Hyper-extractive counties in the U.S.: A coupled-systems approach

Joseph A. Aistrup [a,*], László J. Kulcsár [b], Jacob A. Mauslein [c], Sarah Beach [b], David R. Steward [d]

[a] Department of Political Science, 117C Eisenhower Hall, Kansas State University, Manhattan, KS 66506, USA
[b] Department of Sociology, Antropology, and Social Work, 204 Waters Hall, Kansas State University, Manhattan, KS 66506, USA
[c] Department of Political Science, 244 Waters Hall, Kansas State University, Manhattan, KS 66506, USA
[d] Department of Civil Engineering, 2118 Fiedler Hall, Kansas State University Manhattan, KS 66506, USA

ABSTRACT

In this paper, we advance a theoretical framework for defining hyper-extractive coupled-systems in the United States. Our purpose is to extend a model constructed for an agricultural system in Southwest Kansas into a general theory that can be used to successfully classify counties across the U.S. that depend on the extraction of natural resources. We begin with developing the theoretical foundations for the hyper-extractive coupled-system. We then fit this theory within the existing literature regarding the classification of rural counties. Finally, drawing on a coupled human–natural systems theoretical framework (Liu et al., 2007), we develop a new spatially based empirical measure of rural context that captures the complex, multidimensional interactions between humans and their natural environments. GIS hot spot and factor analytic techniques are used to empirically identify existing coupled-systems, linking contiguous counties in the rural U.S. based on 35 indicators of land use, employment patterns, demographics, physiography, and climate. In addition to identifying three different types of hyper-extractive counties across the U.S., our approach reveals a number of other coupled-systems based on agriculture and ranching, mining, manufacturing, scenic amenities, and forestry and fishing.

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Introduction

Coupled human–natural systems exist all over the world wherever humans interact with their environment. Although all these interactions are significant, some are clearly more important than others on the basis of the type and scale of human actions and the ecosystem being affected by these human actions (Liu et al., 2007). Thus is the case for the High Plains (Ogallala) Aquifer. The entire aquifer spans 450,000 km² and comprises 27% of the irrigated land in the United States (Dennehy, 2000, 6). Despite the High Plain's arid environment, irrigation from the aquifer enables farmers to plant water intensive crops like corn, soybeans, cotton, and alfalfa (Custodio, 2002). In turn, value-added agricultural industries, including confined feeding operations for cattle and hogs, dairy, ethanol plants, and meat-processing facilities have sprung up in the region to take advantage of the abundance of irrigated feed grains and finished live animals. Nowhere in the High Plains is this more true than in Southwest Kansas, where large scale confined feedlots provide finished cattle for several of the world's largest meatpacking factories (Broadway & Stull, 2006).

These local economies may be seen as examples of successfully overcoming the economic and demographic challenges that rural places have been facing since the 1970s, resulting in population growth in these counties whereas the norm for most rural counties is population stagnation or decline. However, the one-dimensional vertical concentration of industries based on the extraction of a non-renewable natural resource makes such systems vulnerable. We refer to this pattern of development as a "hyper-extractive" coupled-system, given the basis of this economic structure and the unique social and demographic characteristics triggered by it.

In this paper, we advance a theoretical framework for defining hyper-extractive coupled-systems in the United States. Our purpose is to extend the archetypal example hyper-extractive coupled-system in Southwest Kansas into a general theory that can be used to classify counties across the U.S. We begin with developing the theoretical foundations for the hyper-extractive coupled-system. We then fit this theory within the existing literature regarding the classification of rural counties. Finally, drawing on a coupled human–natural systems theoretical framework (Liu et al., 2007), we develop a new spatially based empirical measure of rural context that captures the complex, multidimensional interactions

* Corresponding author. Tel.: +1 785 532 6900; fax: +1 785 532 7004.
E-mail address: jaistrup@ksu.edu (J.A. Aistrup).

between humans and their natural environments. GIS hot spot and factor analytic techniques are used to empirically identify existing coupled-systems, linking contiguous counties in the rural U.S. based on 35 indicators of land use, employment patterns, demographics, physiography, and climate. In addition to identifying hyper-extractive counties across the U.S., our approach reveals a number of other coupled-systems based on agriculture, mining, manufacturing, scenic amenities, and forestry and fishing.

Theoretical framework for hyper-extractive coupled-systems

Four major conceptual themes serve as the basis for the theory of hyper-extraction coupled-systems: (1) boomtown development; (2) path dependence; (3) extractive-based rural economies; and (4) regional economic clusters.

The boomtown literature (Black, McKinnish, & Sanders, 2005; Brown, Dorius, & Krannich, 2005; Malamud, 1984; Smith, Krannich, & Hunter, 2001) argues that boomtowns develop and prosper almost overnight, largely based on making a profit from the extraction of resources (mostly mining operations) from the land. Their rapid growth, often doubling a town's population in 5 years or less, and subsequent busts are legendary (Smith et al., 2001). The social and environmental externalities of boomtowns are grave, leading to higher crime rates, prostitution, gambling, divorce, and alcohol abuse, and often, environmental catastrophes that still haunt these rural landscapes.

