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Article

Toward a Remote Sensing Solution for Regional Sustainability Assessment and Monitoring

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Abstract: Regional sustainability encourages a re-examination of development programs in the context of environmental, social and economic policies and practices. However, sustainability remains a broadly defined concept that has been applied to mean everything from environmental protection, social cohesion, economic growth, neighborhood design, alternative energy, and green building design. To guide sustainability initiatives and assess progress toward more sustainable development patterns, a need exists to place this concept into a functional decision-centric context where change can be evaluated and the exploitation of resources better understood. Accepting the premise that sustainable development defines a set of conditions and trends in a given system that can continue indefinitely without contributing to environmental degradation, answers to four critical questions that direct sustainability over the long-term must be addressed: (1) What is the present state of the environmental system, (2) Is that pattern sustainable, (3) Are there indications that the environmental system is degrading, and (4) Can that information be incorporated into policy decisions to guide the future? Answers to these questions hinge on the development of tractable indices that can be employed to support the long-term monitoring required to assess sustainability goals and a means to measure those indices. In this paper, a solution based on the application of remote sensing technology is introduced focused on the development of land use intensity indices derived from earth-observation satellite data. Placed into a monitoring design, this approach is evaluated in a change detection role at the watershed scale.

Keywords: sustainability assessment; remote sensing; development intensity; landscape metrics; environmental monitoring; principal components analysis

1. Introduction

While the concept of sustainable development is comparatively simple to understand, achieving sustainability within the context of the urban landscape is a more complex and uncertain activity [1]. Definitions abound characterizing sustainability as a level of human consumption or activity that can continue into the future without engendering environmental decline, and in each example, sustainability implies that a balance between the conflicting ideals of economic growth and environmental viability can be maintained [2,3]. This balancing process also assumes a poorly articulated temporal dimension over which components of the environmental system remain unperturbed while human welfare is enhanced. Time, in this equation, represents an indirect determinant of sustainability. However, its role and implications have not been widely examined. In practical terms, time rests at the center of sustainable development agendas, feeding back into the decision making arena as human actions are directed to meet sustainability goals. Persevering biological diversity, maintaining water quality, preventing soil degradation together with the remaining targets of what is means to develop "sustainably" can remain elusive when policy fails to integrate the temporal dimension into an evaluative framework.

Consideration of developmental sustainability over the long-term focuses attention on the vexing issues of measurement and assessment as well as the more complex questions that surround geographic and temporal scale [4]. Policy instruments that establish specific sustainability goals require well defined means to track progress and modify directives as regional development unfolds. Incorporating a monitoring requirement as an on-going element of sustainability policies, while crucial, remains a challenge due the recognition that: (1) sustainability represents a contested and value-laden ideal with characterizations that defy universal agreement [5,6], and (2) tractable sustainability metrics that integrate easily into the decision-making process remain largely conceptual in nature [7–9]. Moving the concept of sustainable development from the "theoretical" to the practical requires systematic temporal data collection that supports an accessible methodology whose products communicate decision-relevant information. In this paper, a methodology is presented that assists the assessment of development trajectories based on the analysis of data acquired from earth observation satellites. Through the application of remote sensing technologies, the spatio-temporal dynamics indicative of sustainability trends can be revealed and a series of decision products can be assembled to review and direct development directives.

2. The Assessment Question

In any decision making process, there is an implicit need to evaluate the ramifications of a choice before that choice is made. Examining the scope and consequence of an action as it unfolds is a familiar activity in the analysis of environmental impact [10]. This form of pro-active thinking, while understood in the context of environmental impact assessment, is far more complex when applied to the broadly defined concept of sustainability [11]. Complexity has contributed to the introduction of a range of assessment methods that target sustainability at a mix of global, national and regional scales, employing criteria ranging from the economic, social, and technological to the purely ecological [12,13]. Evaluating progress toward sustainability goals under these contrasting and often conflicting criteria, and across spatial scales that frustrate easy comparison, introduces a level of confusion that risks casting sustainability as essentially a political ideal with little scientific support [14,15]. For assessment to continue in a meaningful way, two important issues must be resolved: (1) questions regarding measurement, scale and definition, and (2) clarification of the specific target(s) of assessment.

Currently, sustainability assessment has been explained as (1) a tool to assist policy makers in selecting actions that contribute effectively toward realizing a sustainable society [16], or (2) a means to ensure that plans make an optimal contribution to sustainable development policies [17]. Categorizations of sustainability assessment tools reveal an array of approaches with a range of targets [18]. In the majority of examples, assessment relies on the development and subsequent application of a sustainability index; a summary measure that attempts to communicate a salient quality of a system relative to its capacity to function "sustainably". As illustrated in the literature, these indices are as diverse and contested as the definition of sustainability [9,15]. A listing of the more commonly cited sustainability indices has been compiled by Böhringer and Jochem [15]. Although the indices listed are not extensive, they demonstrate the difficulty of capturing the "root" characteristics that inform the concept of sustainability, further underscoring the larger matter of scale as it relates to the spatial and temporal dimensions that connect actions to the performance of both development policies and environmental outcomes [19,20].

2.1. Adopting a Regional Focus

When assessing sustainable development, it becomes necessary to determine where: (1) ecological functioning and human activities intersect with pronounced intensity [21] and (2) maintaining balance between ecological functioning and human actions is critical to resolving conflict when development trends induce adverse environmental patterns [22]. Recently, the regional focus that been advocated as the most appropriate scale for sustainability analysis and assessment [12,23]. At the regional scale, the complex interactions between ecological, social and economic phenomena are more closely linked within a landscape unit that can be delineated on the basis of anthropocentric criteria (*i.e.*, a watershed). Operating at this scale of analysis, indicator variability in a landscape subject to anthropocentric influences serves as an integrative signal of sustainability. Here, for example, the removal of a biological community, modification of a habitat, alteration in patch size of a land use parcel evidence unsustainable development and become a detriment to ecological stability. At this level of regional analysis, development trends that contribute to deviations in the degree of naturalness within the watershed unit, together with geometric patterns known to alter the distribution of energy, resources and species diversity should force a reconsideration of existing programs and guide management activities toward more sustainable arrangements. Realizing sustainability at the regional scale concentrates attention to the development and implementation of a tractable method of assessment that can encourage well-informed and timely reactions to changing landscape conditions. As suggested by Graymore *et al.*, such a method not only supplies information regarding the status of the system of interest, but is also holistic, quantifiable, policy relevant and simple to understand [24]. Presenting accessible information derived from easily obtained data that can address the spatial and temporal requirements for regional assessment introduces the remote sensing solution.

