freshwater ES, deriving information at two different spatial scales based on hydrologic units. High-resolution remote sensing data (1–2 m resolution) were used to incorporate historical information from land-cover (LC) transitions since 1976 to differentiate reclamation processes and characterize the forest class. Consistent ES tradeoffs were confirmed in areas characterized by surface mining processes that reported significant losses of carbon sequestration, habitat quality, and freshwater ES. The interaction of complex anthropogenic processes within the specific landscape led to the definition of different ES bundles, characterized not only by coal mining processes but also by the distribution of settlements and developed areas. The utilization of relatively small hydrologic catchments (1–25 km²), the comparison with a more extensive set of spatial units, and the inclusion of high-resolution data with multiple LC classes that included historical information, allowed the authors to infer knowledge about the interactions between ES changes and their drivers in the study area. The results can be used to implement conservation, as well as development-restoration strategies, by including ES assessments to promote a more sustainable land management approach in the rural-mining region of Central Appalachians and support future alternatives to extractive economies.

1. Introduction
The progressive anthropization of the terrestrial biosphere, driven in its latest phase by industrialization processes, has led to widespread alterations in the Earth’s biomes and ecosystems (Crutzen 2002; Ellis 2011). Land-use change processes have mostly been driven by urbanization and natural resources management practices guided by extractive economies. The global demand for ecosystem goods and services, generally derived by non-sustainable management practices, such as traditional intensive agriculture, deforestation, and mining, has led to tradeoffs among ecosystem services (ES), and especially between provisioning and regulating, cultural and habitat services (Foley et al. 2005; Carpenter et al. 2009). While provisioning services (food, fiber, fisheries or timber provision) are generally well perceived by individuals and markets because they are commonly associated with direct economic values, other ES, like habitat services, regulating services, or cultural services, are traditionally not easily perceived by people and institutions. Indeed, habitat services, regulating services, and cultural services are barely associated in traditional economies with explicit market values, and so in industrial societies, they were generally overlooked and traditionally poorly managed (Costanza et al. 2017). Agriculture and urban activities have long been reported as leading causes of increased nutrients like nitrogen (N) and phosphorus (P) and the aquatic ecosystems’ impairment (Carpenter et al. 1998).

In the case of mining regions, the extraction of depletable abiotic natural stocks or assets (e.g. mineral deposits, coal, oil, and gas), has often led to decreases in carbon sequestration (C), N and P pools, flood control and biodiversity protection (Simmons et al. 2008; Heather et al. 2011). A recent review of mining impacts on ES (Boldy et al. 2021) revealed a need to improve the inconsistencies that exist in defining and assessing ES when performing comparisons across studies. Boldy et al. (2021) pointed to the lack of comparisons between short-term and long-term impacts on ES after the rehabilitation of mining areas, and suggested the use of ES metrics that clearly

CONTACT Vincenzo Cribari vincenzo.cribari@gmail.com

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address mining impacts that could affect human wellbeing.

In the Central Appalachian mountains, where surface coal mining represented the primary driver of landscape change (Townsend et al. 2009), a general impairment of carbon storage, watershed and water quality protection ES was found in former surface mining areas (Zipper et al. 2011). Significant losses of habitat functions were caused by the obliteration of perennial and ephemeral streams in mountaintop mining (MTM) areas, where inadequate ecological restoration has been generally conducted (Palmer and Hondula 2014). Other studies in rural-mining areas of Ohio (USA) reported that historical mining-type uses were not positively correlated with recreational uses, like cabins and forest tourism (Munroe et al. 2017). Mishra et al. (2012) quantified relevant economic impairments to recreational activities due to the presence of abandoned mined land (AML), high reclamation costs, and water quality problems associated with coal-mining damages. These results confirmed how substantial losses of regulating and cultural services affect human wellbeing and, ultimately, the sustainability and diversification of future economic activities (Rodriguez et al. 2006).

Energy companies have conducted studies on land-use tradeoffs and ES to assess future uses of large post-reclaimed areas in Ohio. They included different requests among the company’s stakeholders, encompassing both ecological protection uses and demands of economic development. Among the alternatives, authors reported oil and gas development using hydraulic fracturing (‘fracking’), timber harvesting through sustainable forestry, specialized habitats like wetlands associated with compensation credits, pasturing with managed pasture leasing, crop production, real estate sales, and future solar development (Lohner et al. 2019). Studies conducted in Kentucky (US) have analyzed the distribution of ES interactions and bundles at the county level (Bai et al. 2021), as well as the discussion of the overall ES benefits derived from the application of widespread forestry-based reclamation approaches (Zipper et al. 2011) at the watershed scale (Gurung et al. 2018). Both studies reported limited information in differentiating relevant socio-ecological drivers, like surface mining, and their interactions with ES delivery and changes across the study areas analyzed.

As the ES framework gradually grew and consolidated, crucial elements for its implementation have been identified in the development of methods used to explain the mechanisms of interaction and association among multiple ES (Foley et al. 2005; MEA 2005; Carpenter et al. 2009), and in understanding the relationships between ES and the different social and biophysical drivers that characterize their distribution and change (Mouchet et al. 2014; Bennett et al. 2015). Such methods can be relevant in understanding the flow of ES among beneficiaries (Villamagna et al. 2013), and their spatial allocation within different social-ecological systems (SES) to correctly address the target areas for shaping relevant policies and avoid scale mismatches problems (Cumming et al. 2006). Even the use of ES tradeoffs, to indicate mechanisms of exchange between ES, has often been reported in the literature with generic or misleading uses (Mouchet et al. 2014). To avoid misinterpretations, we adopted the following definitions provided by Bennett et al. (2009). Interactions among ES relationships can be characterized by tradeoffs, defined as inverse variation between two ES (one service increases and the other decreases), as well as by synergies when both services increase (i.e. multifunctionality) or decrease (Bennett et al. 2009). When analyzing changes in ES interactions, the spatial and temporal scales are both relevant (Rodriguez et al. 2006). Land-changes typically occur over time with different intensities and spatial changes generally affecting not only gross quantity differences but also allocation quantities (Aldwaik and Pontius 2012; Pontius 2019; Cribari et al. 2021). These changes in the landscape may affect ES delivery, flow, and capacity across the land and beneficiaries (Villamagna et al. 2013), even within individual spatial units such as municipalities or small catchments.

Raudsepp-Hearne et al. (2010) proposed a method to quantitatively identify bundles of ES, defined as ‘sets of services that appear together repeatedly’. The method used a multiple correlation analysis (MCA) to identify ES tradeoffs and synergies and a cluster analysis based on partitioning approaches and K-means clustering for defining the ES bundles. The ES values were obtained combining several existing social and ecological datasets, mostly from provincial and national government database, and derived at the municipal level using 144 Canadian municipalities. The authors reported the association of drivers with ES in qualitative terms suggesting that the inclusion or discussion of specific subsystems (i.e. ‘drivers, feedbacks, and management schemes’) may allow for the identification of critical interactions among ES on the landscape.

