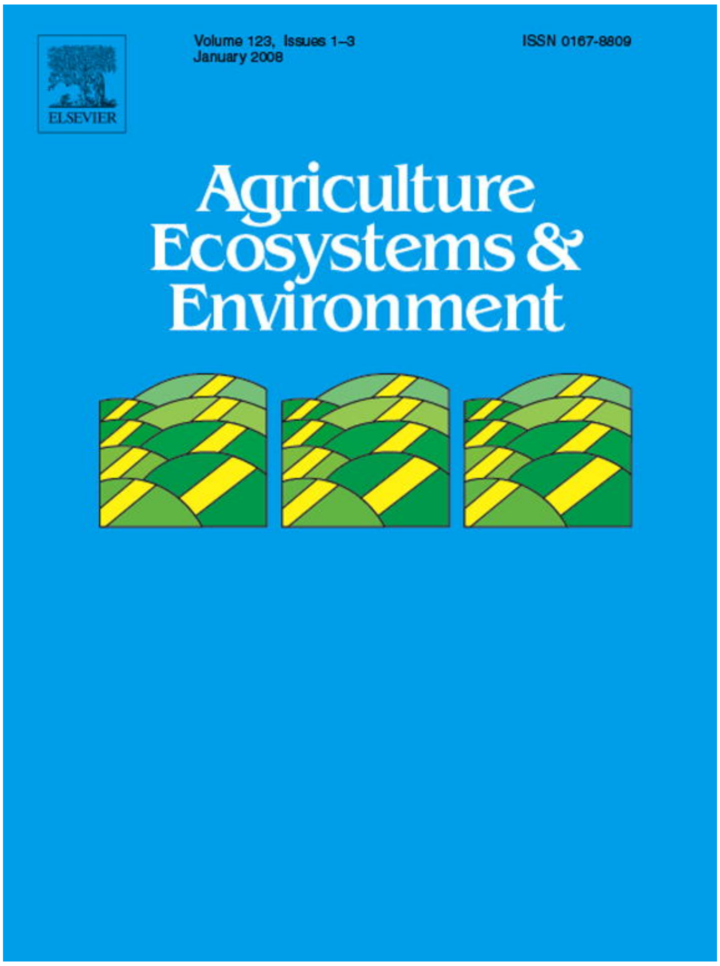
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Agro-ecoregionalization of Iowa using multivariate geographical clustering

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Abstract

Agro-ecoregionalization is categorization of landscapes for use in crop suitability analysis, strategic agroeconomic development, risk analysis, and other purposes. Past agro-ecoregionalizations have been subjective, expert opinion driven, crop specific, and unsuitable for statistical extrapolation. Use of quantitative analytical methods provides an opportunity for delineation of agro-ecoregions in a more objective and reproducible manner, and with use of generalized crop-related environmental inputs offers an opportunity for delineation of regions with broader application. For this study, raster (cell-based) environmental data at 1 km scale were used in a multivariate geographic clustering process to delineate agroecozones. Environmental parameters included climatic, edaphic and topographic characteristics hypothesized to be generally relevant to many crops. Clustering was performed using five *a priori* grouping schemes of 5–25 agroecozones. Non-contiguous geographic zones were defined representing areas of similar crop-relevant environmental conditions. A red–green–blue color triplet was used for visualization of agroecozones as unique combinations of environmental factors. Concordance of the agroecozones with other widely used datasets was investigated using MapCurves, a quantitative goodness-of-fit method. The 5- and 25-agroecozone schemes had highest concordance with a map of major land resource areas and a map of major landform regions, with degree of fit judged to be good. The resulting agroecozones provide a framework for future rigorous hypothesis testing. Other applications include: quantitative evaluation of crop suitability at the landscape scale, environmental impact modeling and agricultural scenario building.

Keywords: Agroecopause; Agroecozone; MapCurves; Multivariate geographic clustering

1. Introduction

Identification of relatively homogenous regions of expected crop performance within landscapes has potential benefits for improved agricultural policy formation and resource conservation (USDA, 2006). Agro-ecoregionalization has been used to identify land resource potentials and limitations relevant to agriculture in spatially explicit terms. Agroecozones (AEZs) serve as fundamental geographic units providing information on the location and extent of crop-relevant resources, their capabilities, and the potential for future uses as part of strategic planning (Fan et al., 2000; Swinton et al., 2001; Liu and Samal, 2002; Munier et al., 2004; Patel, 2004). Previous AEZ delineations (e.g., FAO, 1996; Caldiz et al., 2001; Swinton et al., 2001) have been crop specific, utilizing detailed information on crop requirements, and have relied on expert opinion and hierarchical frameworks. Regionalizations that depend on observer interpretations on the basis of personal experience are unsuitable for statistical extrapolation (Metzger et al., 2005). Hierarchical approaches are affected by the order of inputs, and require the subsuming of lower-level processes within higher order regions, which requires *a priori*

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understanding of landscape structure and function (Liu and Samal, 2002; Zhou et al., 2003). Regions defined by these methods then, are highly, if not entirely subjective, and are generally not reproducible (Bunce et al., 1996; Bernert et al., 1997; Swinton et al., 2001; Liu and Samal, 2002; Leathwick et al., 2003; Hargrove and Hoffman, 2004; Thompson et al., 2005). Additionally, traditional AEZ delineation approaches fail to identify transition zones between AEZs (Liu and Samal, 2002), adding further ambiguity to boundary location and meaning. To use statistical inference in landscape analysis of agricultural problems, stratification of land into relatively homogenous regions using an objective aggregation approach is necessary (Metzger et al., 2005).

Crop growth simulation models have been used to predict crop yields, and would seem to lend themselves to AEZ delineation. While these process-based models provide excellent yield forecasting within fields, they have limited application across large geographic regions because: (1) the point-like experimental plots upon which they are parameterized are not representative of environmental conditions of larger areas (Kravchenko and Bullock, 2000; DeWit et al., 2005); and, (2) many models are based on ideally managed crop systems generally not representative of environmental and management heterogeneity within regions (Wassenaar et al., 1999; Hansen and Jones, 2000; Batchelor et al., 2002; Viglizzo et al., 2004).

In response to the limitations of expert opinion-based modeling, hierarchical frameworks, and location-specific process-based growth models, a number of analytical methods of regionalization have been developed with applicability to agroecozoning. Multivariate models are popular owing to the particular advantages of objectivity and explicitness, greater defensibility, and improved transferability (Hargrove and Hoffman, 2004; Pullar et al., 2005). Growth in computing power and increased availability of spatially explicit environmental data has made the analytical approaches increasingly feasible (Leathwick et al., 2003; Zhou et al., 2003). Geographic information systems (GIS) have also been critical to the development of regionalization models (Pariyar and Singh, 1994; Ghaffari et al., 2000; Patel, 2004). Geographic information systems enable use of spatial data in a digital environment, integration of data from separate scales, and have application for data developed for agricultural research (Corbett, 1996). While GIS reduces subjectivity in the delineation process, its use is no guarantee of objectivity if ‘‘manual methods’’ or other expert opinion-driven methods are simply transferred to the digital environment. Use of multivariate models in combination with GIS, however, may offer improvements toward greater objectivity and repeatability.