2.2. The Earth-Observation Alternative

The role of earth observation satellites in environmental analysis is well documented [24]. Remote sensing technology represents a well understood means of collecting earth-surface data without direct contact and its capacity to support sustainability assessment has been examined with promising conclusions [25–28]. The remote sensing alternative that earth observation systems represent concentrate focus on three central features of remote sensing science: (1) the capacity to derive unique measurements of landscape properties based on the analysis of electromagnetic energy reflected or emitted by objects at the surface, (2) a predictable repeat measurement cycle that enables orbital instruments to revisit a region of interest and monitor its status, and (3) an archival capacity that facilitates the storage and retrieval of surface measurements for time-sequenced analysis. By capitalizing on these system attributes, opportunities exist to exploit remote sensing and integrate this technology into an operational sustainability assessment program [29].

Integrating remote sensing with sustainability assessment hinges on the selection and application of scientifically sound indices. Such measures must aptly characterize landscape conditions and communicate relevant information regarding progress toward or away from sustainable development patterns [15]. Therefore, a useful index should not only quickly inform a target audience, but also reduce the complexity of a specific condition to those qualities or trends that clearly explain its disposition [24]. Several of the more critical attributes that influence the development of an indicator derived from remotely sensed data include:

- *General Relevance*—consideration of relevance helps to determine how well the indicator characterizes the environment and facilitates definition of process and change.
- *Conceptual Integrity*—integrity speaks to the overarching rationale, which may be theoretical or practical, which supports and justifies the use of the indicator.
- *Reliability*—focus on reliability centers around the question of how successful using the indicator will be now and over time, and the level of explanation that can be delivered based on its use.
- *Scale Appropriateness*—scale directs our attention to the ability of the indicator to detect the desired environmental quality at the appropriate temporal and spatial scale as dictated by the problem or purpose.
- *Statistical Sensitivity*—sensitivity relates to the level of measurement precision and accuracy that can obtained from the indicator as well as the level of confidence that can be ascribed to the results it produces when applied.
- *Robustness*—focusing on the potential for the indicator to produce consistent results under a range of external conditions and environmental perturbations, robustness directs selection to look critically at those factors that influence its capacity to deliver useful measures of the environment.

A variety of indices that summarize landscape conditions using remotely sensed data have been introduced. These measures range from vegetation transforms and landscape metrics to customized band ratios and statistical approximations [24]. The key to selecting an index relevant to the assessment of sustainability relates exclusively on its relationship to one or more quantifiable properties of the landscape that can be measured remotely. Relevance, in this context, is largely a function of how well that index can be connected by theory or practice to established environmental principles and resolved by a sensor instrument. The selected index, therefore, forms a fundamental spatial and temporal expression of the relationship between human activity and ecological balance. In this study, the concept of "intensity" was chosen to frame the analysis and a suite of ecological principles were identified that could demonstrate modifications of the landscape in a manner relevant to the general definition of sustainability. Evidence suggests that the intensity of human dominated landscape affects ecological processes of natural communities in observable ways and the more intense the activity, the greater the effect on those natural processes [30]. A fully developed land use system may display few functional natural ecological components, whereas the less developed land use system will possess ecological processes that remain largely intact [30]. Employing "intensity" as the assessment target, a set of measures can be identified to quantify distinctive patterns indicative of intensity shifts and associated deviations in ecological stability that may result [31–33]. To conform to the research design, the measures selected must be descriptive quantities that are:

- Derived from standard remote sensing data products
- Supported by empirical evidence to correlate with understood environmental processes, and
- Amenable to statistical analysis

These requirements narrow the list of applicable indices to metrics that not only summarize critical environmental conditions, but also serve as effective surrogates for human impact and activity. For this analysis, five measures were identified that fulfilled all requirements:

- *Normalized Difference Vegetation Index (NDVI)*—NDVI remains a widely used vegetation transform in the study of environmental process and change [34]. The index is a slope-based measure that combines the visible and near-infrared channels of a multispectral sensor to characterize the state and abundance of green vegetative cover and biomass. NDVI was designed to produce a measure that separates green vegetation from its soil background according to the relation:

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{RED})/(\mathrm{NIR} + \mathrm{RED}) \quad (1)$$

The result of the calculation produces values ranging from −1.0 to 1.0 where 0 represents the approximate value of no vegetation and negative values indicate non-vegetated surfaces [24,35].

- *Impervious Surface*—Artificial structures such as pavements, roads, roof tops that are covered by materials impenetrable to waters are indicative of the built-environment and the replacement of natural cover with urban surface. The degree of surface area that defines an impervious state serves as a useful indicator of development intensity and human induced modification of the landscape. Impervious surface has also been shown to induce hydrologic changes and impact water quality [36,37]. In this study, impervious surface was estimated based on land cover and NVDI using Boolean overlay and reclassification methods. High density urban cover and NDVI categories indicative of non-vegetated surface where selected from their respective raster layers. High density urban was reassigned the value of 1 and NDVI categories below −0.30 were reassigned values of 1 producing a simple 0 or 1 Boolean relationship that was combined into an impervious surface layer through GIS overlay.

- *Fragmentation*—As applied in this study, fragmentation explains the breaking up of a habitat or land use types into small parcels. As a spatial process, fragmentation is a contributing factor in land transformation stemming either from natural processes or as a consequence of human activity. In either instance, fragmentation can produce a range of ecological effects including loss of habitat area [38]. The Fragmentation Index identifies areas which have a high number patches in and strong decreasing area. The formula is represented by the following equation:

$$F = (n - 1)/(c - 1) \tag{2}$$

where n = number of different classes present in the kernel and c = number of cells considered.