This study aims at extending the method developed by Raudsepp-Hearne et al. (2010) in a rural-mining region of the Central Appalachians to analyze ES interactions and identify ES bundles. The study area consists of the Headwaters of the Coal River, the first river in West Virginia where coal was found by European settlers in 1742 and began to be mined shortly after (Eggleston 1975). This area has been characterized by intense mining activities, industrial and post-industrial land uses, counteracting processes of settlements growth and abandonment, severe environmental pollution with relevant habitat losses,
novel ecosystems, and by multiple reclamation processes that often spatially overlap in the landscape being the outcomes of activities that occurred during different temporal intervals (Cribari et al. 2021). This study extends the current research by using spatially explicit ES models that combine fine-resolution datasets (5–30 m) with historical information and ES assessments conducted at the local scale (Raudsepp-Hearne and Peterson 2016; Roces-Díaz et al. 2018). This study emphasizes freshwater ES by including metrics that can link ES change to human wellbeing. Secondly, we seek to understand if the knowledge of ES interactions could help in addressing conservation policies and strategies in working landscapes characterized by mining legacies. Our work continues the use of emphasizing ES in restoration ecology (Palmer et al. 2016) since it can be used to validate many of the natural systems projects and funding for landscape restoration and reclamation to aid investments and policymakers.

2. Materials and methods

2.1. Human-environment interactions in the rural-mining region of Central Appalachians

The rural-mining region of the Central Appalachians is characterized by relevant land-change processes driven by social and technological transitions (Geels 2002) occurred during the last century and a half to fuel the industrialization phases of the US economy (Davis 2000; Marley 2016). The effects of extractive industries characterize large tracts of the region’s landscape, from the almost complete substitution of the original mixed mesophytic forests to the industrial cycles of coal mining and gas fracking (Stanisica et al. 2020). In the region where mountain top removal and valley fills (MTR, MTRVF) operations are diffused, like in the Southern Coalfields of West Virginia, several cumulative impacts interact. Environmental impacts generated by coal extraction (Bernhardt and Palmer 2011; Wickham et al. 2013) may cohabit within other stressors driven by human activities that bring to additive effects on the landscape and with in-stream biotic conditions (Merriam et al. 2011). Even when the reclamation can be considered completed by the regulatory agencies on specific mining permits, MTRVF areas still produce adverse effects in their surroundings, like stream impairment, acid mine drainage, invasive species, and large coal sludge impoundments, to cite a few (Epstein et al. 2011). In the MTRVF areas, land degradation problems assume a geological event’s scale since the evolutionary clock of ecosystems is de facto reset (Ross et al. 2016), bringing to a substantial ‘regime shift’ of ecosystems (Folke et al. 2004). Entire forested areas, including the hydrologic systems of former mountain ridges, are replaced by novel anthropogenic ecosystems (Morse et al. 2016): new fast-growing grasslands on now flattened top-areas emerge as a combined effect of the Surface Mining Control and Reclamation Act (SMCRA, 30 U.S.C. §1201).

Moreover, the effects of pre-SMCRA operations often cohabit or may overlap within the same areas. As a consequence, vegetated or forested areas in different reclamation or successional phases may coexist in the same catchments of the study area (Cribari et al. 2021). These sites in transitional stages can derive as an effect of former strip-mining reclamation processes (before SMCRA) or may include forest stands recovering from clear cuts. These early forest stands can also fluctuate in an ‘arrested’ stage of succession due to the combined effects of degraded forest ecosystems and invasive species (Skousen and Zipper 2014; Dellinger and Eric 2021). These areas can still deliver ES, but they were subjected to intense alterations. As a result, the conditions of forest stands and soils, and the ES, cannot be compared to those of the second succession forest (Holl 2002, 2020; Simmons et al. 2008; Fox et al. 2020), recognized as the dominant ecosystem in Central Appalachians (Butler et al. 2015).

2.2. The Headwaters of West Virginia Coal River: features and available datasets

The study area corresponds with the Headwaters of the Coal River (WV) and its two main branches: the Clear Fork and the Marsh Fork. The Hydrologic Unit Code 12 (HUC-12) (Seaber et al. 1985) catchments with the highest mean elevation (674 m.) correspond to a plateau characterized in the past by agricultural uses, now shaped by small settlements, suburban areas, and open fields mixed with woods marked by the presence of former mining facilities. The settlements become denser in the proximity to the town of Beckley (WV). The remaining part of the watershed is characterized by mountains with the highest elevations around 1000 meters, with steep slopes and narrow winding ridges: the dendritic and deeply incised valleys characteristic of the Appalachian Plateaus physiographic province (Ehike et al. 1982). In these catchments, mountains are mainly characterized by forested areas and surface mining operations, while valley floors are characterized by small settlements, coal processing facilities, and infrastructures.

The area is composed of six HUC-12s, covering a total of 58,661 hectares (586.61 km²). The HUC-12s have been subdivided into 89 smaller hydrologic units, named Custom Hydrologic Units (CHUs), derived from the freshwater ES (FwES) model and stream data. CHU’s size range from a minimum of 122.6 to a maximum of 2432.4 hectares. The average
area of CHUs is around 660 hectares, highlighting a spatial scale that is equivalent to what other ES studies defined as a size ranging between the local and the municipality scale of analysis (Raudsepp-Hearne and Peterson 2016; Roces-Díaz et al. 2018). The importance of conducting small-scale studies that combine detailed ES models with assessments and interactions at broader scales has been previously noted (Nelson et al. 2009), although most studies focused on ES assessments at larger scales, from municipality, to county and regional scales (Pandey et al. 2016; Spake et al. 2017; Roces-Díaz et al. 2018). Indeed, the scale of analysis at the site or local level, which may include explicit heterogeneous landscape data, can be crucial in understanding interactions and feedbacks with critical human and biophysical drivers (Turner and Gardner 2015).