Many of the communities settled over the High Plains aquifer went through extended periods of growth starting in the 1950s with the introduction of irrigation technologies, followed by an additional burst of population growth in the late 1970s through the 1990s with the expansion of the meatpacking industry. Thus, even though the boomtown literature is relevant, it is most applicable to communities with accelerated growth and bust cycles versus High Plains agriculture communities like those in Southwest Kansas, which have taken longer to develop and in many cases have yet to bust.

The theoretical framework for "path dependence" also strongly influences the model of a hyper-extractive coupled-system. Path dependence, a concept first identified by economists (Arthur, 1989; David, 1985) is present if agent actions at one point in time affect the choices available to future agents. For many extractive agricultural regions, labor-saving technology or programs favoring absentee ownership lead to out-migration of workers, thus reducing demand for retail outlets, food services, etc. As those industries shrink, the labor pool becomes still smaller, with an aging population, and even more specialization (Johnson and Rathge, 2006).

The literature on extractive rural economies reinforces this version of the path dependence model (Adamchak, Bloomquist, Bausman, & Qureshi, 1999; Albrecht, 1993; Flora, Flora, Spears, & Swanson, 1992; Funk & Bailey, 2000; Kraenzel, 1955). This literature emphasizes that the socio-economic basis of many rural areas are extractive rural economies, based either the harvest of a renewable resource or the mining of a non-renewable mineral deposits. The common theme uniting these extraction-based communities is that a large majority of them are in decline, losing jobs and population. These factors combined together reduce the marginal return on each unit of production, encouraging producers to seek greater economies of scale and increased production via mechanization, energy consumption, and larger scale operations with fewer employees. Once this form of path dependence begins, it is both vicious and long-term.

On the other hand, the literature on "regional economic clusters" (Drabenstott, 2003; Drabenstott & Sheaff, 2002; Drabenstott, Henderson, Novack, & Abraham, 2004; Katz, 2000; McDaniel, 2003; Winkler, 2010) suggests a different type of path dependence for some rural extraction-based systems, one based on the

expansion of an industry or set of related industries in a county or region. The basic idea is rather straightforward in both principle and practice. An economic cluster focused on one type of product or service (e.g. aircraft, computers, meatpacking, plastics, optics, recreation or wine) in a region creates external economies of scale for producers, suppliers, financial institutions, manufacturers, and/or related service providers associated with the economic cluster. These economic clusters are also able to more easily attract skilled, semi-skilled, and unskilled labor forces necessary to make the economic cluster productive and competitive. In the value-added agricultural clusters, the labor force has a strong immigrant flavor, particularly from Mexico and other Central American countries (Broadway & Stull, 2006). For both types of path dependencies, growth or decline, the nature of the decisions made in the past impedes any specialized region wishing to "reinvent themselves" by attracting new industries (Martin & Sunley, 2006).

A dependence on the mining of the common pool resource of fresh water is a prominent component of some extractive agricultural economic clusters (Hardin, 1968; Kromm & White, 1992; Opie, 1993). Aquifers, like the High Plains Aquifer, are classified as a common pool resource because the action of one irrigator — either efficiently or inefficiently using water from the aquifer — has little impact on the condition of the aquifer as a whole. Thus, there is little incentive for one irrigator to substantially alter his/her behavior regarding the use of this common pool resource (Ostrom, 1990). Often, this leads to abuses to the common pool resource as each individual acts to maximize his/her use of the resource. This condition has led to issues of sustainability (Kromm & White, 1992; Opie, 1993) and environmental boundedness as captured by the work of Deborah and Frank Popper (1987, 1999). The Poppers, who focus their research on the High Plains Aquifer, note that the area's arid environment can only sustain certain types of land uses in the long-term. Development patterns that exceed the capacity of the land and water resource to sustain it or development patterns that cannot afford to import the necessary resources to sustain production are doomed to failure.

While in many cases the abuse of a common pool resource is exemplified in land-use patterns, this is not always the case. For years, the issue of how to regulate the common pool resource of both inland and coastal marine fisheries to prevent to over-harvesting of a variety of fish stocks has maintained a prominent place in the common pool research literature (Dietz, Ostrom, & Stern, 2003; Schlager, 1994; Ostrom, Gardner, & Walker, 1994). As this literature shows, hyper-extractive coupled-systems can take a variety of forms.