- *Diversity*—As a landscape metric, this measure is one means to evaluate the relative number of parcels (patches) present in the landscape. In this study diversity was determined by the relation

$$\text{Diversity} = (p \times ln(p)) \tag{3}$$

where Σ is the summation of all land types in the study area, p is the proportion of each land type in the spatial unit of measure (pixel) and ln is the natural logarithm.

- *Dominance*—Serving as an expression of landscape stability, dominance describes the pattern explained by the most abundant land type [39]. In this study dominance is used to characterize the relative degree of environmental complexity according to:

$$\text{Dominance} = ln\ \mathrm{S} + \Sigma\ p_{\mathrm{k}} \times ln\ p_{\mathrm{k}} \tag{4}$$

where S is the number of habitat types, p_{k} proportion of area in habitat k.

Individually, each measure provides a means to integrate landscape ecological concepts into an environmental expression. Furthermore, as an applied metric they summarize the spatial dimension of landscape conditions in a manner sensitive to the requirements of sustainability assessment. As these indicators coalesce into a monitoring design through the use of earth-observational satellite data, they contribute to an adaptive management paradigm. As data feeds decision making and policy review, the continuing and dynamic nature of sustainability planning can be supported. The features of that monitoring design are introduced in the following section.

3. Methodology

It has been argued that sustainability identifies a goal that no one yet knows how to achieve [40]. A complicating factor in the process of planning and assessing sustainable development is largely a consequent of the heuristic nature of the problem. Incremental improvements toward a desired future state area realized through a combination of observing and responding to changes [41,42]. Monitoring becomes a pivotal activity in that process, and timely, cost-effective approaches are needed to make progress toward a sustainable system. The assessment and monitoring methodology developed in this study relies on the application of moderate-resolution data acquired from the Landsat system of satellites to feed a watershed-level assessment program. To demonstrate this approach, a time-sequence data set consisting of decadal Landsat 5 Thematic Mapper imagery was obtained beginning in 1989 and culminating in 2011. The Landsat 5 Thematic Mapper is a sun-synchronous satellite with a 16 day repeat interval. The sensor collects reflected electromagnetic radiation in 5 spectral bands with 30 meter spatial resolution and one and thermal channel with a spatial resolution of 120 meters. Landsat 5 was decommissioned on 5 June 2013 and replaced with Landsat 8, which became operational in mid-April of that same year. A Landsat image covers a geographic area of approximately 128 square kilometers that are organized in path and row scenes and index based on an identification numbering system that identifies image path/row location and time of year. The images used for this study are listed in Table 1.

Table 1. Landsat TM imagery used for analysis.

Image Date	Scene ID
17 May 1989	LT50190321989137XXX02
2 May 2001	8LT50190322001122XXX02
30 May 2011	6LT50190322011150EDC00

Anniversary dates during the leaf-on season were selected for a central Ohio location delineated by the Upper Scioto River watershed (Figure 1). Landsat overpass dates meeting a 0%–10% cloud-free requirement fell within May of each time slice, however perfect 10-year time increments were not possible which necessitated selecting the best available image. The satellite scenes for Path 19, Row 32 were converted to radiance values, geometrically registered to the 1989 base year and subjected to a dark-object subtraction. Dark-object subtraction was performed to remove any contaminating influences of the atmosphere. These pre-processing procedures insured that the imagery was a standardized as possible to permit change over time comparisons. Finally, a watershed mask consisting of the digital outline of the study area boundary was applied to each image set to preserve only the data that fell within the Upper Scioto River watershed for analysis. The watershed serves as an ideal natural delimiting feature for analysis and is a well understood organizing spatial unit for environmental assessment [43]. The Upper Scioto River watershed in Ohio exemplifies a landscape in transition. Comprising 1160 square kilometers, the watershed includes sections of nine counties that display a range of land covers and use patterns ranging from remnant forest and extensive agriculture to densely urbanized landscapes. Land development and urban growth pressures have been actively re-shaping the watershed over the last 20 years which has encouraged local jurisdictions to formulate urban growth management plans to accommodate projected population increases [44]. The interplay between population driven land use pressures and the desire to incorporate sustainability principles into the policy making process provides a realistic backdrop against which a monitoring and assessment methodology can be tested.

Analysis followed a three phase procedure (Figure 2). The initial phase centered on the calculation of the selected landscape metrics. For each time step in the study, the five landscape indices were derived from the imagery. To produce the landscape measures an unsupervised image classification procedure was used to create a sequence of land cover surfaces for the study area. The general method for generating the land cover data was based on a procedure adapted from Mundia and Aniya [45]. Unsupervised image classification employs a cluster analysis logic to identify natural groupings of pixels in the image based on their radiance values. The natural clusters are then interpreted and placed into informational classes that describe the land cover categories of interest. For this study, the method of K-means classification was selected. Initially, a 15 class solution was used to seed the process and following a post classification assessment of the clustering results, the initial K-means solution was refined by combining natural classes into to seven land cover (informational) categories. The final land cover classes were consistently applied across all image dates (High Density Urban, Medium Density Urban, Low Density Urban, Active Cropland, Bare Soil, Vegetated/Forest, Water). Because land cover forms the basis for the calculation of the landscape metrics used in this study, establishing the overall accuracy of the classification results frames the boundaries of confidence and error inherent to the interpretation of landscape patterns and change. Classification accuracy was determined using a procedure focused primarily on the 2011 land cover surface. Using land use maps published by the Mid-Ohio Regional Planning Commission together with aerial photographs acquired from the National Aerial Photography Program produced within 2 years of the 2011 date, a random sampling method was employed to collect 300 points across the study area. Random points were selected based on latitude and longitude expressed as decimal degrees and entered into an error matrix for calculation. Classification accuracies of the final land cover surfaces obtained by this method fell within the 86%–90% range across the data set. Classification accuracy was highest for Medium Density and Low Density urban cover while High Density urban cover and Bare Soil where subject to misclassification. Post classification clumping and merging were used to correct classification error maintaining an overall accuracy rate of 89% Confined by the 30 meter spatial resolution of the Landsat TM imagery, the 89% land cover accuracy produced from the K-means procedure was sufficient to the purposes of this study. Landscape metrics were then calculated using a 5 pixel by 5 pixel moving window from the land cover data set for each time step in the study using the Idrisi Selva geospatial analysis system.