Information from three different land cover classifications (LCC), analyzed in a land-change study during a time interval of 40 years (Cribari et al. 2021), has been used to incorporate the temporal data used in the InVEST ES models (Sharp et al. 2020). The main LCC used in the models was derived from a 1-m resolution, six-class LCC realized in 2016 for the WV state (Maxwell et al. 2019). This dataset was implemented with information derived from two historical LCCs, from 1976 and 1996, obtained with remote sensing methods that include accuracies assessments (Cribari et al. 2021). LC transitions were derived from the land-change study to incorporate the differentiation of forest and vegetation classes based on distinct ages and characterize surface mining reclamation processes before and after the SMCRA enactment, identifying landscape patterns otherwise not reported or visible in the traditional datasets available (Cribari et al. 2021). Data from the visual interpretation of specific classes and from other sources was also included (Table S1) in the final LCC that comprised 14 classes (Figure 1). This LCC, that generally represents the main dataset used in the InVEST models, was downscaled in the different ES models using geospatial rasters with resolution ranging from 5 to 15 m. This spatial resolution range allowed us to preserve spatial information, like the former tiny patterns of strip-mining operations contained in the rasters, without affecting the variance that fine-resolution data provide and consequently the results of the ES models (Grêt-Regamey et al. 2014). Moreover, the land-change analysis conducted in the same study area of this research provided relevant information for identifying the main drivers associated with landscape legacies and changes and understanding important historical and socio-ecological dynamics of the region (Cribari et al. 2021). Indeed, the previous knowledge of the social-ecological system has been considered fundamental to support the understanding of mechanisms for determining the ES selection and modeling phases (MEA 2005; Ostrom 2007; Grêt-Regamey et al. 2014).

2.3. ES models

Eight ES were considered in this study. The ES models have been selected by including metrics that can effectively represent the most relevant socio-ecological processes underway in the study area. Specific attention has been given to addressing issues related to the impairment of freshwater ES in the region, mainly derived by the impacts of mining activities (Merriam et al. 2011). Both groups of ES, those modeled in InVEST and those derived by a custom model used for the freshwater ES, have been chosen using standard criteria and replicable methods.

In the case of the freshwater ES, they were defined by operationalizing a theoretical method and a cascade system defined by Keeler et al. (2012). The approach proposed linked the freshwater ES to standardized notations used for reporting water quality data concerning USA national-level policies derived from the Clean Water Act of 1972 (CWA, 33 USC §1252). Since the freshwater ES were derived from ecological baselines metrics, they were used to directly determine how changes in ES affect human well-being, with assessments not limited to the scale of mining sites (that government agencies have traditionally used to evaluate permits issues), but considering ES changes across larger areas that include ES beneficiaries. Thus, the two sets of ES models used in this research should facilitate the comparison of ES results with those from studies conducted in mining contexts, as indicated by Boldy et al. (2021), or be replicated in other research were anthropogenic signatures and not only the environmental gradients are relevant.

2.3.1. Habitat quality

The InVEST HQ model is generally used to support environmental policies in decision-making and conservation planning contexts. Using a deterministic spatial approach, the HQ model can represent a first phase for conservation assessments, or be used as an alternative to models designed to assess biodiversity richness based on species-based approaches (Nelson et al. 2011; Terrado et al. 2016; Di Febbraro et al. 2018). The HQ model is often proposed as a proxy to derive information about biodiversity. However, due to its similarities with habitat integrity models based on the assessments of environmental stressors (Theobald 2013), its use can embrace the assessment of landscape’s ecological integrity (Liquete et al. 2016). It is worth noting that the integration of biodiversity assessments into the ES framework
is an active field of research since conceptual incongruities arise when habitat services are included into decision-making frameworks to operationalize the use of ES (Kumar 2010; Haines-Young and Potschin 2018). For this reason, some authors suggested to clarify the use of these types of models to differentiate the overall ecosystem conditions like in general analyses of biodiversity, from the assessment of specific ES, like in the case of habitat nurseries (Liquete et al. 2016).

The proposed model characterizes the disturbance of LC classes representative of specific ecosystems by integrating the terrestrial stressors and the historical data derived from the land-change study, like the former strip-mining areas in reclamation stages (Cribari et al. 2021). It allows for the mapping of the most pristine and less disturbed area, consistently with the available data, and compare those areas with the other ES mapped in this study. The model’s parameters
used to define the threats (Table S2) and the sensitivity of land cover (Table S3) have been derived from the literature of similar studies and adapted to the study area.

2.3.2. Carbon storage and sequestration

The Carbon Storage and Sequestration model in InVEST is based on the estimation of carbon density in four carbon pools (aboveground biomass, belowground biomass, soil, and dead matter), following a method analog to the one used in the Intergovernmental Panel on Climate Change (Eggleston et al. 2006). The four carbon pools have been estimated for the LC classes using parameters derived from the literature and adapted to each specific class. Due to the conditions of reclaimed soils and reforested mine sites, to estimate the final pools, different values have been combined using several sources (Sperow 2006; Avera et al. 2015).

For forest stands, carbon pools values have been mainly derived from the Eastern US forest stands data (Smith et al. 2006). Different stands ages have been considered to model carbon sequestration (C) for the forest reclaimed classes. Since there is no differentiation of tree species composition available for the study area, the values were derived using the regional estimation for the Northeast US forest for

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**Figure 2.** Ecosystem Services maps obtained in InVEST.
timber volume and carbon stocks on forest grown after clear-cuts. The values have been averaged from the three more common forest stands: the aspen-birch, the maple-beech-birch, and the oak-hickory stand (Smith et al. 2006).

For each forest class, it has been considered a different forest stand age derived from the historical datasets (Table S4). Since Smith et al. (2006) did not provide biomass measures (C_below), for below-ground biomass it has been used as an estimate equal to the 25% of the total tree (Ravindranath and Ostwald 2008). To estimate the carbon pool (C_soil) for soil reclaimed classes, the estimations provided for the WV soils (Sperow 2006) were applied to 20 years, and 40 year age reclaimed soils. The soil values obtained are consistent with those found from studies conducted on mining sites where data showed that mineral soil C values were less than 30% compared to unmined spots in the same area (Avera et al. 2015). The Carbon Storage and Sequestration model is the only InVEST model used in this study that can be compared with a tier-two modeling. Indeed, tier-two InVEST models are generally able to address more detailed information with greater spatial and temporal heterogeneity and the generation of more refined estimates (Tallis and Polasky 2011).

### 2.3.3. Sediment delivery ratio

The Sediment Delivery Ratio (SDR) model in InVEST is generally applied to estimate the landscape’s sediment retention capacity and the regulating ES used to evaluate erosion control and water protection services at the watershed scale (Sharp et al. 2020). The SDR model derives from the Revised Universal Soil Loss Equation (RUSLE) proposed by Borselli et al. (Borselli et al. 2008). The model generates different outputs. Keeler et al. (2012) suggested that in the assessment of watershed services and ES payment projects, the delineation and understanding of multiple ES is fundamental for a complete evaluation of water services and that the use of the most suitable biophysical metric should be adapted to the purposes of the specific study. The complex interactions of pollutants in the study area and the profound alterations conducted on the hydrological cycle by underground and surface mining operations (Lindberg et al. 2011; U.S. EPA 2011; Miller and Zégre 2014; Nippgen et al. 2017) represent a significant limitation for exhaustive application of this model to satisfactorily understand the relationships among water-related ES. For this reason, the model has been used to conduct an overall assessment of sediment retention services on a tier 1 level (Tallis and Polasky 2009) using two outputs: the total amount of sediment exported to the stream per watershed, and the total amount of potential soil loss in each watershed (Sharp et al. 2020). The complete list of the data used in the model, as well as the references used to derive the metrics, are reported in the supplementary materials.