Hyper-extractive coupled-systems represent one of the more complex interactions between human and natural systems. The setting of these systems is buried within classic rural extractive-based (agriculture, forestry, fishing or mining) systems. Even though negative population change, out-migration and aging cohorts are the most common forms of path dependence among these rural counties; hyper-extractive coupled-systems have found a means to develop their extractive-based economies to overcome this rural decline path dependence. Thus, hyper-extractive coupled-systems are rural in character, dependent on the extraction of natural resources at a rate that is above the norm, and have a recent history of population growth and in-migration, which may have an Hispanic/Latino ethnic emphasis. With these system markers, we analyze hyper-extractive coupled-systems among rural counties in the U.S. Based on the boomtown literature, we expect these hyper-extractive coupled-systems will suffer from social externalities.

A wide variety of social-demographic, employment, natural resource, and environmental factors define hyper-extractive coupled-systems. Identifying hyper-extractive counties across the U.S. requires a research design that takes full advantage of all these types of variables. Dichotomous classifications, such as farming or

mining dependence are based on one factor and may well describe a county from that perspective, but are less effective in capturing the complex interactions among various human and natural factors that together trigger hyper-extraction.

Classifying rural communities

There are a wide variety of county classification systems currently used by government agencies and social scientists. Most start with the U.S. Census Bureau (2010a, 2010b) basic definitions of urban and rural areas. Urban areas are "densely developed territory, and encompass residential, commercial, and other non-residential urban land uses," broken down into urban areas (1000 people per square mile) and urban clusters (500 people per square mile). Rural areas consist of "all population, housing, and territory not included within an urban area" (U.S. Census Bureau, 2010a, 2010b). The Rural–Urban Continuum Codes, formally known as Beale Codes and published by the Economic Research Services (ERS) (Brown & Elo, 2011; Hines, Brown, & Zimmer, 1975; Parker, 2010) uses two variables, population and proximity to Standard Metropolitan Statistical Areas to classify counties into nine types. Similarly, the ERS uses "County Typology Codes," which distinguish counties based on six separate economic dependence categories and seven coinciding policy-related categories (Parker, 2005). The ERS also uses Rural–Urban Commuting Areas and Urban-Influence Codes in addition to the Rural–Urban Continuum Codes (Parker, 2010). The Urban-Influence Codes separate counties by population size, degree of urbanization, and degree of adjacency to metro areas to delineate variations in economic opportunities due to proximity to metro areas (Parker, 2007).

In addition to the classification systems developed by government agencies, scholars have also devised their own systems of identifying counties. A healthy literature has evolved around the topic of rural places that attract tourists. Beale and Johnson (1998) and Johnson and Beale (2002) identify recreational counties based on factors that include recreational employment, per capita county spending on lodging (excess of $100), and evidence suggesting the existence of recreational activity in the county. McGranahan (1999), on the other hand, developed an additive natural amenities index, which consists of six indicators, including warm winters, winter sun, summer humidity, topography and water area. Winkler's most recent work focuses on destination counties by distinguishing among counties based on dependence on natural resources, "comparing destination dependent counties to farming and mining dependent counties" (Winkler, 2010, 12). Winkler explains, "[t]his scale differs from prior scales introduced by McGranahan (1999) and Beale and Johnson (1998) and Johnson and Beale (2002) in that instead of measuring features that might attract people to place, it measures the outcome of amenity development as conceived as a combination of counter urbanization, second homes, and high housing values" (2010, 33).

Finally, another set of scholars classify rural places, as opposed to counties. For example, Winkler, Field, Luloff, Krannich, and Williams (2007) use Census Places as the basis for analysis, explaining that the use of Census Places enables them to demarcate variations within counties.[1]

There are several strong components of this literature that are worth exploiting for our purposes. This literature has an implicit focus on land-use patterns. Distinguishing among different types of destination counties, or developing typologies for counties based on an economic dependency, or creating a continuum based on the level of urban influence, all in their own way, seek to identify the

most predominant land use pattern (as defined by economic activities) in a county. Even though, by themselves, these approaches do not constitute a coupled human–natural systems approach; taken a whole, a coupled-systems approach is implied.

There is, however, one basic critique that can be applied to this literature on the classification of rural counties. Measurement theory is not used to check the empirical validity of these classification schemes. To be sure, there is much to theoretically justify these classification themes. Measurement theory, however, goes beyond the substantive theory to determine if there is empirical/statistical support, what social scientist call construct validity (Knoke et al. 2002; Kim and Mueller 1978). Thus, even though this study centers on the identification and measurement of hyper-extractive counties in the U.S., achieving this research objective requires us to apply measurement theory to the classification of rural counties. In doing so, our theoretical approach varies from our predecessors. For this reason, this effort should not be viewed as a replication study per se, or as an attempt to falsify the findings or classification of others, rather as an amalgamated theoretical approach using a fundamentally different methodology.

