Delineating and Resolving Ecoregions Statistically: Sorting Out Contexts for Wildlife Habitat

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OVERVIEW

Ecoregions are partitions of geographic space that use to some kind of model of environmental patterns and process to delineate these partitions. That model may be motivated theoretically or empirically.

As with any type of map, the form of the ecoregions will necessarily reflect the intentions of the mapmaker. The suitability of a particular ecoregionalization to answer a specific question will thus rely on the degree of correspondence between the question of interest and the data and model used to produce the ecoregionalization.

Here we explore how input data and thematic resolution interact to produce alternative ecoregionalizations of Nebraska. Specifically, we are interested in assessing the suitability of including current land cover information into an ecoregionalization to support wildlife-habitat relationship modeling and forecasting of range distributions.

METHODS

Environmental conditions in Nebraska were summarized by 67 variables (Table 1) in a geospatial database. The selection of variables reflects likely constraints on species ranges. The data were represented in an EMAP fine-resolution hexagonal grid with a nominal spatial resolution of 40 km^2.

Rescaling the original environmental variables at different spatial resolutions to the hexagonal grid led to compositional variables for land cover and soils, simple areal averages for climate and elevation data, and a binary stream buffer variable.

Data were submitted to a multivariate geographic clustering algorithm (Hargrove and Hoffman, 1999 and *in press*) that segments the data volume into *n* convex clusters in a normalized high-dimensional state space, where *n* is requested by the user. The algorithm offers a degree of statistical objectivity, repeatability, and equitable weighting among variables that cannot be found in other ecoregionalization procedures.

Ecoregionalization algorithm was developed on a Beowulf-type parallel supercomputer built from discarded commodity PCs at Oak Ridge National Laboratory (Hargrove et al., 2001).

Twenty alternative ecoregionalizations were produced. Land cover data were either included for a total of 67 input variables or excluded for a total of 47 input variables. Thematic resolution (i.e., number of clusters requested) was varied from 10 to 100 clusters in increments of 10.

Table 1: Environmental Variables Used in Ecoregionalizations

Land Cover (20-class vector)
1) Ponderosa Pine Forests and Woodlands
2) Deciduous Forest/Woodland
3) Juniper Woodland
4) Sandsage Shrubland
5) Sandhills Upland Prairie
6) Lowland Tallgrass Prairie
7) Upland Tallgrass Prairie
8) Little Bluestem-Gramma Mixedgrass Prairie
9) Western Wheatgrass Mixedgrass Prairie
10) Western Shortgrass Prairie
11) Barren/Sand/Outcrop
12) Agricultural Fields
13) Open Water
14) Fallow Agricultural Fields
15) Aquatic Bed Wetland
16) Emergent Wetland
17) Riparian Shrubland
18) Riparian Woodland
19) Low Intensity Urban/Residential
20) Commercial/Industrial/Transportation

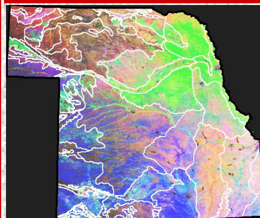
Soils (6 variables)
- % coarse textured soils
- % moderately coarse textured soils
- % medium textured soils
- % moderately fine textured soils
- % fine textured soils
- % hydric soils

Precipitation (20 variables)
- average monthly precipitation for March-September (7)
- coefficient of variation of monthly precipitation for March-September (7)
- average total winter (December-February) precipitation
- coefficient of variation of total winter precipitation
- average total growing season (April-September) precipitation
- coefficient of variation of total growing season precipitation
- average total fall (September-November) precipitation
- coefficient of variation of total fall precipitation

Temperature (19 variables)
- average monthly minimum temperatures for September-March (7)
- coefficient of variation of minimum temperatures for September-March (7)
- average cumulative growing degree days base 0°C for January-March and January-April (2)
- coefficient of variation of cumulative growing degree days base 0°C for January-March and January-April (2)
- number of frost-free days

Terrain (2 variables)
- elevation
- presence/absence of 500m stream buffer

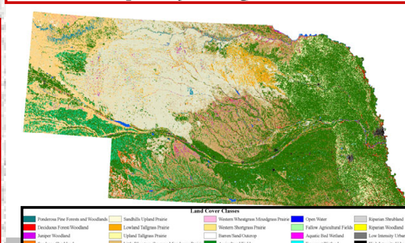
NE-KS Land Surface Phenology & Omernik's Level IV Ecoregions

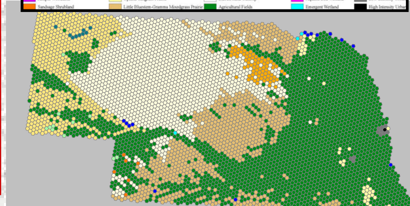


Principal Components Analysis of AVHRR maximum NDVI biweekly composites from 1990-2000 reveals strong seasonalities in regional vegetation and land uses.
- Red (DOY 159-172) displays peak separation date for C_4 grasses.
- Green (DOY 215-228) displays peak separation date for corn and other irrigated and dryland row crops.
- Blue (DOY 61-74) displays peak separation date for winter wheat.