#### 2.3.4. Visitation: recreation and tourism

The InVEST Recreation and Tourism (RT) model was used to include the evaluation of cultural ES provided by the landscape natural features in the study area. Previous studies demonstrated how the number of geotagged photographs derived from social media data can be successfully used as a suitable proxy to measure outdoor recreation and nature-based tourism (Wood et al. 2013). Some adjustments have been made to adapt the RT model due to some limitations, some inherent with the model, like user characteristics and preferences (Tenerelli et al. 2017; Foltête et al. 2020), and some related with the content of the Flickr-derived content data for the study area. With references to the study area data, the main limitation was associated with the content of the geotagged photos uploaded on the Flickr platform. Indeed, several images within the study area presented contents not related to this study’s purpose. To avoid this restriction, the RT model was used to derive the total number of images at the CHU spatial level during the time interval 2005–2017. The outliers were then removed through a content analysis assessment of the photographs; only contents related to the natural landscape’s cultural and recreational uses were selected. The number of images used (Table S6) and some examples about the images selected (Figure S1) are provided in the supplementary materials.

#### 2.3.5. Freshwater ES

A custom model was explicitly defined to replicate the broad range of pollutants interactions that affect freshwater ES (Postel and Carpenter 1997) in the study area. The custom model applies the theoretical framework proposed by Keeler et al. (2012) to a spatial model organized at the landscape scale to map the freshwater ES.

Previous studies suggested that the economic values of freshwater resources to humans can be affected by changes in water quality (Freeman 2003). Even the existence of a close affinity between the Water Designated Uses, from the U.S. Clean Water Act of 1972, and the final ES derived from freshwaters resources has been previously reported (Stevenson and Smol 2015; Copeland 2016; U.S. EPA 2016); while some suggested an update of the legal framework provided in the Clean Water Act in order to integrate it with the recent ES framework (Ruhl 2010). The framework proposed by Keeler et al. (2012) explicitly links how changes in water quality, measured through specific biophysical metrics or other methods, may affect
different freshwater ES with effects on goods, economic values and beneficiaries.

In the freshwater ES model, the Affected Designated Uses (ADU) of water bodies are derived from the impaired waters state list approved by the US Environment Protection Agency (EPA) in 2019 (WVDEP 2016). The waterbody’s quality is determined by the presence or absence of a specific criterion’s threshold values in the ADU list. The criteria include the presence of dissolved metals (iron, aluminum, and selenium), fecal coliform bacteria, and other biological impairments (Table S7). The WVDEP (2016) report combined information derived from different sources. Consequently, the information provided at the streams scale doesn’t follow a uniform spatial scale or HUC, but it follows the coding derived from river tracts mapped with uniform values. Four freshwater ES have been directly derived from the ADU list. When a specific criterion exceeds the acceptable threshold, the model considers the relative ES as not delivered. Therefore, the model does not quantify ES magnitude and is limited to the spatially binary mapping of ES, providing only the presence or absence of the specific ES at the CHU spatial level. In this way, the model adapts existing water quality information by linking it to the ES framework (Table S8). This approach for defining ES values has been presented in Villamagna et al. (2013). In the study, the authors described how ecological thresholds could determine the ecosystem’s capacity to provide a service and if the service is acceptable or is too degraded.

The CHUs were defined using hydrological modeling in a GIS environment based on a flow accumulation grid with 10 m cells. First, the river sections characterized by uniform data have been aggregated into single units. A flow direction and accumulation grid derived from a hydrologically corrected digital elevation model (Strager et al. 2010) was used to derive the catchments relative to each stream or river section. Afterwards, using the hydrologic grid, each stream has been associated with a catchment. In this way, a univocal direct spatial relation that links the streams data (polylines) to their catchments (polygons) was defined. The model associates the value of freshwater ES in each CHU directly from the main stream’s catchment conditions. An example of the process used to derive the CHU and the data used to derive the hydro DEM are included in the additional materials (Figure S2, S3). A final consideration regards that several catchments are not independent of each other since they may result as a function of the upstream CHUs. To make this condition explicit in the model, the degree of nestedness in the CHUs was mapped considering the number of streams flowing into each catchment (Figure S4).

2.4. Analyzing ES interactions

Different methods were applied to investigate ES’s relationships derived from the models’ outputs using two different spatial unit sets to aggregate the variables’ values: the CHU and the HUC-12 level. The ES models’ variables used in the multivariate statistics were derived from spatial rasters with different distributions (Table 1).

The ES models’ outputs were obtained from the raster maps using mean values extracted with the Zonal Statistics commands in ArcGIS. The data from the ES models have been normalized (0–1) to allow the comparisons among the different ES variables using the highest scores, like in formula (1) as suggested by Geneletti et al. (2018).

\[ n_{\text{score}} = \frac{\text{score}}{\text{highest score}} \]  

2.4.1. Multiple correlations

Two multiple correlations analyses (MCA) were conducted to examine tradeoffs and synergies among ES, while polar plots and histograms were used to visualize ES’s interactions (Foley et al. 2005). The main MCA was based on the outputs of eight ES models with mean values derived from the 89 CHUs. All ES values were normalized using (1), except values from the freshwater ES that were reported with dummy variables. Spearman’s correlation coefficient was used for the MCA based on CHUs since the variables were obtained

| Table 1. Data used for the CHU model. |
|--------------------------------------|
| **ES models** | **Model type** | **Indicator** | **Spatial Distribution** |
| InVEST Models (3.8) | Habitat Quality | Biophysical model | Habitat Quality | Continuous |
| Carbon Storage and Sequestration | Total Carbon | Continuous |
| Sediment Delivery Ratio | Sediment Export | Continuous |
| Visitation: recreation and tourism | Soil Losses | Continuous |
| Support of aquatic life | Number of geotagged images | Continuous |
| Water contact and recreation | Aquatic life | Continuous |
| Water supply for human consumption | Water Contact & Recreation | Continuous |
| Agricultural and Industrial Uses | Water Supply | Continuous |
| Freshwater ES Custom Model (FwES) | Water Uses | Continuous |
| | | | |

Data:...
from mixed distributions (Kabacoff 2015; Spake et al. 2017). Scatter plot matrices were created using the Psych package (Revelle 2020) in R (R Core Team 2020) to derive the strength and sign of correlation. The second MCA, and the polar plots, were obtained using average ES values derived from the raster maps using the six HUC-12 units; the average values were then normalized using (1) to allow their comparison. Polar plots were obtained with the ggplot2 package (Wickham 2016) in R. The second MCA was included to understand what limitations could affect ES results after the spatial aggregation (using larger spatial units) and the normalization of the outputs.