Theoretical approach and research design

Liu et al. (2007: 1513) specify that a coupled-systems approach should have some combination of four features: (1) taking advantage of both social and natural systems variables in the analysis, (2) being multidisciplinary, (3) integrating research methods across disciplines, and (4) being "context specific" while understanding temporal dynamics. For this research, we focus on how human interactions with their surrounding environment affect land use and resource use patterns in U.S. counties. Our scale is national in scope focusing on counties, which is a higher scale with less resolution than most other coupled human and natural systems analyses. This higher scale also means that our analysis does not entail a focus on land cover or land cover change. Even though our scale is higher, we use a coupled natural and human systems approach to inform and guide our research design and analysis. We do recognize the scale issue, however, and thus refer to these identified rural contexts as "coupled-systems" versus the more common terms of "Coupled Natural and Human" systems (CNH) or "Coupled Human and Natural Systems" (CHANS) or "Social Ecological Systems" (SES) (see Brondizio, Ostrom, & Young, 2009; Liu et al., 2007; Ostrom, 2009; Redman, Grove, & Kuby, 2004; Walker et al., 2002; Walker, Holling, Carpenter, & Kinzig, 2004; Wilson, Low, Costanza, & Ostrom, 1999).

Except for the weather data, all data are were collected during the period of 2000–2002. We use this period because all of the data are available for this period at this time. Many of the 35 county level indicators used in the analysis come from Woods and Poole (2010). Woods and Poole collects these data from U.S. Census Bureau, the Bureau of Economic Analysis, and other federal sources. The authors also supplemented the Woods and Poole data set with data from a variety of other government sources. Table 1 provides a list of these variables and data sources.[2]

The first set of indicators focus on social-demographic patterns. Included are variables characterizing each county's population,

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[1] Flora and Flora (2008, 17) use a community capitals framework that consists of the seven types of capital: natural, cultural, human, social, political, financial, and built.

[2] A natural question is how did we choose these 35 indicators, over other possible operationalizations of the same concepts. We started with a very large and expansive list of variables and used exploratory factor analysis to cull through this list and eliminate variables that did not meaningful contribute explanation. For example, there are a number of possible representations for age, including median age. Our exploratory factor analysis found that the percentage of population over 65 years of age was the most robust and consistent contributor. Thus, this is the indicator included in the analysis.

Table 1
Variables and sources included in the analysis.

Variable	Source
Population	Woods and Poole (2010) [a]
% Urban	Woods and Poole (2010) [a]
% Pop Change	Woods and Poole (2010) [a]
% Migr Foreign	Woods and Poole (2010) [a]
% Migr County	Woods and Poole (2010) [a]
% Migr State	Woods and Poole (2010) [a]
% Pop > 65	Woods and Poole (2010) [a]
% Hisp/Latino	Woods and Poole (2010) [a]
% African American	Woods and Poole (2010) [a]
% Low Income	Woods and Poole (2010) [a]
% Middle Income	Woods and Poole (2010) [a]
% < High School	Woods and Poole (2010) [a]
% Only High School	Woods and Poole (2010) [a]
% Some College	Woods and Poole (2010) [a]
% College Grad	Woods and Poole (2010) [a]
% Gov't Emp	Woods and Poole (2010) [a]
% Real Estate Emp	Woods and Poole (2010) [a]
% Retail Sales Emp	Woods and Poole (2010) [a]
% Accomm Emp	Woods and Poole (2010) [a]
% Health Emp	Woods and Poole (2010) [a]
% Manuf Emp	Woods and Poole (2010) [a]
% Mining Emp	Woods and Poole (2010) [a]
% For/Fish/Ag Support	Woods and Poole (2010) [a]
% Agriculture Emp	Woods and Poole (2010) [a]
% Cropland	U.S. Department of Agriculture (2002) [b]
$ Crops per Acre	U.S. Department of Agriculture (2002) [b]
$ Livestock per Acre	U.S. Department of Agriculture (2002) [b]
% Irrig per Crop Acre	U.S. Geological Survey (2000) [a]
% Irrigation	U.S. Geological Survey (2000) [a]
Per Cap Irrigation	U.S. Geological Survey (2000) [a]
Per Cap Water Use	U.S. Geological Survey (2000) [a]
Topography	McGranahan (1999)
Avg Jan Temp	McGranahan (1999)
Avg July Hum	McGranahan (1999)
% Water Area	McGranahan (1999)

[a] Data collected in the 2000.
[b] Data collected in 2002.

population change, migration patterns, urbanization, and age distribution. Socio-economic status is represented by a set of income (percent of low income and middle income) and education (percent less than high school, high school, some college, and college graduate) variables. Racial/ethnic composition is measured by the percent of African-Americans and percent of Hispanics/Latinos. We include these additional indicators because our coupled-systems hyper-extractive theory suggests that migration patterns, racial and ethnic characteristics, and SES indicators are tied theoretically to the hyper-extractive construct.