Figure 1. Upper Scioto River Watershed.

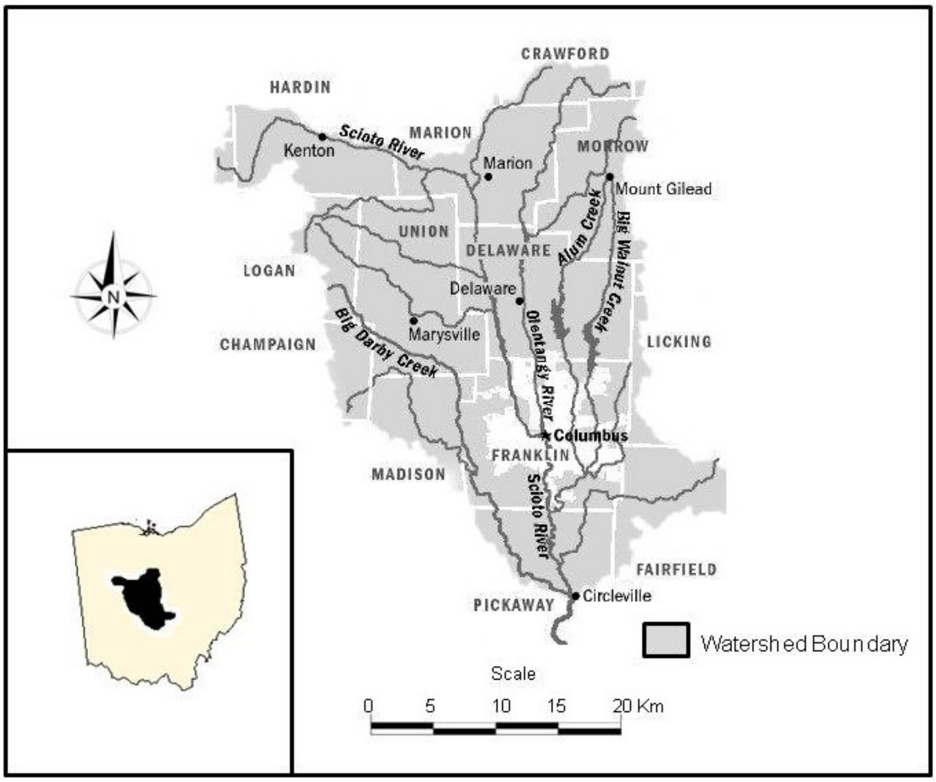
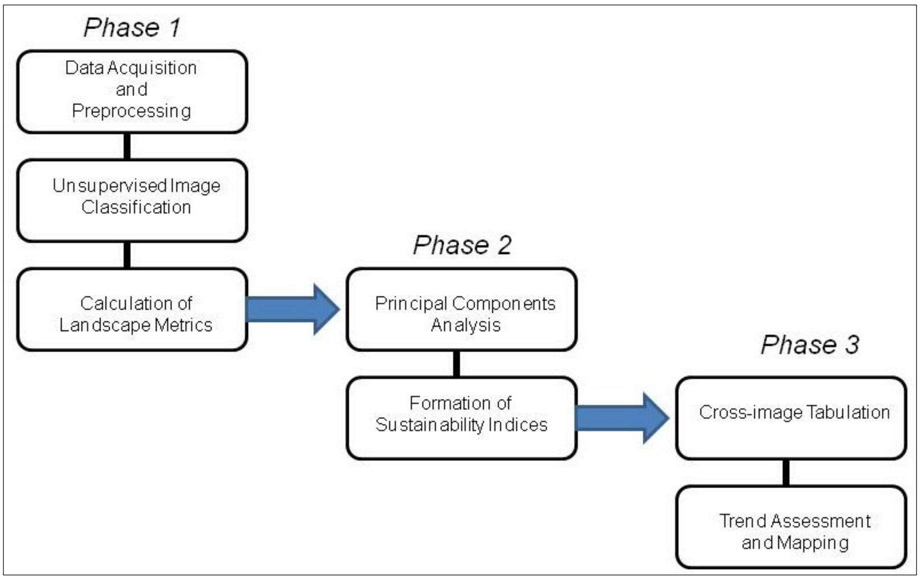


Figure 2. General methodology and work flow.



Phase two of this study concentrated on the formulation of a composite sustainability index from the intermediate descriptions of landscape condition produced in phase one. Producing a summary measure that could communicate policy-relevant information regarding the relationship between development and environment employed the method of Principal Components Analysis (PCA). Principal Components Analysis is a commonly used technique to compress data by truncating a set of variables, leaving out those which are of the least importance to the information stored in the data. The process is referred to as dimensionality reduction, where a vector containing the original data is reduced to a compressed vector of new, uncorrelated, underlying components. In this study, principal components analysis (PCA) was used to extract from the set of sensor-derived landscape variables a reduced set of components that accounts for most of the variance in the original data set. The results produce a linear combination of the p variables that form a summary index of "regional sustainability" determined by the interpretation of the pattern by-which the original variable contribute to the new component structure.

The final phase of analysis focused on evaluating the spatial and temporal variations in "regional sustainability". Numerous methods have been developed to examine the pattern of change in remotely sensed data [46–48]. Based on the goals of this study, the method of cross-image comparison was selected. Cross-image comparison is a GIS-variant of contingency table analysis. In a contingency table, values within each category have no intrinsic numerical value, but associations can still be detected. Accordingly, an association means that the distribution of frequencies across the levels of one category differs depending upon the particular level of another category. A significant association simply means that the values of one variable vary systematically (*i.e.*, at a level greater than chance) with values of the other variable. When there is no association between variables, they are described as being *independent*. Thus, independence in a two-way table means that there is *no association* between the row and column variables. When applied to mapped data, categories can be examined across time and changes between dates can be summarized. To facilitate cross-image comparisons the factor scores of the observations (pixels) produced from Principal Components Analysis for the "regional sustainability" variables were assembled into three ordinal categories (High, Medium, and Low) based on natural breaks in the data.