States within the U.S. Midwest are rapidly transforming their economies to embrace bio-based industries such as biofuel production (e.g., CIRAS, 2002; Battelle, 2004). Crops not currently grown as commodities are likely to be important elements of this transformation. Limiting factors of potential alternative crops may not be well understood across the entire range of adaptation, and therefore may be problematic for traditional AEZ delineation methods (FAO, 1996). For example, switchgrass (*Panicum virgatum*), a perennial grass currently under scrutiny as a potential dedicated energy crop, is a highly variable species with a wide range of ecotypes (Boe, 2003). Significant management $\times$ cultivar $\times$ environment interactions that affect survival, growth and yield have been reported (Sanderson et al., 1999; Lemus et al., 2002; Casler and Boe, 2003; Heaton et al., 2004; Van Esbroeck et al., 2003; Berdahl et al., 2005; Casler, 2005; Cassida et al., 2005; Lee and Boe, 2005; Virgilio et al., 2007). Therefore, a method for producing more generalized AEZs, as an alternative to traditionally delineated AEZs, may be beneficial.

The purpose of this study was to delineate AEZs using a quantitative analytical approach. The aim was to identify different combinations of environmental factors as distributed spatial units of similar potentials and limitations, and that would have broad application to numerous crops, including potential alternative crops. We defined AEZs as areas of similarity of combined crop-relevant climatic, topographic and edaphic conditions. Principal components analysis (PCA), and multivariate geographic clustering (MGC) in combination with a red–green–blue color triplet were used to delineate AEZs (Hargrove and Hoffman, 1999, 2004). Capture, storage, and preliminary preparation of digital environmental data were conducted in a GIS. Visualization and display of the AEZs were also conducted in the GIS. A quantitative comparison with two existing categorical land regionalizations was conducted using a goodness-of-fit model. We use Iowa, USA, as a case study to demonstrate our method and its potential applications.

2. Materials and methods

2.1. Study area

The study area was Iowa, USA, a world leader in corn (*Zea mays* L.) and soy (*Glycine max*) production (IDALS, 2004). Iowa is located between 89.5° and 96.5° west longitude, and 40.5° and 43.5° north latitude. Total area of Iowa is 145,743 km^2, and elevation ranges from 146 to 509 m above mean sea level. Iowa's climate is humid continental, moist year round with long, hot summers (Strahler and Strahler, 1984). Principal soil orders are mollisols, alfisols, inceptisols and entisols (NRCS, 1999). About 89% of the land area of Iowa is in cultivation, and corn and soybean account for 93% of total land area harvested (IDALS, 2004). Iowa is likely to experience major agricultural transformation in the 21st century in response to perceived bio-based economic opportunities (ISU Biorenewables Office, 2003).

2.2. Development of the environmental dataset

We have taken a ''generic'' approach in quantitative regionalization of land resources by including in our models environmental parameters hypothesized to be potentially growth limiting for a wide variety of crops. Our aim was to categorize land resources in a way that is relevant to crops which are functionally, anatomically, and physiologically different from each other (i.e., have different limiting factors). Parameters chosen for the dataset were based on those described by Nix (1981), Loomis and Connor (1992), Prentice et al. (1992), Booth (1996), FAO (1996), and Young et al. (1999). Mean values of environmental predictors within spatial units of analysis (e.g., raster cells) were reasoned to be relevant to crop performance within spatial units. Variability, or dependability, of environmental parameters within analysis units was also reasoned to be relevant to crops. Therefore, standard deviations of environmental parameters were included in the dataset. Environmental parameters fell into three categories: climatic, topographic, and edaphic. Environmental data were obtained digitally and subsequently stored, managed, manipulated, and displayed in ArcGIS 9.1 (ESRI, 2005).

Eight climate parameters were included in the models (Table 1). Climate parameters were derived from daily weather observations for the period 1985–2004, at 98 National Weather Service Cooperative Stations (NWSCS) evenly distributed across Iowa (Fig. 1; IEM, 2005). This network provides the highest spatial density of observations for the parameters of interest and for the period of observation. To widen the inference window beyond state boundaries, daily weather data from ten additional NWSCS among the six adjacent states were included in the dataset (Fig. 1; HPRCC, 2005; MRCC, 2005; MCC, 2005). Growing season was determined for each observation station as the number of days between the mean day-of-year in spring with less than 20% chance of the air temperature falling below 0 °C, and mean day-of-year in fall with a greater than 20% chance of the air temperature dropping below 0 °C. Climate parameters were calculated as means and standard deviations across the period of observation. Mean and standard deviation values of climate parameters at each observation station were then used to interpolate a raster surface of 1 km resolution using ordinary kriging (ArcGIS 9.1 Geostatistical Analyst; ESRI, 2005). Kriging has been shown to have better results than other methods of spatial interpolation for estimating climate characteristics, and to be visually more plausible (Collins and Bolstad, 1999). The kriging method of spatial interpolation was therefore chosen for its conceptual straightforwardness, suitability for the data, and interactive modeling approach in ArcGIS (9.1; ESRI, 2005). For each climate parameter an iterative process was used to create the best-fit model (e.g., least weighted squared error). Interpolation included a maximum of six neighbors (minimum of three). In each case the spherical model provided the best fit, and residuals were randomly distributed. An example of the spatial distribution of prediction error is presented in Fig. 2.

Ten topographic parameters were included in the models (Table 2). Many topographic characteristics can be described as ''spatially permanent''. That is, such characteristics change very little over time, especially compared to weather and climate, which change more rapidly over time at a location. The mean of a topographic characteristic within a spatial unit is useful for making comparisons among spatial units. However, we argue that amount of dispersion around a mean is also a desirable description of heterogeneity of spatially permanent environmental characteristics. For example, two spatial units may have the same mean elevation, but very different standard deviations. A spatial unit with higher standard deviation of mean elevation has greater topographic relief than a spatial unit with smaller standard deviation. This type of difference among spatial units may be relevant to differences in crop productivity among spatial units. Therefore, means and standard deviations of topographic characteristics are included in the models. Topographic parameters were derived from the publicly available national elevation dataset (NED; USGS, 1999) in raster format at 30 m resolution, and resampled to 100 m resolution (ArcGIS 9.1; ESRI, 2005). The NED

Table 1
Summary of climate parameters

Parameter	Units	Description
Mean annual precipitation	mm	Total annual precipitation averaged for 1985–2004
Standard deviation of mean annual precipitation		Amount of interannual variability of total precipitation
Mean growing season length	Days	Total number of days between date in spring of 20% or less probability of frost, and date in fall with 20% or greater probability of frost, averaged for 1985–2004
Standard deviation of mean growing season length		Amount of interannual variability of growing season length
Mean growing season precipitation	mm	Total precipitation between frost-free dates, averaged for 1985–2004
Standard deviation of mean growing season precipitation		Amount of interannual variability of growing season precipitation
Mean growing season heat units	°C	Total number of °C above 0°, between frost-free dates, averaged for 1985–2004
Standard deviation of mean growing season heat units		Amount of interannual variability of growing season heat units