The next set of indicators represent of combination of indirect and direct measures of land and resource use. The indirect indicators focus on employment patterns. Included in the analysis is the percentage of government (combining local, state, federal and military employment), real estate, retail sales, accommodations, healthcare, manufacturing, mining, agriculture employees and combined percentage of forestry employees, fishing employees, and agriculture support services employees (referred to as forestry, fishing, and agricultural services) in each county, respectively. Some of these variables denote urban land use and development patterns in rural counties. Thus, high levels of government employment suggest the presence of a large government institution or service provider (e.g. state university or military base) in a county. High levels of manufacturing suggest that a county's development has a strong industrial/working class flavor. Higher levels of employment in healthcare may suggest that a county has a regional medical center. Higher levels of employment in the retail sales sector suggest urban development patterns of shopping centers and malls.

Other employment indictors go beyond characterizing urban patterns of development in rural counties. Higher levels of real estate

employment suggest there is a strong pattern of growth and expansion in county, which in rural areas may mean urban encroachment on rural farmland and/or ranchland. Higher levels of employment in hotel and restaurant accommodations suggest the county draws tourists through scenic amenities or some other attractions. Higher levels of employment in mining and forestry, fishing, and agriculture support services are surrogate for resource use patterns in rural areas due to the connection between these types of employment and the extraction of natural resources (minerals, grazing, lumber, fish, or crops) from the land. Given our purpose, we are especially interested in employment patterns related to mining, forestry and fishing, and agricultural employment patterns.

Included are direct indicators of land use. These variables are the percentage of the county that is cropland, value of crops sold per acre, and the value of live animals sold per acre. The first two variables are indicators of the dominance of farming, while the latter variable is more of an indicator of ranching and grazing activities. All three of these indicators of land use are calibrated to the total number of acres in the county to properly tap into the extent to which farming and/or ranching dominates the land use of a county.

The analysis includes four measures of water use. First, per capita water use assesses the overall water consumed (by all uses) per resident. Second, per capita irrigation accesses the extent to which this water use is for irrigation. Because these first two water use measures are calibrated on a per capita basis, higher population counties will have lower per capita water usage. We counterbalance this bias with the percentage of all land in the county that is irrigated and the percent of crop acres that are irrigated. Both variables tap into the extent to which irrigation dominates the landscape.

Finally, we borrow from the scenic amenities literature to include indicators of topography and weather patterns. Specifically, we use the US Geological Survey's indicator of topography classifying each county into one of 21 ordered categories ranging from the flat plains at the low end to high mountains at the high end. A second indicator of topography is the percentage of the county that is shoreline. Our indicators of weather patterns are the average humidity level in July and the average temperature in January.

We use a two-step interdisciplinary measurement design to identify rural coupled-systems. In the first step a geographer's perspective dominates. We follow Waldo Tobler's (1970) first law of geography: "everything is related to everything else, but near things are more related than distant things." With Tobler's law in mind, we first conduct a series of "hot spot" (Getis−Ord G_I^*) analyses of all the county level indicators except for topography and weather patterns. All 3075 counties in the contiguous U.S. are included in the hot spot analyses to properly account for spatial relationships. ArcGIS 10 is used to conduct the hot spot analyses. G_I^* is calculated:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \overline{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j} \right)^2 \right]}{n-1}}} \tag{1}$$

where: x_j is the attribute value for feature j; $w_{i,j}$ is the spatial weight between features i and j; n is equal to the total number of features.

$$\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n} \text{ and } S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\overline{X})^2}$$

(ArcGIS Resource Center, 2009)

A hot spot analysis identifies clusters of features with high values (hot spots) and clusters of features of low values (cold-spots). "The

local sum for a feature and its neighbors is compared proportionally to the sum of all features… Hot spots have a high value and will be surrounded by other features with high values as well." (ArcGIS Resource Center, 2009) Cold-spots, on the other hand, have low values and will be surrounded by other features with low values.[3] For each feature, G_i^* calculates a Z-score variable with $\mu = 0$, $\sigma = 1$.

For most hot spot analyses, investigators focus only on statistically significant Z scores ($Z \geq \pm 1.96$). Our purpose for conducting G_i^* is more expansive. We conduct the hot spot analysis to create a set of Z-score variables, which are then substituted for the original data. These Z-score variables allow the geography of nearness (Tobler's first law) to have first dibs on "grabbing" the variance for defining the commonality of contiguous counties. These hot spot Z-transformed variables are used in second step of this interdisciplinary research design.

The only variables for which we do not conduct hot spot analysis are the topography and weather variables. These variables are already geographically attuned, given that these are indicators of the natural environment. We do, however, transform these variables to Z scores ($\mu = 0$, $\sigma = 1$) and code the direction of these Z variables such that positive scores reflect values that are more conducive to greater human activity (Less July humidity and higher January temperature are scored positive). Given the number of variables and resulting maps, we do not show the results from these hot spot analyses, however they are available upon request from the authors.

In the second step, we conduct an exploratory factor analysis on the Z-score variables produced from the hot spot analysis and the Z-transformed topography and weather variables. As opposed to the first step, which includes all counties to maintain spatial relationship among counties, only rural counties are included in the factor analysis. We define rural counties as non-SMSA counties ($N = 1991$).