4. Results and Discussion

Producing quantitative expressions of regional sustainability has become a focal point of research [49]. The results of this study, employing remotely sensed data to derive measures relevant to the task of sustainability monitoring, are promising. Principal components analysis identified two latent structures from the data set with eigenvalues approximately 1.00 or greater consistently across the analytical time horizon. Beginning with the 1989 baseline year, correlations among the variables describe emerging relationships that separate ecological measure from the single metric that explains human activity (Tables 2–4).

Table 2. Correlation matrix for 1989 data.

Variable	Diversity	Dominance	Fragmented	NDVI	Impervious Urban
Diversity	1	0.723407	0.976255	0.891674	0.261840
Dominance	0.723407	1	0.794081	0.802705	0.207362
Fragmented	0.976255	0.794081	1	0.862341	0.251453
NDVI	0.891674	0.802705	0.862341	1	0.198566
Impervious Urban	0.261840	0.207362	0.251453	0.198566	1

Table 3. Correlation matrix for 2001 data.

Variable	Diversity	Dominance	Fragmented	NDVI	Impervious Urban
Diversity	1	0.702498	0.971592	0.865368	0.272676
Dominance	0.702498	1	0.794488	0.800350	0.359469
Fragmented	0.794488	0.971592	1	0.840738	0.274762
NDVI	0.800350	0.865368	0.840738	1	0.345045
Impervious Urban	0.359469	0.272676	0.274762	0.345045	1

Table 4. Correlation matrix for 2011 data.

Variable	Diversity	Dominance	Fragmented	NDVI	Impervious Urban
Diversity	1	0.660495	0.969890	0.423436	0.874922
Dominance	0.660495	1	0.771569	0.454202	0.770771
Fragmented	0.969890	0.771569	1	0.444827	0.852687
NDVI	0.874922	0.770771	0.852687	1	0.452494
Impervious Urban	0.423436	0.454202	0.444827	0.452494	1

Consideration of the eigenvalues derived from the correlation matrices further demonstrates this separation. In the 1989 example, two main structures in the data were determined; a component (C 1) that accounted for 72% of the variance in the data and component 2 (C 2), explaining a less dominant theme, accounting for 17% of the variance. The contribution of the original landscape variables to these new structures is given in Tables 5–7. Clearly, Component 1 is defined by the diversity, dominance, fragmentation and NDVI metrics. Here, loading patterns exceed 0.85 in all cases. The second component (C 2) is characteristic of the pattern on impervious surface, which loads positively on C 2 with a value of 0.94. Similar relationships were revealed across the time horizon (Tables 5–7).

Table 5. Variance Explained and Eigen-structure for 1989 PCA.

PCA Component	C 1	C 2	C 3	C 4	C 5
% Variance	72.220918	18.430777	6.290041	2.867761	0.190494
Eigenvalue	3.611046	0.921539	0.314502	0.143388	0.009525
Eigenvector 1	0.504174	−0.052883	−0.478352	−0.141023	−0.703068
Eigenvector 2	0.460339	−0.098888	0.832846	−0.225552	−0.183858
Eigenvector 3	0.508694	−0.067808	−0.275502	−0.482549	0.654124
Eigenvector 4	0.173745	0.982881	0.036795	0.046212	0.016359
Eigenvector 5	0.494914	−0.129503	−0.017105	0.833217	0.209156

Table 6. Variance Explained and Eigen-structure for 2001 PCA.

PCA Component	C 1	C 2	C 3	C 4	C 5
%Variance	72.780534	17.388555	6.340500	3.295886	0.194525
Eigenvalue	3.639027	0.869428	0.317025	0.164794	0.009726
Eigenvector 1	0.461910	0.014400	−0.816374	−0.265629	−0.222277
Eigenvector 2	0.492018	−0.198354	0.496694	−0.114981	−0.677236
Eigenvector 3	0.500570	−0.192417	0.242041	−0.447445	0.673509
Eigenvector 4	0.490975	−0.067764	−0.051447	0.844703	0.195400
Eigenvector 5	0.230066	0.958557	0.159995	−0.049905	0.012210

Table 7. Variance Explained and Eigen-structure for 2011 PCA.

PCA Component	C 1	C 2	C 3	C 4	C 5
% Variance	74.866979	14.448906	7.330705	3.177811	0.175589
Eigenvalue	3.743349	0.722445	0.366535	0.158891	0.008779
Eigenvector 1	0.482566	−0.232354	−0.470455	−0.159927	−0.682815
Eigenvector 2	0.441761	−0.012334	0.846468	−0.199333	−0.220120
Eigenvector 3	0.494663	−0.200491	−0.200131	−0.478633	0.667810
Eigenvector 4	0.307413	0.939835	−0.148628	−0.010582	0.002325
Eigenvector 5	0.482476	−0.149577	−0.004610	0.839934	0.198328

Based on these results, the overall variance explained by these two components show a dominant component consistently accounting for over 70% of the variance and a secondary trend that defined by 14%–18% of the variance in the original variables. The pattern of component loading, explaining how each variable contributes to these new measures, shows that diversity, dominance, fragmentation and NDVI maintain positive loadings on Component 1, with correlations on this new measure ranging from 0.87–0.96. Impervious surface, serving as a surrogate for land transformation where vegetated areas have been modified by some method of land development, contributed to the pattern defined by Component 2. Loading patterns for this variable ranged from 0.94–0.79 across the time period of this study (Tables 8–10).

Table 8. Pattern of Variable Loading 1989.

Loading	C 1	C 2	C 3	C 4	C 5
Diversity	0.958070	−0.050766	−0.268262	−0.053400	−0.068616
Dominance	0.874770	−0.094930	0.467064	−0.085409	−0.017944
Fragmented	0.966658	−0.065093	−0.154503	−0.182725	0.063839
NDVI	0.940473	−0.124318	−0.009592	0.315511	0.020413
Impervious Urban	0.330163	0.943535	0.020635	0.017499	0.001597

Table 9. Pattern of Variable Loading 2001.