2.4.2. ES bundles
A partitioning cluster analysis was conducted to identify the bundles of ES, following the approach introduced by Raudsepp-Hearne et al. (2010). The cluster analysis was performed using the 89 CHUs. Due to data derived from mixed distributions, the partitioning around medoids (PAM) method (Kaufman and Rousseeuw 1987) was used within the Cluster package (Maechler et al. 2019) in R. It is worth noting that, unlike K-means, medoids correspond to actual observations located at the most central points within each cluster. Since the PAM method is not based on the use of means, it is less sensitive to outliers (Kassambara 2017).

Cluster validity is probably the most common problem of clustering in unsupervised learning algorithms and consists in determining the optimal number of clusters in a dataset (Halkidi et al. 2001; Lantz 2015; Manly and Alberto 2017). Different clustering validation techniques can be used to validate different solutions (Halkidi et al. 2001; Lantz 2015) or avoid nonexistent clusters (Kabacoff 2015). We applied the silhouette method (Rousseeuw 1987; Kaufman and Rousseeuw 2005) to determine the optimal number of clusters, using the package factoextra (Kassambara and Mundt 2020) in R. The algorithm calculates a silhouette score (average silhouette width) based on multiple clusters in a dataset. The optimal number of groups is identified using a validity graph and comparing the number of clusters (k) with the average silhouette width. The highest average silhouette width indicates the optimal number of clusters (Malik and Tuckfield 2019).

After we defined the optimal number of clusters, we compared maps with different clustering solutions, to visually assess how changes in the number of ES bundles could explain the information derived from the overall knowledge of the landscape. This approach supported the qualitative interpretation of the drivers (Mouchet et al. 2014) that was explicitly acknowledged utilizing the detailed information contained in the high-resolution LCC. The methodology was applied to overcome some of the limitations generally reported for determining the appropriate number of ES bundles (Raudsepp-Hearne et al. 2010; Spake et al. 2017) and introducing a validation phase, generally reported in clustering methods (Everitt et al. 2011; Kabacoff 2015). Since the medoids corresponded to central observations in groups classified by specific ES thresholds, they were used to characterize and discuss each ES bundle. Finally, the spatial autocorrelation of the ES bundles was tested using Global Moran’s I (Getis and Ord 1992) with inverse distance (ESRI 2020).

3. Results

3.1. ES models and polar plots
Figures 2 and 3 display the maps with the results of the ES models. While Table 2 and the polar plots (Figure 4) present the results derived using the HUC-12 spatial units. Table 2 shows the results before the normalization based on (1), while in Figure 4 the values have been normalized.

The polar plots (Figure 4) show significant differences between the two groups of watersheds characterized or not by the presence of MTR sites. Substantial tradeoffs in the HUC-12 catchments with MTR sites occur between ES derived from the SDR model outputs, Sediment Export (SE) and Soil Loss (SL), and the second group of ES formed by habitat services (Habitat Quality and Aquatic Life). Carbon Sequestration (C) in these catchments is still generally high due to the prevalence of forest classes, but average values are lower than other catchments. Recreation ES appears to be significantly higher in one sub-watershed due to the lake’s presence that emerges as an essential visitor’s attractor within the entire study area.

The results of the freshwater ES in the polar plots (Figure 4) should be interpreted with care and read together with the maps (Figure 3) and the average values presented in Table 2. In this case, we found that the normalization phase can lead to contradictory interpretations of the results. Indeed, freshwater ES exhibits overall poor levels of delivery in the whole study area. However, due to the combined effects of normalization and spatial aggregation (MAUP effect), the freshwater ES are reported with relatively high absolute values in the polar plots. Therefore, an incomplete reading of the results, in this case, may lead to misleading interpretations. More details are given in the discussion section.

3.2. Multiple correlations
The MCA conducted at the CHU level identified 28 possible pairs of ES, with 18 pairs significantly correlated. The scatterplot matrix (Figure 5) shows the results of the MCA and the strength of correlation between pairs of ES. Six ES pairs were highly correlated (Spearman coefficient, r ≥ .5 and p < .001), five
pairs were moderately correlated (Spearman coefficient, $r \geq .3$ and $p < .01$), and seven pairs were weakly correlated ($r < .3$ and $p < .05$).

SE and SL values were strongly correlated ($r = .98$), identifying a strong interaction between soil losses and the amount of sediments reaching the stream at the CHU spatial level. Significant ES tradeoffs were identified between SE and SL, and almost all the other ES. SE and SL showed a statistically highly significant negative correlation ($P < .001$) with HQ ($r = - .70$, $r = .75$) and with C ($r = - .56$, $r = .51$). They were negatively correlated with almost the entire set of aquatic ES, except WOU values since it did not produce any significant result due to the almost uniform dataset with few variations.

The MCA identified significant negative tradeoffs between coal extraction from MTR sites, expressed by the highest values of SE and SL at the CHU level, and the entire set of ES services, from supporting ES, to regulating, provisioning, and cultural ES. In terms of ES synergies, the MCA model identified statistically highly significant positive correlation ($P < .001$) between AL and WS ($r = .50$), C and HQ ($r = .45$), WCR and WS ($r = .43$), HQ and AL ($r = .35$). Those synergies identified potentially positive interactions among ES, indicating that multifunctional processes are active in some catchments across the landscape. MCA results based on data at the HUC-12 scale were reported in Figures S5.

Figure 3. Freshwater Ecosystem Services obtained with the custom model.
### ES bundles

The silhouette method, used to determine the optimal number of clusters, identified five clusters corresponding to the highest average silhouette value ($SV = 0.58$) (Figure S7). Nevertheless, after observing the ES bundles’ distribution, we decided to choose a solution based on six groups. Indeed, the last bundle (the fourth bundle in Figure 6) emerged almost entirely as a subset of the first ES bundle. We opted for the second solution since the more extensive clustering with six groups supported the differentiation of catchments that belong to heavily mined areas with MTR sites from catchments primarily located in the valley floor areas. The solution based on six ES bundles allowed us to discuss a more extensive set of biophysical and human drivers to clarify the interactions with ES changes, thanks to the LCC with fine resolution, and the inclusion of specific LC classes (e.g. the inclusion of former strip mining areas and the forest classes derived from the land-change study).

Figure 6 shows the map with the six ES bundles. While the map with the five ES bundles solution has been included in the supplementary materials for comparison (Figure S7). The medoids values that characterize ES bundles are reported in Table 3 and Figure 7. WOU was excluded from the cluster analysis since it did not add any significant information to the model.