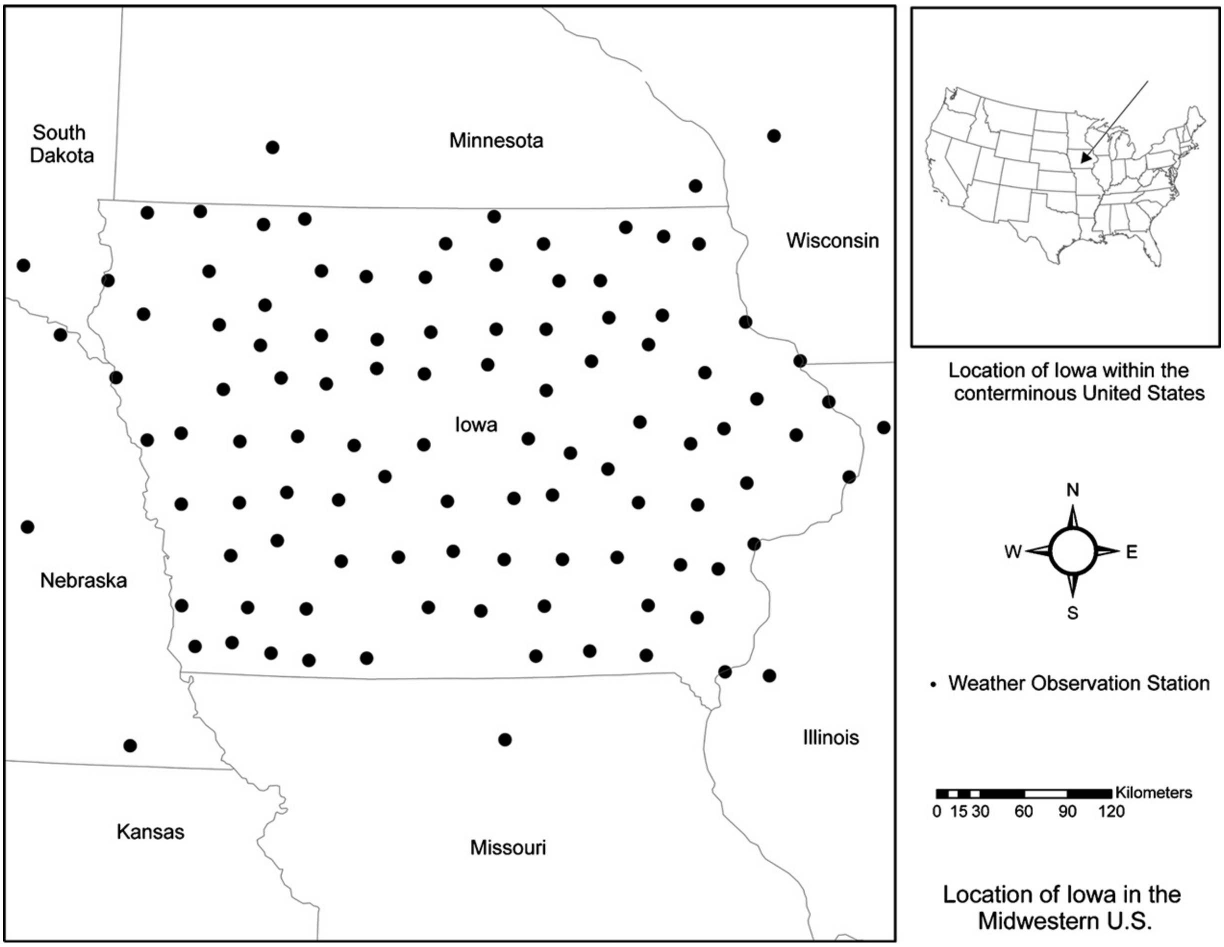

Fig. 1. The study area within the conterminous U.S., and the National Weather Service observation network within the state of Iowa.

consists of merged sets of digital elevation models (DEMs) at the 1:24,000 scale for the conterminous USA. The NED provides the best available data, and is updated bi-monthly. The source data are US Geological Survey 7.5-min (30 and 10 m resolution) DEMs. Vertical accuracy of the NED is estimated as ±7–15 m (USGS, 2007). Means and standard deviations of topographic parameters were calculated using the Zonal Statistics Tool and a 1 km raster in ArcGIS 9.1 (ESRI, 2005).

Fourteen soil parameters were included in the agroecozone models (Table 3). Soil data were obtained from the publicly available Iowa Soil Properties and Interpretation Database 7.0 (ISPAID, 2004), which consists of rasterized soil maps originating from the Natural Resource Conservation Service, including the SSURSGO and STATSGO datasets (ISPAID, 2004). The ISPAID dataset contains values for selected soil characteristics from the top 18 cm of soil, in a raster format at 100 m resolution. Similar to topographic characteristics, we included spatial means of soil parameters as variables in our models, as well as standard deviations of soil characteristics. Means and standard deviations were calculated using the Zonal Statistics Tool with a 1 km raster in ArcGIS 9.1 (ESRI, 2005).

2.3. PCA and multivariate geographic clustering

Agroecozones were created using PCA and MGC following a procedure described by Hargrove and Hoffman (2004). The MGC method utilizes a non-hierarchical k-means algorithm consisting of a reversible transformation between two realms: one in two-dimensional geographic space and one in multidimensional data space. First, normalized variable values for each raster cell were used in a PCA (SAS Institute Inc., 2001) where 32 components were retained to create 32-dimensional data space. Using varimax rotation, the 32 components formed 32 orthogonal axes in the data space into which each cell was then plotted. Similarity of cells within the 32-dimensional data space was then coded as Euclidean separation distance. Cells were then grouped using an iterative algorithm beginning with a user-specified number of agroecozone clusters k. Map cells were examined sequentially to find the most widely separated cells to provide initial centroids, one for each cluster. Each map cell was then assigned to the closest centroid and the coordinates of cells within a group were averaged to produce a new, adjusted centroid for each cluster. Iterations continued until less than one half of one percent of the cells changed cluster assignments during an iteration. Cells