We use exploratory factor analysis to uncover the latent class factors underlying these rural coupled-systems. Even though there are a number of different approaches to conducting a factor analysis of these data, we choose the most common method, Principal Components (PC). The PC statistical model for p variables and q factors is defined as:

$\Psi = p \times p$ diagonal matrix of uniqueness,
$\Lambda = p \times q$ factor loading matrix
$f = 1 \times q$ matrix of factors
$x(1 \times p) = $ Z-transformed vector of variables expressed as a system of regression equations:

$$x = f\Lambda' + e \qquad (2)$$

where $e = 1 \times p$ vector of uncorrelated errors with a covariance equal to Ψ

We use this factor analytic model for three reasons. First, all of the variables included in the analysis have been transformed into Z scores, most of them based on the hot spot analysis. Each of these variables has an approximately normal distribution. Second, the application of measurement science and our coupled-systems approach are relatively new to the classification of counties. An exploratory factor analysis at this phase of the research process is thus appropriate, especially considering that the analysis includes 35 indicators. Finally, PC is a method that provides a reliable outcome.

We rotate the factor solution using oblimin rotation (oblique) with Kaiser normalization versus an orthogonal rotation. Orthogonal rotations assume that each factor is not correlated with other factors. In this case, we view this assumption as untenable. We fully anticipate that the underlying latent class factors of these rural coupled-systems will have some correlation with each other. Oblimin rotation allows any natural correlation to occur among the rural coupled-systems. Finally, we delimit the number of factors by setting a minimum Eigen-value to 1.0.

Even though we are conducting an exploratory factor analysis, this does not mean that we lack strong theoretical underpinnings. Given the previous literature, we expect to find rural coupled-systems that have components that are:

1) Farming and/or ranching dependent (Parker, 2005)
2) Mining dependent (Parker, 2005)
3) Manufacturing dependent (Parker, 2005)
4) Forestry, fishing, and agricultural services dependent
5) Scenic amenities/tourist dependent (Beale and Johnson 1998; Johnson and Beale 2002; McGranahan, 1999; Winkler, 2010)
6) Adjacent to urban centers (Parker, 2005)
7) Water/irrigation dependent (Kromm & White 1992)

We also expect that farming and ranching dependent areas will also show signs that they are aging communities. Given the influx of Hispanics into rural areas of the Southwest, we also expect it to load with ranching and/or mining dependent counties. At the same time, a single factor is unlikely to represent hyper-extractive land use and development patterns, because hyper-extraction itself is a hybrid type of development pattern, a combination of latent class characteristics.

As opposed to previous research, which tends to classify counties by one characteristic, our factor analytic research design allows counties to be classified as high or low on more than one component. For example, a county, which scores high on the dimension of scenic amenities, may also score high in terms of mining employment. Even though we know that counties that are tourist destinations are often located in mountainous terrains where mineral extraction is taking place too, it is also the case that many tourist destinations lack mining employment and vice versa. So, it is the nature of some development patterns for a county to fit predominantly into one coupled-system, but also score high on another coupled-system. Unlike previous classification schemes, this is not an "either/or" approach.

In the case of hyper-extractive counties, we expect them to have a dependency on mining, forestry, fishing or agricultural services, and/or water/irrigation and agriculture. Among social-demographic variables, we expect hyper-extractive factors to load on positive growth, in-migration, and Hispanic population. We believe that it is the intersection among factors that will produce some of the more interesting theoretical outcomes from this analysis.

Table 2 shows the pattern matrix for the analysis of 1991 non-SMSA counties. For ease of presentation, all loadings of less than an absolute value of 0.3 are blanked out. Low loadings of this magnitude indicate that the variable in question is not strongly driving the composition of that factor. Finally, it is important to note that each factor represents of continuum of positive and negative loading characteristics, ranging from -1 to 0 to $+1$. In describing each factor, we focus on this continuum.[4]

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[3] The hot spot analyses conceptualized the spatial relationships as an unspecified fixed distance band to ensure that all the features, in this case county polygons, are weighted equally.

[4] It is common practice to attempt to clean a factor analysis by eliminating variables that don't load on a factor and that load on multiple factors. In this way, analysts create factors that are largely distinct from one another. Even though we did eliminate variables that did not strongly load on any factor, we did not eliminate variables that load on multiple factors. Our reason is that coupled-systems are complex and theoretically can be interrelated with one another. Developing clean factors is not and should not be the goal of this endeavor.

Table 2
Pattern matrix from factor analysis.