The first ES bundle is formed by catchments with relatively high carbon values and very low HQ; SE and SL values are relatively high and above the rest of the study areas’ averages. The overall poor quality of freshwater ES is explicitly stated by the three FwES that never met the minimum water quality standards (WQS) established by the Clean Water Act. These catchments are generally contiguous to MTR areas and where former surface mining’s adverse effects (strip-mining, highwall-mining) are spread out in the landscape.

The second ES bundle is formed by catchments with relatively high C values and low HQ, SE has low values, while SL has average values. The only freshwater ES that reaches the minimum levels is the WCR service. It is worth noting that most of these CHUs (76%) consist of relatively independent catchments without tributaries or upstream watersheds (Figure S4; degree of nestedness $= 0$). Two subsets characterize these catchments: former strip-mining sites with ongoing pre-SMCRA reclamation processes still characterized by metals presence (mostly iron) in the streams, and relatively dense urban fringes mixed with former coal processing facilities.

The third ES bundle coincides with catchments with active MTRVI operations, mostly former headwater streams (86% of these units are independent
catchments); these CHUs are characterized by a large presence of barren land covers, disturbed areas, fast-growing grasses, and poor soils. These catchments have the highest SE and SL outputs and the lowest C and HQ values. All the freshwater ES are below the acceptable thresholds. These catchments have the lowest ES values in the entire study area.

The fourth ES bundle consists of areas mostly characterized by valley floors; 60% of these catchments are dependent units with at least one upstream catchment (Figure S4; degree of nestedness ≥1). SE and SL are relatively low and close to average values. HQ values are among the highest in the study area. All the freshwater ES are below the minimum water quality standards; WCR is not allowed, generally due to fecal contamination, probably caused by the presence of settlements with inadequate centralized sewer systems (WVDEP 2006). Watershed-scale studies in similar areas of the state demonstrated residential development strongly impair in-stream habitat conditions and macroinvertebrate community structure with additive effects to those of mining (Merriam et al. 2011). AL is not supported, probably

**Figure 4.** ES polar plots comparing HUC-12 catchments.
due to the accumulation of pollutants that the main river trunks receive from the tributaries and upstream basins, which mostly coincide with the CHUs of the second bundle, with areas characterized by former strip-mining operations or denser settlements.
The fifth bundle is characterized by the highest C values in the study area. HQ does not have very high values since this ES bundle’s catchments are very dispersed and fragmented across the landscape and formed by isolated units often bordering high disturbed areas. All the freshwater ES have values above the minimum requirements: this is the bundle with the best freshwater services. One of the catchments in this bundle incorporates the lake with the highest visitor presence in the entire study area.

The sixth bundle has a high C level, the highest HQ values, and the lowest SL and SE values in the entire study area. WCR and WS are below the minimum values, while AL is above the required level. These socio-ecological units appear to be not interested in surface mining activities in the past. These are populated catchments with small settlements. WCR and WS are probably damaged even in this case due to the fecal contamination caused by inadequate sewerage systems and failing septic systems (WVDEP 2006).

4. Discussion

4.1. Advantages and limitations of the approach

Using a combination of ES models, our research examined for the first time the impact of the mining dominant land use on ES interactions and bundles in a rural-mining region of Central Appalachians, where diffuse surface mining processes, including MTR operations, characterize a substantial part of the current landscape.

The main MCA based on CHUs showed significant ES tradeoffs in catchments subjected to MTR mining operations with consistent losses of habitat, provisioning, and freshwater ES. Areas with former
strip-mining processes mined before 1977 showed a slow recovering of some ES (C, HQ), with freshwater ES generally still impaired in unclaimed areas. Some limitations related to the datasets used in the ES models should be considered, particularly in the case of carbon sequestration modeling. Forest C values (C_above, C_below, Table S4) were derived from US Eastern forest stands grown on generic soils (Smith et al. 2006), disregarding the generally detrimental effects of mining activities on forest stands growth due to disturbed soils (Holl 2002; Fox et al. 2020). In some catchments, positive synergies among habitat, carbon sequestration, freshwater, and even cultural ES were found, pointing to the preservation and existence of multifunctional processes in the study area (Mastrangelo et al. 2014), although in limited or isolated portions of the headwaters.

4.2. ES interactions and spatial scale problems

The study was based on ES models derived from high-resolution LCCs that included historical data from a previous land-change analysis (Cribari et al. 2021). The small scale of the hydrological units (CHU), which presented reduced heterogeneity and detailed land cover information, allowed us to help isolate and understand some general dynamics among key factors and ES bundles. This approach has overcome some of the limitations previously reported in ES bundles research, where coarse resolution and larger spatial units represented a constraint for interpreting the mechanisms that may unveil relationships among socio-ecological drivers and changes in ES distribution (Spake et al. 2017). The study confirms the importance of using historical knowledge for addressing ES interactions (Tomscha and Gergel 2016). Although we did not directly address ES interactions over time in the study area, these effects can be reconstructed in broad terms by analyzing the relevant land changes that occurred in the study area across the time intervals previously analyzed (1976–2016). The knowledge derived from the land-change analysis helped derive two kinds of information. The first set consisted of the detailed spatial mapping of the LC classes transitions incorporated into the ES models. The second set of information was relevant to understand the main historical socio-ecological processes associated with landscape changes in the area since these dynamics were particularly relevant for addressing ES interactions and ES bundles composition.

The comparison of the ES results using different spatial units allowed us to identify some interdependencies when analyzing ES interactions at different spatial scales (Grêt-Regamey et al. 2014; Raudsepp-Hearne and Peterson 2016; Roces-Diaz et al. 2018) and to address some general caveats related to the interpretation of the results presented in this paper.

As previously reported, the effects of normalization and aggregation of ES indicators have often represented two critical steps in the assessment of ES tradeoffs and synergies (Geneletti et al. 2018). Indeed, in ES interactions’ studies results were often aggregated to relatively large spatial units and then converted, through normalization, into dimensionless values to allow their assessment. The combination of the two phases could bring misleading and contradictory effects. For example, Roces-Díaz et al. (2018) found that ES tradeoffs relationships detected at the local level changed to significant positive synergies at larger scales like municipalities and counties.

In the current study, the combination of the normalization and aggregation phases at the HUC-12 scale conducted to slightly different results that needed to be carefully evaluated. The HUC-12 MCA results (Figure S5) followed a general strengthening of the correlation coefficients, except in the case of WS where all the signs of the interactions were inverted, and in the case of the correlation between RC and AL that changed from a weak negative value to a moderate positive value. Polar plots diagrams (Figure 4) helped identify how the values of WS services increased significantly due to the normalization phase; indeed, the metrics before the normalization (Table 2) showed that the level of WS delivery was generally weak in the entire study area, except in a limited number of catchments (Figure 3(c)). The HUC-12 scatterplot matrix (Figure S5) identified weak synergies between WS, SE, and SL. Whereas the CHU scatterplot matrix identified weak tradeoffs between WS, SE, and SL. Nevertheless, the incorrect interpretation of these results could cause misleading conclusions. Indeed, at the HUC-12 scale, MTR sites can coexist with relatively unspoiled catchments that can maintain a good capacity to provide water supply services (Figure 1). Moreover, another element of confusion concerns the fact that former underground mining outlets may have been mapped as a source of water supply in some catchments of the study area (Dinger et al. 2006; WVDEP 2016). The above information showed how the combination of the aggregation and normalization steps could lead marginal landscape dynamics to appear more critical when analyzed at larger scales, or through diagrams such as polar plots.