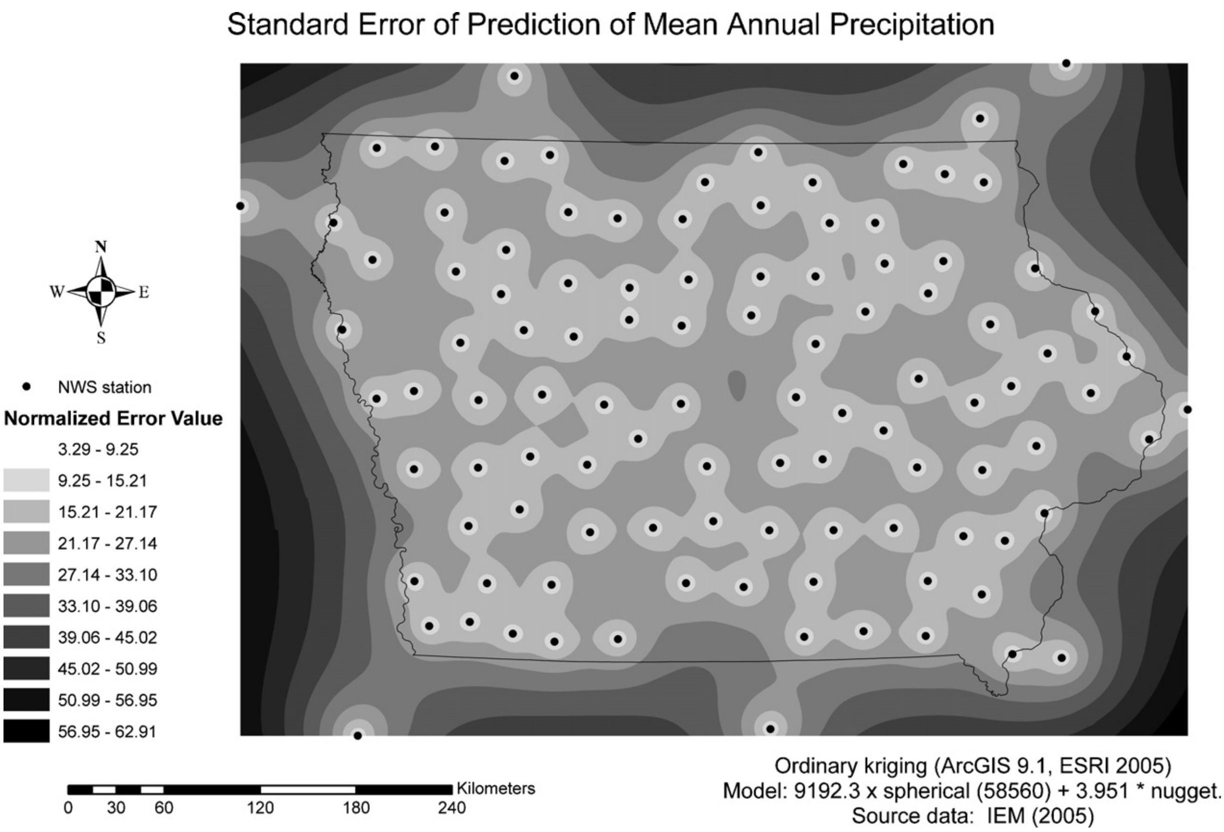

Fig. 2. Spatial distribution of estimation error associated with interpolation of mean annual precipitation. Error is greatest near and beyond state borders, and near the geographic center of the state where fewer weather observation stations are located.

were then reassembled in geographic space and mapped with a red–green–blue (RGB) color triplet created from the top three PCA components (Hargrove and Hoffman, 2004). The unique color of each AEZ was derived by the mixture of RGB determined by relative contribution of each of the top three components to each AEZ, and reflects the degree of similarity among AEZs. Advantages of MGC include production of self-seeded, self-describing zones, and similarity of environmental heterogeneity among zones.

Here, use of PCA was not for reduction of dimensionality (i.e., parsimony) for which it is conventionally used. Rather, it permitted: (1) use of all the variability of the data to discriminate agroecozones; (2) transformation of raster cells back into geographic space with ecologically relevant units; and, (3) the assignment of colors to AEZs using the first three components with the RGB color triplet.

2.4. Comparison to other categorical maps

The 5-, 10-, 15-, 20-, and 25-agroecozone maps were compared with two existing categorical land regionalizations: the Major Land Resource Areas of Iowa (NRCS, 2002), and the Iowa Landform Regions (Prior, 1991). MapCurves (Hargrove et al., 2006), a quantitative goodness-of-fit method was used to determine the degree of concordance between the AEZ schemes and each of the existing categorical maps, and

Table 2
Summary of topographic parameters

Parameter	Units	Description
Mean elevation	m	Average elevation above sea level
Standard deviation of mean elevation		Amount of variability above and below mean elevation
Mean slope	Degrees	Average steepness of slope
Standard deviation of mean slope		Amount of variability in steepness of slope
Mean aspect	Degrees	Average compass direction of slopes greater than 0° above horizontal (0–360°)
Standard deviation of mean aspect		Amount of variability in slope direction
Mean heat load index		Average amount of heat load (0–1)
Standard deviation of mean heat load index		Amount of variability in heat load index
Mean solar index		Average relative potential solar incident radiation; 1–∞
Standard deviation of mean solar index		Amount of variability of solar radiation index

Table 3
Summary of soil parameters

Parameter	Units	Description
Mean plant-available water capacity	mm	Average water capacity
Standard deviation of mean plant-available water capacity		Amount of variability of mean plant available water capacity
Mean cation exchange capacity	mequiv./100 g soil	Average cation exchange capacity
Standard deviation of mean cation exchange capacity		Amount of variability of cation exchange capacity
Mean organic matter	%	Average percent of organic matter within the surface horizon
Standard deviation of mean organic matter		Amount of variability of mean organic matter
Mean permeability	mm/h	Average rate of water infiltration
Standard deviation of mean permeability		Amount of variability of permeability
Mean of low value of pH range		Average low value of the pH range
Standard deviation of mean low value of pH range		Amount of variability of mean low value of pH range
Mean percent sand	%	Average percent sand
Standard deviation of mean percent sand		Amount of variability of percent sand
Mean depth to seasonally high water table	m	Average depth to seasonally high water table
Standard deviation of mean depth to seasonally high water table		Amount of variability of depth to seasonally high water table

for comparing the two existing categorical maps with each other. MapCurves (Hargrove et al., 2006) is resolution dependent and is based on categories (rather than cell-by-cell comparison), and therefore does not require that maps being compared have identical number or types of categories. The method determines the degree of spatial overlap, or positive spatial correlation, between two or more maps with the same spatial extent by using a goodness-of-fit algorithm according to the equation:

$$\gamma = \sum \left[\left(\frac{C}{B+C} \right) \left(\frac{C}{A+C} \right) \right]$$

where γ is the goodness-of-fit score, C the amount of intersection of a category between two maps; B the total area of the category on a reference map; and A is the total area of the category on the compared map. The first term provides the proportion of category sharedness between maps, and the second term weights by fractional share of category area. (Weighting prevents distortion of fit by presence of many large, but minimally intersecting categories.) The goodness-of-fit score is the sum of positive spatial correlation among categories between two maps, and ranges between 0 and 100, with higher scores indicating better fit.

3. Results and discussion

The number of AEZs chosen for this study were 5, 10, 15, 20, and 25, providing five portrayals of a landscape at increasing level of detail. In moving from one portrayal to another, all cells were reassigned to a new scheme of clusters. Therefore, the AEZs are non-hierarchical. The non-hierarchical method of MGC does not rely on preconceived notions of landscape structure and allows a uniform classification structure to emerge from the data by using the variance structure present in environmental parameters (Hargrove and Hoffman, 2004).