Variable[a]	Component						
	F_1	F_2	F_3	F_4	F_5	F_6	F_7
Population			0.814				
% Urban			0.983				
% Pop Change	−0.421				−0.733		
% Migr Foreign			0.467		−0.564		
% Migr County					−0.860		
% Migr State					−0.758		
% Pop > 65	0.745		−0.325				
% Hisp/Latino			0.395			−0.718	
% African American	−0.542	0.547				0.457	
% Low Income	−0.380	0.362	−0.602				
% Middle Income	0.627	−0.474					
% < High School	−0.803						
% Only High School		−0.524			0.445		
% Some College	0.773						
% College Grad	0.595		0.432		−0.325		
% Gov't Emp		0.826					
% Real Estate Emp				0.366	−0.476	−0.444	
% Retail Sales Emp		−0.313		−0.525			
% Accomm Emp				0.340	−0.636		
% Health Emp	0.392			−0.315	0.605		
% Manuf Emp	−0.576	−0.534				0.373	
% Mining Emp						−0.792	
% For/Fish/Ag Support		0.728					
% Agriculture Emp	0.447			−0.516	0.363	−0.354	
% Cropland	0.435	−0.322		0.564	0.307		
$ Crops per Acre				0.411	0.460	0.336	
$ Livestock per Acre		−0.388			0.596		
% Irrig per Crop Acre					−0.376		0.634
% Irrigation							0.853
Per Cap Irrigation							0.860
Per Cap Water Use							0.878
Topography		−0.379		−0.679			
Avg Jan Temp	−0.726						
Avg July Hum	0.349					−0.586	
% Water Area		0.363				0.599	

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.
Rotation converged in 25 iterations.
Cumulative Variance Explained: 77.996%.
  [a] All Variables are Z scores.

Findings

The PC analysis with oblique rotation uncovers seven significant components (78% of variance explained) from the 31 hot spot transformed Z variables and four Z-transformed topography and weather variables. These seven components conform to the existing literature, but with a number of important caveats. We find clear evidence of adjacent rural counties, farming and ranching dependent, mining dependent, government dependent, (ERS 2004 Rural Dependency Codes; Parker 2005), and scenic amenities/recreation counties (Beale and Johnson, 1998; Johnson and Beale, 2002; McGranahan 1999; Winkler 2010). To analyze each, we convert the seven components into factor scores using the regression method. Each converted factor score is distributed normally ($\mu = 0$, $\sigma = 1$).

Even though there is much in common with the existing literature, there are, though, some important differences. For example, factor 1 loads positively on the percentage of over 65 years old, people with higher levels of education and middle income, cropland, agriculture and healthcare employment, while it loads negatively on population change, blacks, people with less education, manufacturing employment, and January average temperatures. This component juxtaposes aging farming counties in the Great Plains states to rural more manufacturing based counties in the South Appalachians and mid-Southeast (map available on request). We refer to this juxtaposition of two coupled-systems within a latent class construct as a "linked coupled-system."

The second factor also represents a linked coupled-system. It loads positively on percentage of African Americans, government employment, farm employment, and forestry, fishing and agricultural services employment, while it has negative loadings on middle income, high school graduation, manufacturing employment and percentage of cropland and livestock sold per acre. Fig. 1 shows that the location of the forestry, fishing, agricultural support services, and government services counties is predominantly in the Southeast part of the U.S., while agricultural/industrial counties in the Midwest and Mid-South score low. These coupled-systems are not considered in the rural classifications literature.

Factor 3 loads positively on population, percent urban, percent with college degrees, migration from abroad, Hispanics and crops sold per acre, while it loads negatively on low income and farm employment. This component represents a continuum from "adjacent" counties, which earn their designation because they are in close approximation to major urban centers, while on the negative side of this continuum are deep rural counties, counties whose landscape is dominated by rural, sparse populations, lower income, and agricultural employment (map available on request).

Factor 4 loads positively on agriculture-based variables (livestock sold, crops sold and the percent of farmland). However, it loads negatively on variables associated with scenic amenities, including topography and employment in accommodations, retail sales, and real estate. We find that positive values are associated with counties in non-scenic farming communities in the Great Plains and Midwest, while negative values indicate the presence of scenic amenities counties, located mostly in the Mountain West or in the deciduous forests in the mid-Appalachians through New York and on up into Maine. These linked coupled-systems correspond with Winkler's (2010) research on tourist destinations (map available on request).

Factor 5 loads negatively on population change, migration variables, and other variables associated with population growth (real estate employment), but positively on two indicators of agricultural activities and healthcare employment. Fig. 2 shows these linked coupled-systems. For purposes of presentation, we have reversed the coding for this factor. Counties at the positive end of the continuum are rural growth centers, while those at the negative end are declining rural communities.

Factor 6 represents a bit of a twist on mining dependent counties. This factor loads negatively on Hispanics, mining employment, agricultural employment, and July humidity levels, while it loads positively on manufacturing employment, African Americans and water area. Fig. 3, which reverses the coding on this factor, shows that the Latino/Mining coupled-system is primarily in the lower Great Plains counties stretching from Mexican border north through Oklahoma and into Southwest Kansas, while the coastal industries coupled-system is in the upper Midwest, Great Lakes region and Mid-Atlantic.