Comparing the two aggregation scales helped us understand why ES from biophysical and hydrological processes should be derived and discussed at the appropriate spatial scale to properly address their interactions. The inconsistency of ES results across spatial scales can be potentially misleading not only for comparing the findings among multiple research cases, or for their prediction, but especially in the context of natural resource management and landscape planning. In particular, when dealing with the
necessity of conducting assessments that address and target specific policies correctly, avoiding scale mismatch problems between the governance levels and the environmental systems (Cumming et al. 2006). These problems have often been a critical issue in watershed restoration research, where water policies resulted often misaligned with the social-ecological units analyzed (Sayles and Baggio 2017). Moreover, the finding of recent literature reviews of ES studies conducted in mining contexts (Boldy et al. 2021) showed great inconsistencies when disambiguating between the positive and negative effects of mining, and therefore in the proper ES application when evaluating the impacts of mining activities. Therefore, we suggest that the appropriate scale of analysis should always be considered when addressing ES interactions in these particular working landscapes.

4.3. Modeling freshwater ES in mining regions

By applying the theoretical framework proposed by Keeler et al. (2012) coupled with a spatial model, it was possible to include freshwater ES within the ES interactions and bundles method. Previous studies highlighted the importance of deriving biophysical models and spatially explicit assessments of freshwater ES to associate water policies with services provision at the landscape scale (Allan et al. 2013, 2015; Qiu and Turner 2013). Freshwater ES are critical to include in ES mining studies because they are generally subject to deterioration due to water and soil contamination caused by mining activities and associated industrial operations (Heather et al. 2011; Duarte et al. 2016). The proposed method can be applied in similar contexts and within the US using standard metrics since water quality information is available at the State level and derived from the Clean Water Act and its major amendments (Copeland 2016).

The freshwater ES mapping, derived from mixed datasets verified at the state and federal levels (WVDEP 2016), presents several advantages. The model spatially links ES to metrics that potentially affect human well-being (drinking water, recreation activities) or may capture inherent ecological benefits (e.g. aquatic life), targeting specific spatial units (or social-ecological units) where policies can be verified and implemented. The FwES metrics, derived as state indicators, also make it possible to link and compare the study results to broader frameworks or policies and integrate the results more easily into landscape planning and management, decision-making contexts, and economic models (de Groot et al. 2010). Indeed, the use of FwES metrics in this study provides an example that may help integrate and update or link, as previously suggested (Ruhl 2010), the legal framework of the Clean Water Act with the ES framework.

Furthermore, Boldy et al. (2021) noted the importance of using ES metrics to describe changes in human well-being in the rehabilitation of mining areas; since, in ES studies in mining contexts, this procedure has often been overlooked. For example, specific criteria to map freshwater ES, like the explicit mapping of selenium levels (Figures 3(a) and 6), could be crucial for reclamation processes, mining industries, and communities in the Central Appalachian region (US EPA 2016). Indeed, in MTR areas, impacts of selenium in water bodies represent a major issue since its bioaccumulation in food webs caused teratogenic deformities in fishes and insects (Arnold et al. 2014).

Therefore, selenium accumulation above the allowed threshold values impairs freshwater ES like habitat provision and water supply (Table S7), with consequences that may require long-term stream restoration and extremely high reclamation costs. In West Virginia, the remediation costs required to decrease selenium levels to non-harmful concentrations in streams caused by MTR operations may undermine the final results of reclamation processes associated with the conventional bonds provided by the mining industry (Surber 2013; Surber and Simonton 2017), but also the benefits of miners nearing retirement (Morris 2016). For these reasons, communities in the region face the detrimental effects of social-ecological traps, where reciprocal social and ecological feedbacks maintain the SES in an unfavorable state (Boonstra and De Boer 2014). The inclusion of selenium mapping provided additional information to identify areas that need special attention for the magnitude of the underlying socio-ecological matters; the information can also be used as a first step to broadly assess the economic value of the impaired freshwater ES by considering the costs required for their restoration (Conte et al. 2011; Surber 2013).

Finally, concerning the overall method of ES interactions, it is worth noting the type of mapping used for the FwES, that derived information from different datasets and may include field measures or surveys, can help in reducing the elements of circularity in the overall outcomes (Spake et al. 2017). At the same time, it allows to compare and validate the results obtained with some InVEST models (the SDR model, in this case, derived on a tier-one level).

Further implementation of the FwES model could include continuous (or discrete) spatial data not limited to a binary mapping based on threshold values (Villamagna et al. 2013). Moreover, the use of CHUs derived from spatial units that are not standardized is another limitation of this study. The definition of standard hydrologic units, with dimensions smaller
than HUC-12 (Seaber et al. 1985), could be beneficial in regions such as the Appalachian Mountains where intricate dendritic drainage patterns characterize the landscape.

4.4. Implications for decision making and landscape planning in the region

In the study area, the landscape that emerged after the socio-technological reclamation phases following coal extraction has been characterized by different configurations and patterns over time. The complex articulation of anthropogenic processes and disturbances has led to different ES bundles, characterized both by the intensity of coal mining processes and their ongoing reclamation phases. ES bundles showed that distinctive ES interactions driven by extraction processes coexist in the study area with patterns derived from more general land dynamics, like those characteristic of suburban settings, which interact with the region’s specific features. Communities in the region are long struggling with socio-ecological problems connected to the coal industry and its boom and bust cycles (Bell 2016). Although coal-driven economy and production are generally fading in the Appalachian Coalfields (Zipper et al. 2021), fossil fuel-based industries still represent a dominant economy in WV (Pollin et al. 2021).

Nevertheless, further investments and efforts in the region should be driven by more sustainable approaches for the future and included in the much-needed phase of economic and energy transition (Taylor et al. 2017).