Raster cells were given a cluster assignment based on location in data space regardless of absolute geographic location. This resulted in fragmented AEZs composed of spatially disjoined patches of varying size and of varying distances between patches. Cohesiveness results from spatial autocorrelation present in the environmental data while fragmentation results from cells of differing geographic location having nearby locations in data space. Simultaneous cohesiveness and fragmentation are desirable for three reasons: (1) these properties reveal the non-random organization of the agro-environment; (2) distributed areas of crop-relevant environmental similarity are identifiable with the methodology; and, (3) transitions between AEZs are complex, which may be more representative of existing environmental heterogeneity than discrete boundary lines (McDonald et al., 2005). These desirable outcomes are addressed in further detail below in a discussion of the 5-, 15-, and 25-zone schemes. For brevity, the 10- and 20-zone schemes are not discussed here, but are presented together with the 5-, 15- and 25-zone schemes on-line at http://research.esd.ornl.gov/~hnw/iowa.

3.1. PCA axes and RGB color triplets

All 32 components were retained from the PCA and formed the axes of the data space. The relative contribution of each component is provided in Table 4, with the all of the variation being captured by the 32 components (i.e., cumulative variation explained = 1.00). Varimax rotation (orthogonal) factor loadings were used to interpret the first, second and third principal components, which were used to create the RGB color triplets (Table 5). Climate variables

Table 4
Variation explained by the 32 components

Component	Eigenvalue	Difference	Proportion variation explained	Cumulative variation explained
1	7.95851344	3.00661687	0.2487	0.2487
2	4.95189657	1.41628920	0.1547	0.4035
3	3.53560737	1.54115995	0.1105	0.5139
4	1.99444741	0.42323058	0.0623	0.5763
5	1.57121683	0.20103805	0.0491	0.6254
6	1.37017878	0.28702644	0.0428	0.6682
7	1.08315234	0.03681366	0.0338	0.7020
8	1.04633868	0.02177295	0.0327	0.7347
9	1.02456573	0.15883602	0.0320	0.7667
10	0.86572971	0.07719163	0.0271	0.7938
11	0.78853808	0.07288787	0.0246	0.8184
12	0.71565020	0.10074740	0.0224	0.8408
13	0.61490280	0.05742478	0.0192	0.8600
14	0.55747802	0.02693485	0.0174	0.8774
15	0.53054317	0.02939469	0.0166	0.8940
16	0.50114848	0.10939891	0.0157	0.9097
17	0.39174957	0.02638701	0.0122	0.9219
18	0.36536256	0.04214900	0.0114	0.9333
19	0.32321356	0.03516451	0.0101	0.9434
20	0.28804905	0.02295936	0.0090	0.9524
21	0.26508969	0.02509398	0.0083	0.9607
22	0.23999571	0.04369115	0.0075	0.9682
23	0.19630456	0.02301155	0.0061	0.9744
24	0.17329301	0.02269439	0.0054	0.9798
25	0.15059862	0.01336796	0.0047	0.9845
26	0.13723066	0.01990151	0.0043	0.9888
27	0.11732915	0.04493678	0.0037	0.9924
28	0.07239237	0.00898427	0.0023	0.9947
29	0.06340810	0.00932331	0.0020	0.9967
30	0.05408478	0.02191231	0.0017	0.9984
31	0.03217248	0.01235393	0.0010	0.9994
32	0.01981854		0.0006	1.0000

scored highest on the first factor. All topographic variables, soil cation exchange capacity and mean organic matter scored highest on the second factor. The remainder of soil variables scored highest on the third factor. Based on these loadings, red colors represent dominance of climate within a zone, green colors represent dominance of soil fertility and topographic relief within a zone, and blue colors represent dominance of soil moisture characteristics within a zone.

3.2. The five agroecozone scheme

The coarsest delineation of the Iowa landscape was the five-AEZ scheme (Fig. 3A). This scheme captures maximum dissimilarity of environmental conditions across Iowa. The five-zone scheme illustrates the patchy nature of AEZs and complexity of transitions between AEZs. Agroecozones in this scheme generally occur as globular, cohesive patches distributed across the landscape. Differences occur among AEZs in patch size and number, and patch dispersion, but we posit that the agroecozones map areas within which crops may be expected to have similar performance or yield. Of the five AEZs, four are dominated by one or two very large patches encompassing the majority of zonal area (>79%), and are accompanied by many smaller patches nearby. However, Zone 4, limited to a total area of 12 km^2, is divided into 11 patches, and is located entirely within Zone 3 (Fig. 3A). The large patches of Zones 1, 2, 3, and 5, appear as core areas, or large expanses of the landscape over which specific environmental processes dominate in a relatively uninterrupted manner.

Among the AEZs, size and density of patches generally decrease with increased distance from a core area. This is interpreted as existence of environmental gradients between areas of relative homogeneity, rather than abrupt change across the Iowa landscape at this level of analysis. Transitions between AEZs occur over distance, sometimes forming discrete zones themselves (Fig. 4). We find an analogy to this occurrence in the concept of “ecopause” (Hargrove and Hoffman, 1999), which is a gradual transition between regions when compared to the unequivocal edges described by ecotones. We define agroecopauses, then, as regions of transition between AEZs. A benefit of the agroecopause concept is elimination of problems associated with discrete boundaries, particularly questions regarding the correctness of their position. This is a salient feature of our method compared to traditional AEZ delineation. Agroecopauses allow for presence of non-uniform change of environmental conditions over distance. If agroecopauses

Table 5
Varimax rotation scores on the first three components of PCA

Parameter	Factor 1 (red)	Factor 2 (green)	Factor 3 (blue)
Mean annual precipitation	0.869	0.025	0.166
Standard deviation of mean annual precipitation	0.854	−0.096	0.013
Mean growing season length	0.887	0.128	−0.090
Standard deviation of growing season length	0.841	0.211	−0.096
Mean growing season precipitation	0.780	−0.068	0.071
Standard deviation of growing season precipitation	0.920	0.057	0.020
Mean growing season heat units	0.822	0.058	−0.107
Standard deviation of growing season heat units	0.758	0.178	0.035
Mean plant available water capacity	−0.071	−0.008	−0.640
Standard deviation of available water capacity	0.04	0.178	0.727
Mean cation exchange capacity	−0.209	−0.500	−0.389
Standard deviation of cation exchange capacity	−0.124	−0.512	0.573
Mean organic matter	−0.179	−0.513	0.001
Standard deviation of organic matter	−0.176	−0.316	0.365
Mean permeability	−0.037	0.085	0.455
Standard deviation of permeability	0.052	0.213	0.622
Mean low value of pH range	−0.409	−0.307	0.094
Standard deviation of low value of pH range	−0.302	−0.153	0.353
Mean percent sand	−0.053	−0.137	0.699
Standard deviation of percent sand	0.285	0.070	0.677
Mean depth to seasonal water table	−0.129	0.503	−0.031
Standard deviation of depth to water table	0.085	−0.314	0.478
Mean elevation	−0.779	−0.077	−0.220
Standard deviation of elevation	0.060	0.886	0.014
Mean slope	0.072	0.802	0.001
Standard deviation of slope	0.148	0.862	0.093
Mean aspect	0.026	0.028	−0.043
Standard deviation of aspect	0.003	0.028	0.051
Mean heat load index	0.004	−0.551	−0.048
Standard deviation of heat load index	0.159	0.896	−0.046
Mean solar radiation index	0.005	−0.555	−0.047
Standard deviation of solar radiation index	0.179	0.892	−0.015

are significant elements of the landscape, they present additional features to be considered in agricultural planning and policy. For example, current field-level cultural practices are unlikely to increase biodiversity (Moser et al., 2002). However, crop diversification for increased biodiversity could be planned at the landscape level. Agoecopauses may represent spatial units of greater potential crop diversity and could be targeted for enhancing agro-biodiversity goals.