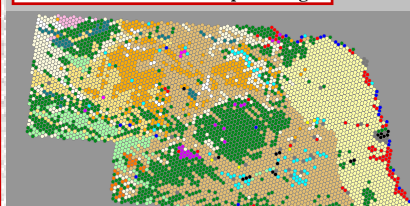
Boundaries delineate Omernik's Level IV ecoregions for Nebraska and Kansas (Chapman et al. 2001).

Nebraska Gap Analysis Program Land Cover Map

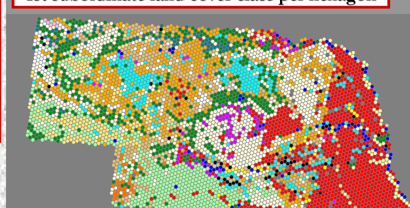




Dominant land cover class per hexagon

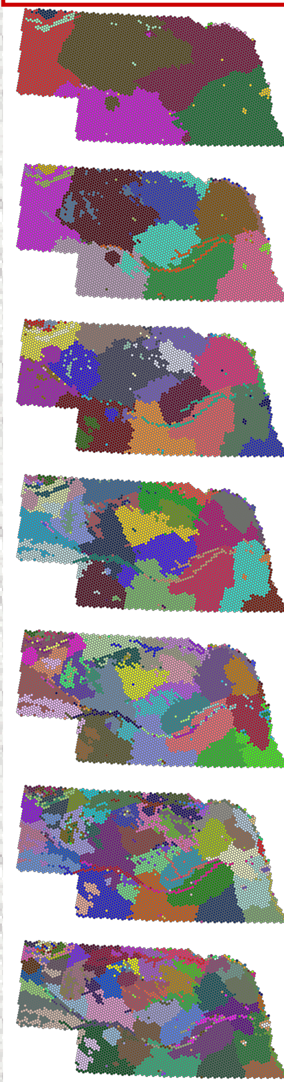


1st subordinate land cover class per hexagon



2nd subordinate land cover class per hexagon

Ecoregionalizations *including* GAP Land Cover Classes



10 CLUSTERS

20 CLUSTERS

30 CLUSTERS

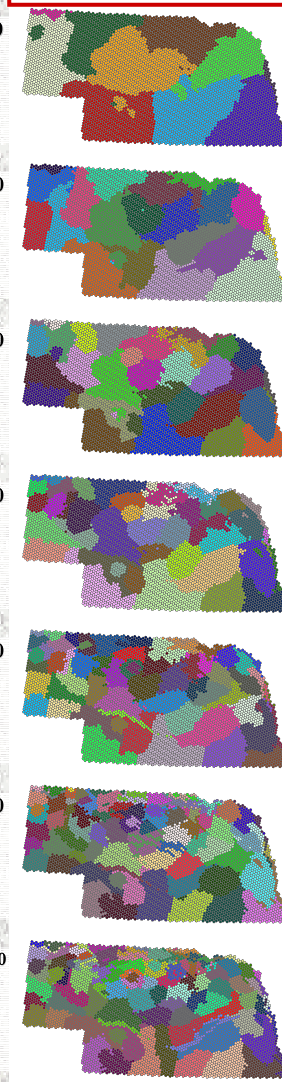
40 CLUSTERS

60 CLUSTERS

80 CLUSTERS

100 CLUSTERS

Ecoregionalizations *excluding* GAP Land Cover Classes



RESULTS & DISCUSSION

- Inclusion of current land cover data strongly influences the results of the ecoregionalization algorithm.
- Inclusion of land cover enables swift emergence of distinct but rare landscapes (e.g., pine woodlands at 10 clusters; Sandhills wetlands at 20 clusters), even though spatial coherence of subdominant land cover classes can be low.
- As thematic resolution (*n* clusters requested) increases, climatic gradients appear to nuance earlier partitions determined by land cover—if included—or by soils data and elevation, if land cover data are excluded.
- Greater thematic resolution aids interpretation when land cover data are included.
- With land cover excluded, increasing thematic resolution leads largely to compact, convex patches indicative of weak partitions of smooth, slow gradients. This effect hinders interpretation.
- Inclusion of land cover informs the ecoregionalization process with realized environmental conditions, rather than the regions of *potential* coherence delineated by the process when current land cover data are excluded.

CONCLUSION

Should current land cover/land use data be used for delineation of ecoregions? That answer depends on the question motivating the ecoregionalization exercise, because ecoregions are not *a priori* spatial units (Henebry and Merchant 2001).

Given that (1) we are interested in modeling current wildlife habitat and forecasting range distributions, (2) Nebraska land cover and land use are rapidly changing (Henebry et al. 2000), and (3) the ecoregion maps resulting from inclusion of the land cover data are more open to interpretation, we find that inclusion of current land cover is indeed appropriate in the ecoregionalization process.

AN INVITATION…

The statistical ecoregionalization technique that we have explored here is generic: it can be applied to many other kinds and sets of geospatial data, including GAP data, whether for a single state or an entire region. We invite those who are interested in trying this approach with their data to contact us!

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