The ES bundles’ analysis depicted a broad heterogeneity among ES in the CHUs, with changes ranging from units in which the ES are overall strongly compromised (bundles one and three) to catchments that suggest the presence of ES hotspots (bundle five). The first set of observations concerns the characterization of a broad group of HUC-12 basins that includes the Lower Marsh Fork and the Clear Fork catchments (Figure 1). These catchments are characterized by heavily mined areas and by the largest number of ES bundles of type one and three, while several CHUs are impaired by selenium concentrations above the minimum levels. ES bundles one and three include catchments characterized by surface mining operations conducted before and after the SMCRA enactment in 1977, with reclamation processes at different stages. Bundle number one defines a strongly clustered group (Moran’s Index = .13, p-value = .00) where the effects of mining are relevant due to the proximity with MTR sites, to the presence of former surface mining operations, and often of underground mining. Bundle three, which generally coincides with MTR operations, is a clustered group (Moran’s Index = .036, p-value = .002) with the absolute lowest levels of ES delivery in the entire area.

Our findings suggest that although the application of post-SMCRA reclamation practices was limited to the mining permits of MTR areas or occurred on former surface mining areas characterized by limited reclamation processes, the negative impacts of surface mining operations spread out across broader areas. Indeed, remining operations were often authorized in the past on AML produced before the SMCRA and generally characterized by inadequate reclamation (Skousen and Zipper 2021). Nevertheless, the results of this study suggest that the operations conducted after the SMCRA enactment did not limit the negative impacts of MTR on neighboring areas and streams, confirming, even in this case, the general weaknesses in the outcomes of reclamation processes (Miller and Zégre 2014; Palmer and Hondula 2014; Reed and Kite 2020). This study confirms the image of a highly disturbed landscape, in which the reclamation processes of MTR sites and surrounding areas are characterized by a general loss of ES, where significant uncertainties mark future ES restoration. Even in the case of the catchments characterized by surface mining operations started before 1977, consisting mainly in strip-mining and high-wall operations, the ES models described a better recovery of ES; but, with conditions, persisting disturbances, and effects that we can imagine as long-lasting if no further reclamation is conducted. Recent estimates of AML found almost 2850 km² of unreclaimed land in the Appalachian region, mostly concentrated in Pennsylvania and West Virginia, with unreclaimed costs equal to $17.6 billion (Dixon 2021). Also, the presence of coal slurry impoundments and brownfield sites present significant risks for the local populations and ecosystems and would require challenging industrial remediation processes due to the high concentration of toxic compounds (like arsenic, cadmium, chromium, cobalt, lead, mercury, selenium) derived from the coal cleaning processes (Bell 2016; Ziemkiewicz 2019).

To intervene in the areas mentioned above, substantial investments may generally be required to complete or implement the overall poor reclamation outcomes of MTR operations. For example, industrial sites for coal processing, like coal impoundments, can be reclaimed, recovering rare earths and other valuable metals and providing economic attractiveness for the industry (Ziemkiewicz 2019; Thomas 2021). In addition, energy practices based on renewable energy, like large-scale photovoltaic systems, can be installed on former degraded lands in the region (James and Hansen 2017; Campoli et al. 2019). Methods like the Forestry Reclamation Approach (FRA) can be utilized to reclaim mined lands to forests and achieve healthy and productive forests (Adams 2017). In all these
cases, reclamation benefits can positively affect both ecological systems and local communities. As provided in the introductory section, ES methods can be utilized to assess future scenarios and discuss the tradeoffs and synergies among ES or with other social-ecological variables, including ES beneficiaries like local communities.

Other HUC-12 catchments in the study area are characterized by less extreme conditions with fewer areas impacted by former surface mining. In particular, the CHUs in bundle five have among the best ES values, particularly for the freshwater ES. While all the ES bundles in the study area are clustered (Moran’s Index > 0, p < .001), the fifth ES bundle has a scattered distribution (Moran’s Index = −.02, p-value = .51) (Figure 6). This last condition highlights that even if this group stands out from the more compromised ES bundles, the conservation of these areas is still subjected to significant risks. Previous studies in the MTR region of West Virginia highlighted the risks to which isolated streams and catchments are exposed, even when they present the most pristine conditions. Therefore, Merriam and Petty (2016) suggested that restoration should be implemented in areas with intermediate habitat quality. By making the spatial distribution and interaction of ES explicit, the current study results effectively locate the presence of isolated catchments with ES hotspots in the study area. The ES bundles can be utilized to establish an ecological network of protected areas with different functions and opportunities that may be integrated into a broader strategy for the rural-mining region. Consequently, actions to improve ES provision should be implemented by applying specific policies in bundles with intermediate ES values like bundles four, six, and two. These actions should also concern water quality improvements, such as updating the settlement sewage systems or addressing the conservation of forest stands growth on former strip-mined areas, and possibly completing reclamation process on marginal AML.

Another interesting finding involves the case of the catchment that includes the Stephen Lake (Figure 7, bundle five, id = 85), an artificial reservoir created in the late 60s. The lake’s catchment is included in the fifth bundle; above all, the number of visitors and the cultural value of this CHU are the highest in the study area. Two considerations need to be highlighted for this area. One concerns the potential that ‘built landscapes’ as part of a broader green infrastructure may have for the supply of ES (Benedict and McMahon 2006; Hansen and Pauleit 2014) and the relevance these practices may have among those promoted for a good Anthropocene (Bennett et al. 2016). Moreover, the relatively high number of visitors introduces the importance that spaces with public accessibility (in this case, the County owns the lake) may have on local populations or tourism in the area. This aspect may suggest that public greenways could be a relevant element to integrate into a successful conservation strategy for this region.

5. Conclusions

Our study confirms the importance of analyzing ES interactions using different spatial scales. The multi-scale assessments allowed us to understand relevant social-ecological relationships among the ES bundles, overcoming some of the traditional limitations of the method. Information derived at the smallest spatial scale utilized (CHU level) allowed us to reduce the heterogeneity of spatial data and tailor the results discussion on sets of social-ecological units where landscape management actions and policy improvements can be addressed focusing on specific issues, like landscape degradation, restoration, and substitutive technological processes. Our study confirms the importance of bespoke studies and the relevance of previous SES knowledge. In our case, the inclusion of historical datasets, used to disambiguate among otherwise uniform data, allowed us to discuss interactions with human and biophysical drivers that are fundamental for addressing the case analyzed and selecting ES metrics that can inform relevant ongoing processes in the landscape and their management. We suggest that the use of ES metrics utilized to address changes among ES, human well-being, and other habitat values should be applied to link ES studies to standard measurements relevant for environmental policy and landscape planning. In our case, the use of standard metrics for the freshwater ES derived from the Clean Water Act framework, although with the reported limitations, provided insight into the impacts of mining and other human pressures on ES changes in the study area examined. The study outcomes explained why blanket solutions are inappropriate in certain contexts while suggesting in-depth analysis for policy and decision-makers using different approaches tailored for different ES bundles.

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ORCID

Vincenzo Cribari @ http://orcid.org/0000-0002-7175-7196
Davide Geneletti @ http://orcid.org/0000-0002-5528-3365

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