3.3. The 15 agroecozone scheme

In the 15-zone scheme (Fig. 3B), AEZs are again patchy, but are of globular and linear shapes. In this scheme, five AEZs dominate in terms of total area (Zones 1, 8, 10, 12, and 13), each composed of one or two large patches encompassing >77% of each zonal area. The remaining AEZs occupy substantially less area distributed among many small patches. This zonation illustrates how the study landscape is composed of diverse subregions of dominant environmental components and processes.

Zones 1 and 15 present an interesting opportunity for interpretation of crop-relevant environmental variation at the subregional scale. Zone 1, composed of 386 patches, lacks a single core area. It contains two large globular patches comprising 92.9% of the zonal area separated by a distance of approximately 118 km and five intervening AEZs. Despite the amount of distance between these two patches, they are more similar to each other than any of the other AEZs. A similar amount of patch dispersal is present in Zone 15 which is composed on many linear patches. Zone 15 also lacks a core area in terms of a discrete compact patch near the geographic center of the zone. Zone 5 contains hundreds widely disperesed small patches juxtaposed with larger very dissimilar AEZs (Fig. 5). The larger surrounding AEZs, then, are an intervening matrix of complex environmental conditions. This combination of widely dispersed patches amidst a complex matrix of environmental heterogeneity may provide a tool for understanding biodiversity and conservation opportunities at the landscape scale. Small distributed patches may offer locations for introduction of specialty crops, for example, into wider more homogenous regions of conventional commodity crops.

3.4. The 25-agroecozone scheme

The 25-zone scheme (Fig. 3C) presents a very detailed picture of the crop-relevant environment within the study

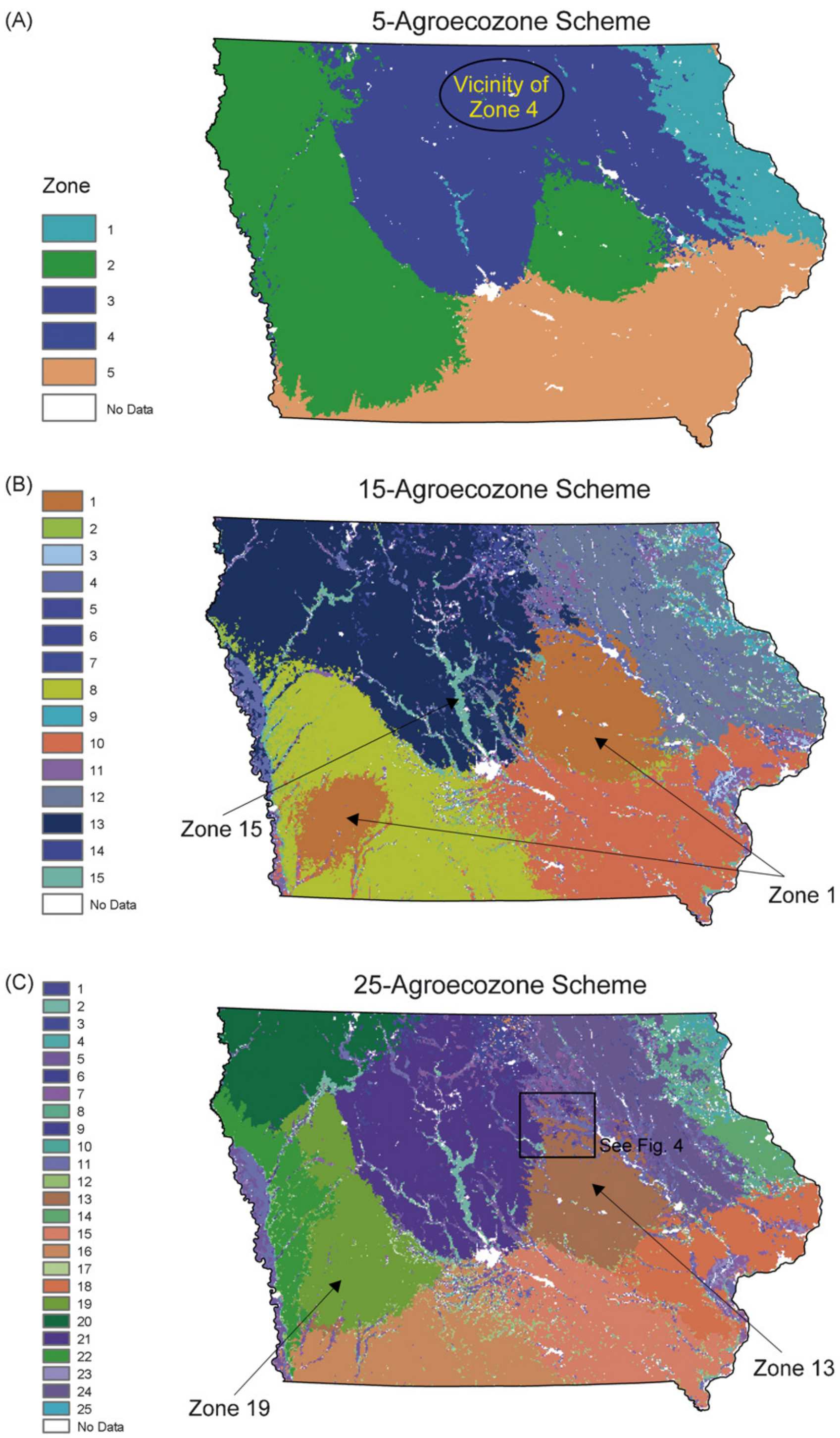

Fig. 3. The 5-, 15- and 25-agroecozone schemes illustrate environmental variation at differing levels of resolution, while colors reflect degree of contribution among the 32 environmental parameters. The five-zone scheme (A) illustrates the coarsest level of description. In the 15-zone scheme (B) several smaller linear zones punctuate the large globular zones which dominate the scheme. The 25-zone scheme (C) provides the greatest detail of hypothesized crop-relevant environmental discretization.

area. Enigmatic juxtaposition of very dissimilar zones is one striking feature of this scheme, while grouping of similarly colored zones is another. Three adjacent zones, 13, 19, and 21, display very different controlling factors in terms of color assignments. Zone 13 is climate dominated (red), whereas Zone 19 is soil fertility and topography dominated (green), and Zone 21 is soil moisture and soil heterogeneity dominated (blue). The 25-zone scheme also depicts large groupings of similarly colored patches, such as the three large reddish AEZs in south-central and southeastern Iowa.