Loading	C 1	C 2	C 3	C 4	C 5
Diversity	0.938585	−0.184952	0.279663	−0.046676	−0.066790
Dominance	0.881150	0.013427	−0.459659	−0.107832	−0.021921
Fragmented	0.954899	−0.179416	0.136281	−0.181640	0.066423
NDVI	0.936596	−0.063186	−0.028967	0.342906	0.019271
Impervious Urban	0.438879	0.893788	0.090085	−0.020259	0.001204

Table 10. Pattern of Variable Loading 2011.

Loading	C 1	C 2	C 3	C 4	C 5
Diversity	0.933657	−0.197493	−0.284823	−0.063749	−0.063979
Dominance	0.854708	−0.010483	0.512470	−0.079456	−0.020625
Fragmented	0.957060	−0.170411	−0.121163	−0.190788	0.062573
NDVI	0.933482	−0.127136	−0.002791	0.334807	0.018583
Impervious Urban	0.594775	0.798829	−0.089983	−0.004218	0.000218

The results of PCA suggest two dominant landscape characteristics within the study area that remained consistent over the 1989–2011 time horizon: (1) an *ecological integrity* condition derived from the diversity, dominance, fragmentation and NDVI surfaces, and (2) and *development intensity* condition, a less dominant feature, defined primarily by the presence of impervious surface. These components communicate fundamental constructs embedded in the concept of sustainability:

- A description of *integrity* that explains the spatial pattern of the natural system and the degree of naturalness that can support ecosystem services, and
- A pattern of *intensity* defining the pattern of human landscape modification and the degree to which ecological services may be compromised.

Insight regarding the spatial distribution of the resulting regional sustainability metrics can be gained by observing the component scores produced via PCA. The component scores document quantitatively the value of each observation (pixel) in relation to the new component index expressed in units of standard deviation. According to this logic, a positive standard score represents a datum above the expected values (mean) while a negative standard score represents a datum below the mean for that condition. For example, *ecological integrity*, displays scores that ranged from −4.0 for predominantly water surfaces to 10.0 for homogeneous vegetated cover. Comparing these scores back to the original landscape metrics from which *ecological integrity* was derived shows these regions to be dominated by comparatively high values of NDVI and low rates of fragmentation (Figure 3).

Development intensity reveals a pattern strongly directed by the form of urban settlement. Areas of dense urban development exhibited scores of 4.0 or higher. Vegetated surfaces occupied the range below 0.0 with highly pervious land types displaying scores from −1.0 to −3.0 (Figure 4). Careful inspection of these results suggest that as land development pressures expand the pattern of development intensity in the watershed, a relative contraction in ecological vitality should be observed. Extending this relationship forward, as the watershed becomes less stable, policy makers may conclude that regional sustainability becomes compromised.

Figure 3. Component score for *ecological integrity:* (**a**) 1989, (**b**) 2011.

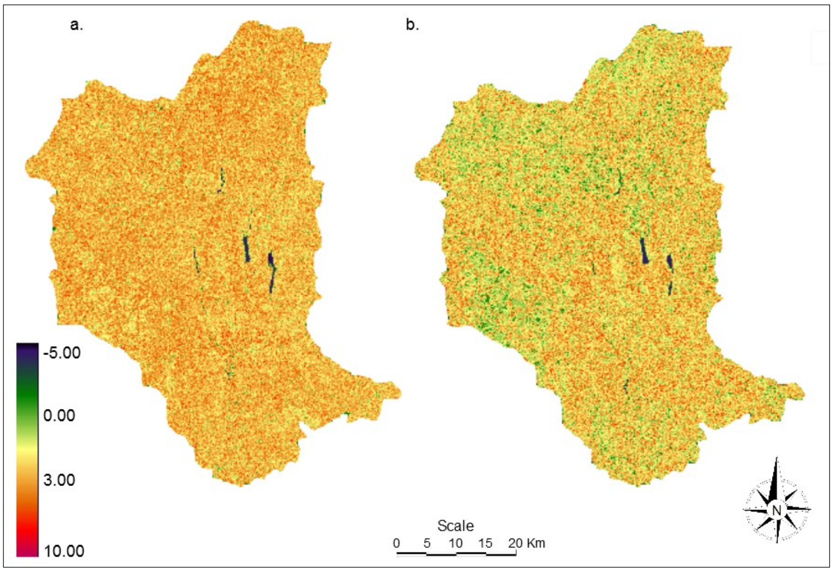
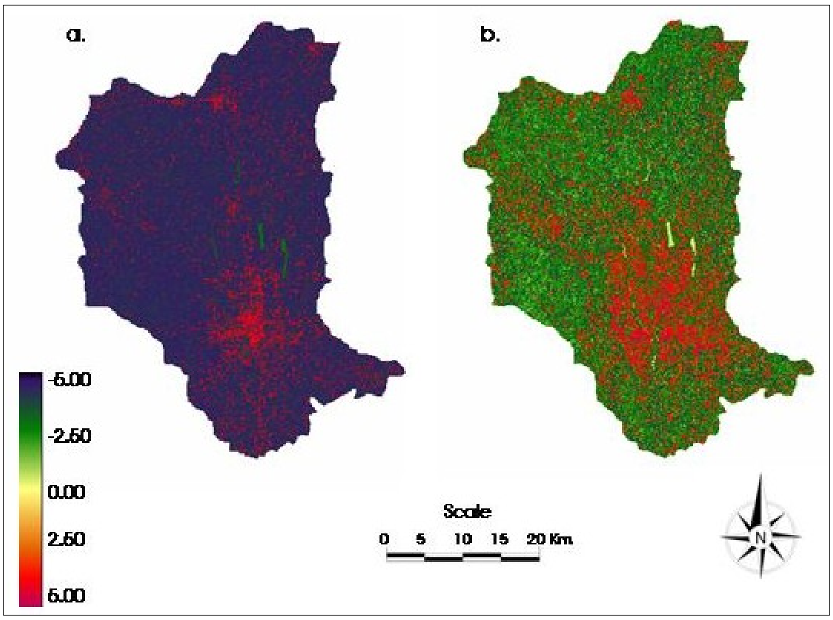


Figure 4. Component score for *development intensity:* (**a**) 1989, (**b**) 2011.