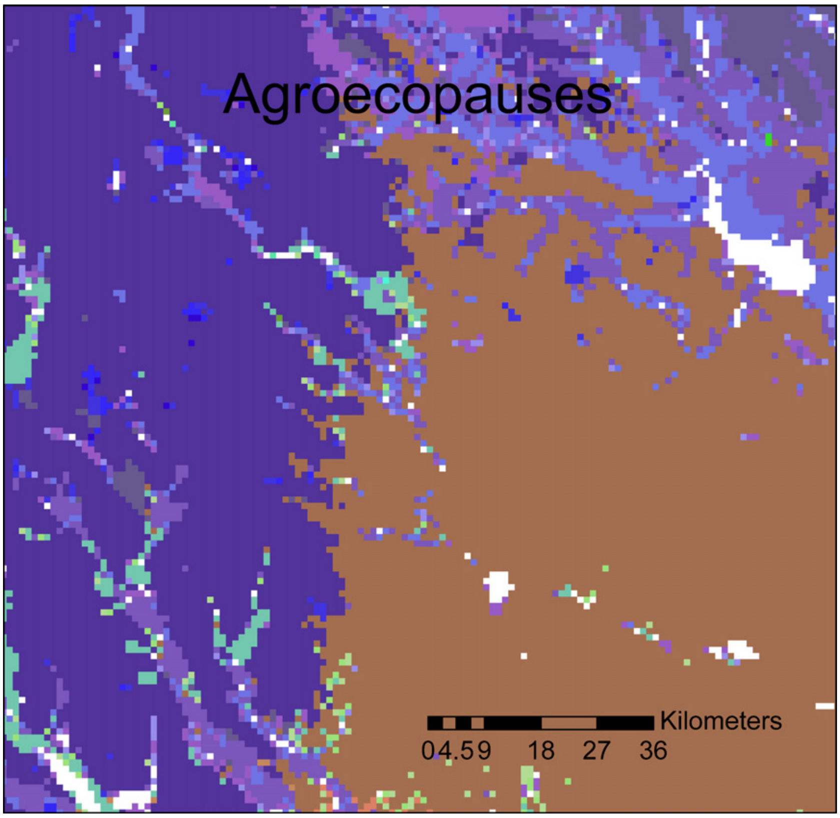

Fig. 4. Agroecopauses: boundaries are complex and transitions between agroecozones occur over considerable distances.

Although MGC results in non-hierarchical zones, these groupings demonstrate how MGC organizes spatial units simultaneously into generalizable environmental processes and differentiated subregional expressions *via* color triplets. This characteristic of the method could be beneficial to policy makers and researchers alike, who may be interested in simultaneous generalized and more detailed analyses.

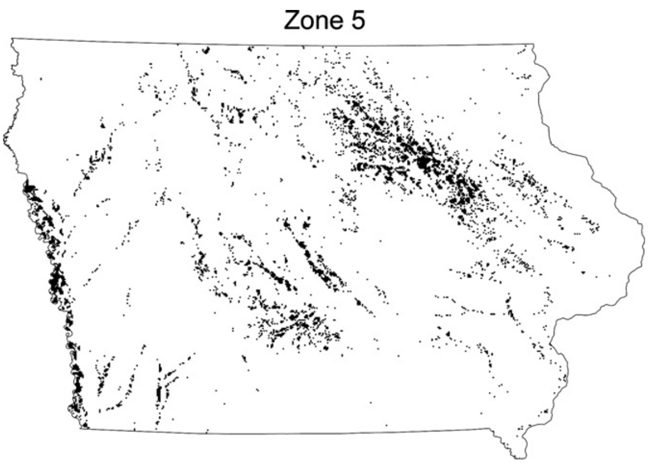

Fig. 5. Distributed agroecozones. Zone 5 of the 15-zone scheme (shown in black), typifies agroecozones which have small total area but are widely distributed across the state. These agroecozones are surrounded by a matrix of complex and often very dissimilar conditions.

3.5. Validity of the AEZs

An inherently desirable component of regionalization is demonstrable validity (Lugo et al., 1999; Liu and Samal, 2002). However, generally accepted quantitative methods for assessing correctness of eco-regionalization schemes, or for estimating statistical significance of differences among regions, do not exist (Hargrove and Hoffman, 2004). Ground-truthing is a method that has been used to evaluate whether ecological map units capture intended ecological variables (Kupfer and Franklin, 2000). Unfortunately, currently available yield data for crops grown throughout the study area (e.g., corn and soy) are aggregated mean yields at the county level (NASS, 2005). This resolution is too coarse for AEZ validation, and counties and AEZs are not of the same size or configuration, precluding one-to-one comparisons.

Metzger et al. (2005) used comparison of their climatic stratification of Europe with previously created classifications to evaluate credibility of their results. This is a tractable approach if the reference maps are themselves validated. In the case of Iowa land classification, two existing regionalization maps are the Major Land Resource Areas of Iowa (MLRAs; NRCS, 2002), and the Landform Regions of Iowa (LRI; Prior, 1991). These maps are traditionally delineated (e.g., subjectively derived) regionalizations of Iowa, and their degree of validity has not been reported. Nonetheless,

Table 6
Goodness-of-fit scores using MapCurves (Hargrove et al., 2006)

	5-AEZ	10-AEZ	15-AEZ	20-AEZ	25-AEZ	MLRAs	LANDFORMS
5-AEZ		51.8	47.1	58.2	60.7	58.4	48.8
10-AEZ			39.5	40.0	38.7	27.6	29.4
15-AEZ				66.1	67.2	28.6	32.0
20-AEZ					58.5	37.1	39.6
25-AEZ						45.5	45.0
MLRAs							76.3

they are widely used in education and research as currently best available sources of information (e.g., Bernert et al., 1997; Waltman et al., 2004; Vogel et al., 2005). Using MapCurves goodness-of-fit test (Hargrove et al., 2006), we quantitatively evaluated concordance of the 5-, 10-, 15-, 20-, and 25-AEZ schemes with each other, and with the MLRA and LRI maps. We also measured concordance between the MLRA and the LRI maps. Results are presented in Table 6.

When compared to the MLRAs and the LRI, the descending rank order of the AEZ schemes is the same: 5, 25, 20, 15, and 10. The same order of fit among AEZ schemes with the MLRAs and LRI is not surprising as the degree of fit between the MLRAs and the LRI is 76.28, a very high score. We expect this high degree of concordance between MLRAs and LRI because the schemes use similar criteria for determining regions and their boundaries (e.g., topography; USDA, 2006; Prior, 1991), and therefore are not independent. The 5- and 25-AEZ schemes have better fit with the MLRAs while the 10-, 15- and 20-AEZ schemes have better fit with the ILR. The degree of fit of the 5- and 25-AEZ, the top ranking schemes, with both the MLRAs and the ILR is ‘‘good’’. The 5- and 25-AEZ schemes have high degree of concordance with each other (60.7), and therefore their similar scores with the MLRAs and the LRI is not surprising. The 10-AEZ scheme has the lowest concordance with the MLRA (27.6), and the 15-AEZ scheme had the least concordance with the LRI (28.6). Among AEZ schemes, the highest degree of concordance is between the 20- and 25-AEZ schemes (67.2), lowest is between the 10- and 25-AEZ schemes (38.7).

The above measures of goodness-of-fit are not a measure of correctness of any of the maps because: (1) it is difficult to justify comparison of maps created for different purposes and using differing criteria and methods (McMahon et al., 2001; Thompson et al., 2005); and (2) as stated above, the reference maps themselves have not been ‘‘validated’’. Therefore, we interpret the results as a sign of an emerging consensus.

Our method is straightforward, empirical and wholly transferable. Expert opinion is required for choice of input parameters, but this is a common feature of all analytical models. Once inputs are chosen, however, our AEZ delineation method is objective, ‘‘data driven’’. Data dependency is in this case a positive outcome, indicating the repeatability of the results. Validity of the AEZs can be seen, then, as a function of the validity and quality of the input data, and the choice of inputs. The data used in the present study are digital and publicly available, and thus not subject to the problems of distribution and physical distortion associated with analogue data (e.g., paper maps) used in previous AEZ methods. By using best currently available data, our AEZ provide updated information compared to previous regionalization schemes. Additionally, our method would facilitate rapid updating of AEZs as input data are revised over time.

There are limitations of this study that should be considered, two of which are discussed here. It is very rare that all data required for a given analysis are measured at the same scale or over the same extent. Interpolation, extrapolation, and aggregation of spatial data, all very common procedures of geographic analysis, introduce modeling error (Openshaw, 1977; MacEachren and Davidson, 1987). Currently, methods are unavailable for evaluating total error in a surface produced from multiple layers of data as well as the propagation of error through each step in surface building. As a result, the amount of total error in the AEZs is unknown. Secondly, the degree to which existing or future crops will respond to environmental variability identified by the AEZs is unknown. Therefore, significance of the environmental variability captured by our AEZs is unknown. The degree of crop response and tolerance to differences among AEZs must be determined in order to assess the significance of differences among AEZs. Yields of existing crops sampled for capture of regional differences, if present, would be the best method to make this determination. Such efforts could be assisted by analysis of satellite imagery, or other remotely sensed data.

3.6. Core applications

A major result of this study is quantification of the environment relevant to crops using a wholly transferable and empirical method. Use of a quantitative method to categorize the environment makes possible the testing of hypotheses of crop performance using environmental parameters as non-random variables (i.e., using robust statistical analysis). Agroecozones delineated by our method make it possible, for example, to create an experimental design for field tests of crops across a known range of environmental conditions and combined environmental factors. This makes possible the choice of trial locations in a spatially explicit and analytical manner. Such a targeted approach has the additional advantage of one-to-one comparisons between measures of crop performance and environmental characteristics across space. An essential requirement for testing such hypotheses is experimental design (i.e., distribution of samples) that measures regional-scale ecological processes, not plot- or farm-level ecological processes. Sample locations, for example, could be stratified among AEZs, and randomized within AEZs. This approach provides an alternative to the traditional agronomic approach of field trials under idealized environmental and management conditions that do not extrapolate well to regional scales (Hansen and Jones, 2000; Batchelor et al., 2002).

Agricultural land use decision-making is scale dependent and must correspond to an appropriate level of agro-ecosystem behavior (Veldkamp et al., 2001). A principal core application of our AEZ delineation method is inventory of crop-relevant environmental characteristics commensurate with the needs of decision-making at higher levels of socio-economic and political organization. At such levels focus is on, for example, commodity quality demands, sustainable land use planning, new crop introduction, and regional economic development (Fan et al., 2000; Hansen and Jones, 2000; Munier et al., 2004; Jagtap and Jones, 2002; Verdoodt and Van Ranst, 2006). Therefore, a primary application of our method is evaluation of crop suitability. Here, AEZs are delineated as relatively homogenous regions of quantified environmental conditions. Specifically, the landscape has been discretized on the basis of crop-relevant environmental characteristics. If crop growth requirements are even minimally understood, the AEZs provide a screening tool in suitability analysis. Because the MGC method results in AEZs with similar variance, they are better suited for such an analysis than traditionally delineated AEZ which have unknown and presumably unequal variances among regions. In crop suitability analysis, future climate conditions might be an important consideration. With the MGC method, estimates of future climate characteristics can be used as inputs in the same way that historical climate data have been used in the present study. For more detailed suitability analysis Patel (2004) recommends addition of supplemental data layers to GIS-based AEZs. Data layers containing particular limiting parameters could identify areas within and among AEZs that exceed crop limits. Unsuitable areas could then be masked from further evaluation.

The MGC method of AEZ delineation using crop-relevant environmental parameters could be a valuable framework for agricultural scenario building (Santelmann et al., 2006). Instead of bounding agroecological problems by arbitrary administrative units (e.g., counties) or hydrologically defined areas (e.g., watersheds), AEZ boundaries reflect ecological processes specific to agriculture. Together with additional information such as infrastructure, population structure, land ownership patterns, and water resources, planners and policy makers could use AEZs to analyze trade-offs associated with changes in policies affecting agricultural production and resource conservation. AEZs could similarly be used as agriculture-centric geographic units for water quality management. If empirical models of the effects of crops and associated management practices on water quality are available, AEZs could be used to predict how changes in crops and management may affect water quality.

Agroecozones represent additional opportunities for study of socio-economic effects of changes in agricultural practices. For example, how are crop diversification-related farm income opportunities distributed across the landscape? What is the spatial distribution of risks associated with adoption of new commodity crops (e.g., perennial biofuel crops)? Does an association exist between erosion risk and AEZs?

4. Conclusions

In summary, the MGC method of AEZ delineation provides several advantages over subjectively delineated AEZ. Most importantly is the empirical and repeatable process. The use of expert opinion in criteria weighting, and varied decision-making in the location, extent and shape of individual regions as used in traditional AEZ delineation, is eliminated. By limiting inputs to those that are specifically crop relevant, the AEZs are more likely to reflect agriculturally relevant differentiation of the environment, compared to non-agriculturally defined regionalizations. The use of MGC using crop-relevant environmental parameters is data-driven, and arguably as valid as the input data. By using best available and most current data, the resulting AEZs provide an updated view of the agricultural environment with specific relevance to crop growth and production, especially compared to older, subjectively delineated regions which do not focus on crops specifically. The method overcomes the limitations associated with discrete boundaries among zones, particularly correctness of position, by creating spatially disjoined patches, complex patch borders, and regions of transition between AEZs. The AEZs produced by this method also provide a valuable framework for agroecosystem and agronomic research, particularly for testing of hypotheses regarding crop growth in association with environmental characteristics, and for evaluation of crop suitability. Because quantitative validation procedures are currently unavailable, future research is necessary to understand the significance of environmental variation captured by our delineation method in relation to a range of crop options. Future research efforts could also examine expected crop performance under altered climate regimes. By framing environmental variability in a crop-relevant perspective, our method provides both a visual and analytical foundation for exploring landscape scale agricultural planning, particularly in the presence of competing multiple land uses and agroeconomic transformations.

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