Across the 1989–2011 time horizon, detectable trends in both *ecological integrity* and *development intensity* evidenced a clear inverse relationship as population growth pressures directed the rate and location of land transformation. During this time period, urban expansion within the watershed witnessed rates of population growth from 5% in the north to rates exceeding 30% southward, converging on the city of Columbus and radiating along transportation corridors (Mid-Ohio Regional Planning Commisson2012). Quantifying the temporal variations in *ecological integrity* and *development intensity* resulting from population trends was accomplished using cross-image tabulation. Using this approach, both the form and significance of the 1989–2011 transition could be assessed. The full cross-tabulation matrix evaluating the 1989–2011 transition is given in Table 11.

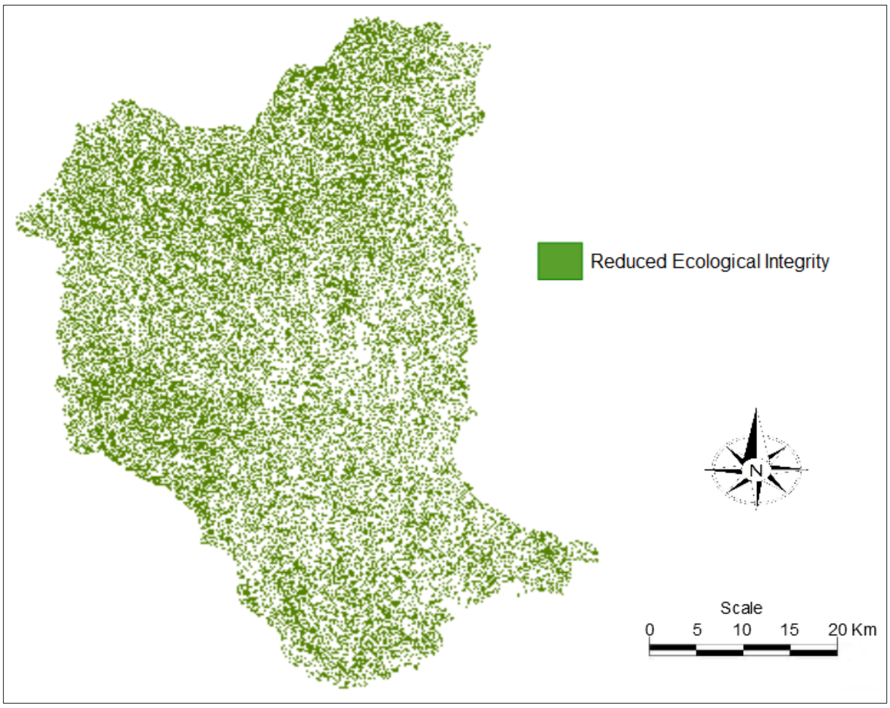
Table 11. Ecological Integrity cross tabulation results, 1989 (rows) 2011(columns).

Ecological Vitality Class	Category 1 (Low)	Category 2	Category 3 (Moderate)	Category 4	Category 5 (High)
Category 1	15744	5102	2115	608	18
Category 2	1287	26,546	86,358	37,911	1136
Category 3	1664	436,926	1,981,871	1,074,213	31,771
Category 4	1539	439,211	2,614,321	1,738,913	59,240
Category 5	25	6487	42,950	31,984	1346

Chi Square = 90,203,448.0; degrees of freedom = 25; p-level = 0.000; Cramer's V = 0.5524; Kappa = 0.6854.

As detailed in Table 11, two shifts in ecological vitality can be noted. The first shift shows a dominant transition from areas of moderately high stability to lower vitality categories. A more subtle change from the highest stability class to a lower status is also observed. Statistically, when *ecological integrity* is compared between 1989 and 2011 the differences are significant as shown by the Cramer's V index of 0.55 at the p-level of 0.00. Using the overall Kappa statistic as a measure of association, the 0.68 value suggests only moderate agreement between map categories between these dates. Examination of the spatial pattern shows shifts in ecological vitality occurring largely at the periphery of the study area following the well understood markings of urban sprawl and infilling (Figure 5).

Figure 5. Spatial pattern of ecological integrity changes 1989–2011.



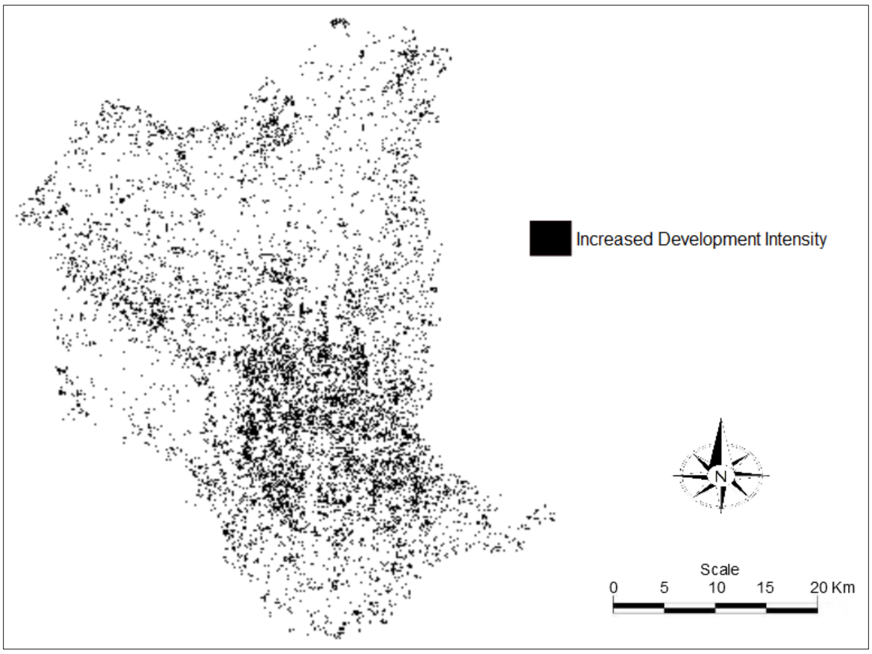
Temporal changes in *development intensity* over the time period document the transition from low density land types to categories describing more dense forms of urban land cover (Figure 6). Although the statistical association between the two time periods is stronger (Cramer's V = 0.73, *p*-level 0.00), the degree of agreement between map categories on a sample by sample basis remained only moderate (Kappa = 0.61) (Table 12).

Table 12. Development Intensity cross tabulation results, 1989 (rows) 2011(columns).

Development Intensity Class	Category 1 (Low)	Category 2	Category 3 (Moderate)	Category 4	Category 5 (High)
Category 1	2,388,730	3,673,077	4979	691,886	1,182,817
Category 2	644	3191	16,600	110	84
Category 5	17,6717	235,858	554	66,320	197,737

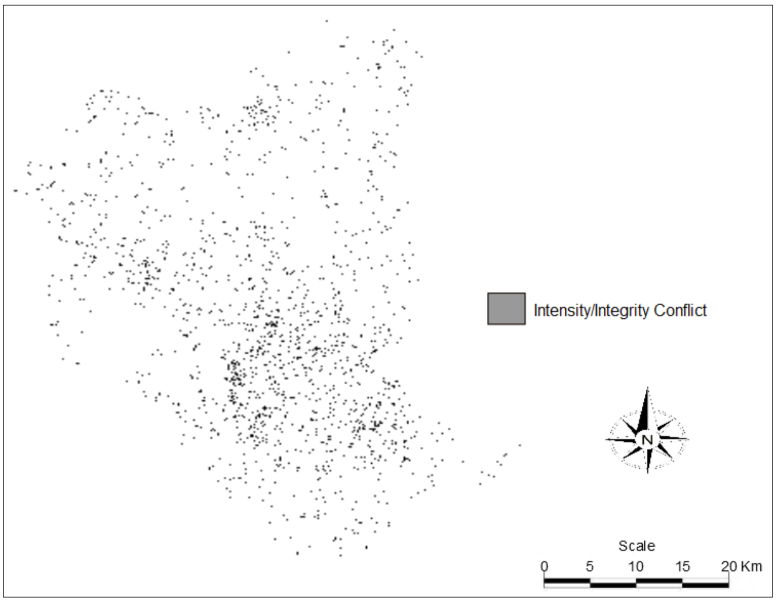
Chi Spare = 95,465,440.0; degrees of freedom = 15; *p*-level = 0.000; Cramer's V = 0.7336; Kappa = 0.6136.

Figure 6. Spatial pattern of development intensity changes 1989–2011.



Within the watershed, variations in development intensity correspond with the pattern of urban spread, following a general southeast to northwest axis. Locations with the highest levels of development intensity were spatially coincident with areas of lowest ecological integrity. This pattern was revealed when these two surfaces were subject to simple GIS overlay. The resulting GIS data layer serves to document the impact of change in the region, highlighting locations where the conflict between intensity increases (urban development and urban spread) and integrity declines (decreasing NDVI, diversity and dominance and increasing fragmentation) are evident. (Figure 7). At this regional scale, two critical conditions suggest modifications that threaten sustainable development: (1) areas where ecological functioning and human activities intersect with pronounced intensity, and (2) areas where the balance between ecological functioning and human actions are in opposition. These central targets of sustainability assessment are critical to resolving conflict when development trends induce adverse environmental patterns. Furthermore, by placing these targets in a spatial context their regional pattern can be "seen" and policy initiatives can be directed specifically at those locations to remediate the adverse situation.

Figure 7. Spatial pattern of potential areas of reduced sustainability.



5. Conclusions

The concept of sustainability and the challenge of sustainable development have been a focus of interest for over two decades. Although the definition of what it means to develop sustainably has been expressed in general terms, moving from the conceptual to the practical and casting sustainability as an actionable and measurable quantity has proved difficult. In a comparatively short time, numerous approaches have been introduced to measure this broad ideal and assess its status at the global, national and regional scale. Of the methods introduced, each aim to address the interaction between human activities and their environmental outcome to better guide how decisions and policies are made within governmental and corporate entities. In the process, each approach has quantified sustainability using different criteria with contrasting objectives, producing a confusing mix that frustrates singular applications. As progress moves toward implementing sustainability assessment strategies, there is a need to ascertain the appropriate spatial and temporal scales at which sustainability, and more specifically, sustainable development, is effectively explained. In this paper, an approach to sustainability assessment was introduced that relied on the application of data acquired from earth-observational satellites in a statistically based procedure to derive functional decision-centric measures that communicate the interaction between human development activities and ecological process. The goal of this research was to craft a tractable methodology that could be accomplished with limited resources and maintained over an extended planning horizon. Through the use of landscape metrics derived from land cover surfaces produced using Landsat TM imagery, an index of *ecological integrity* and an index of *development intensity* where identified though results produced from Principal Components Analysis (PCA) at the watershed scale. Development intensity, representing a driving force and ecological vitality explaining a consequence, encapsulate two important dimensions of sustainable development that suggest policy relevance.

The PCA-derived indices were placed into a monitoring design using a retrospective approach to examined development trends in the study area for the period 1989 through 2011. Employing GIS-based cross-image comparison, regional development trends enabled the assessment of vitality shifts, revealing an association between the expansion of urban land pressures and ecological declines over the analytical time horizon. When the geographic coincidence of vitality declines and development expansion was explored, the spatial pattern of reduced sustainability was observed in a manner that could quickly inform decision makers to modify policy directives where adverse change was apparent. The results of this investigation and the methodology used to produce the regional measures of sustainability are instructive. Although preliminary, the indices obtained and the procedures described in this paper suggest that at the watershed scale of analysis, an assessment protocol can be crafted to support efforts to monitor human activities and explain, in an ecologically sensitive manner, whether development is compromising the long-term sustainability of the local environmental system. Future research will concentrate on the predictive value of the PCA-derived indices and their ability to generalize to other geographic locations.

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Conflicts of Interest

The author declares no conflict of interest.

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