Factor 7 represents intensive water use areas, most of which are associated with irrigated agriculture versus low water intensive use areas. This type of land-use pattern is not typically the focus of county classification schemes. Fig. 4 shows that except for the heavy concentration of rice producing counties in the Mississippi Delta region, most of the intensive water use counties stretch from the Texas Panhandle through the High Plains of Nebraska and
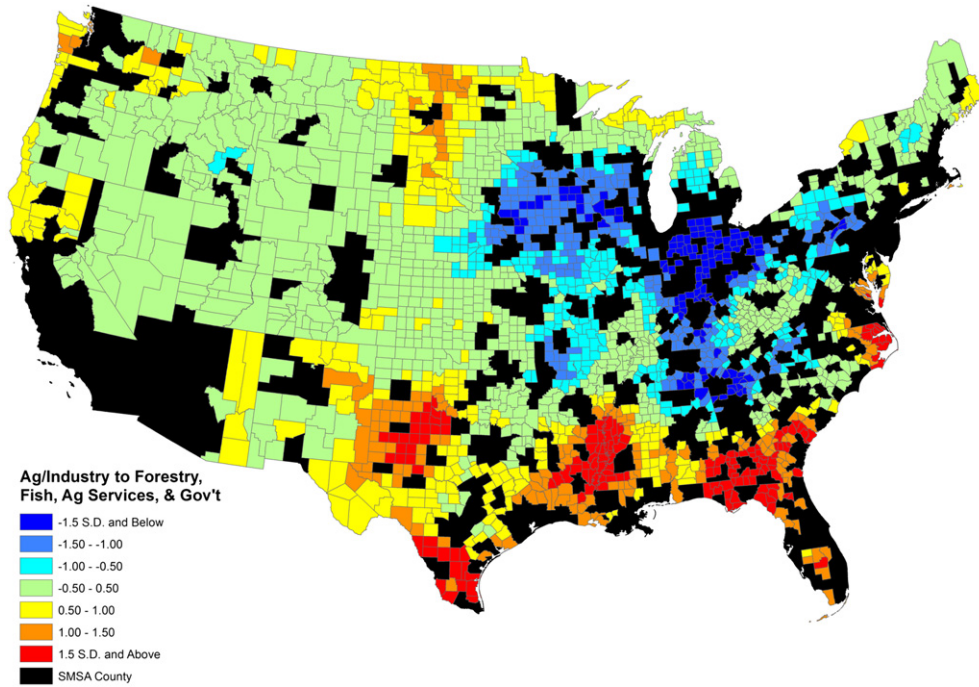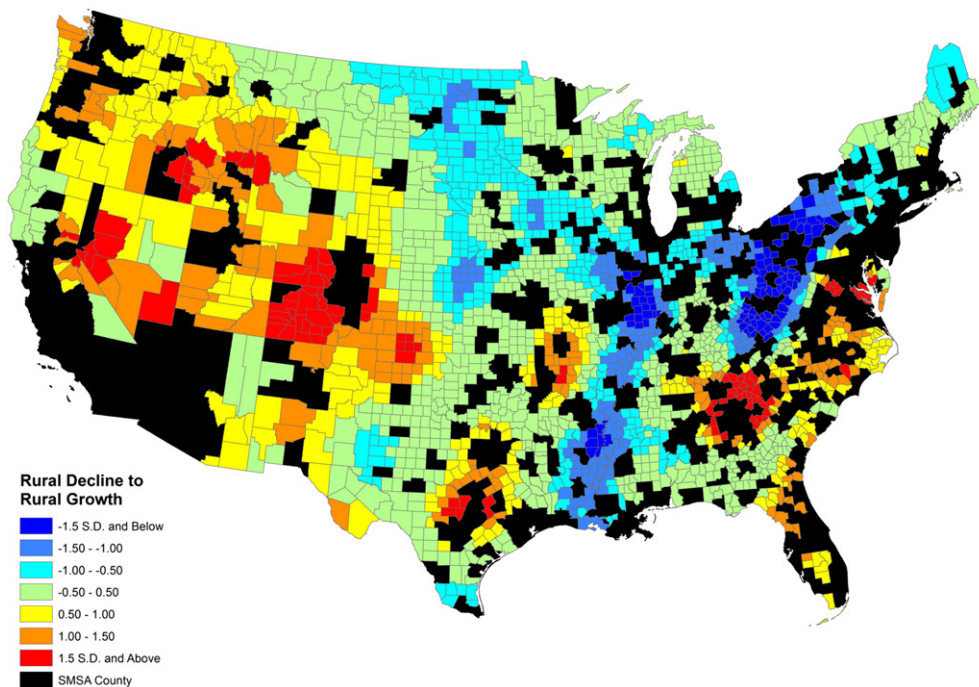
Fig. 1. Darker shades of red represent counties that are high on forestry, fishing, and agricultural support services employment and government employment mostly located in the Southeast. Darker shades of blue represent middle class farming, ranching and rural manufacturing located in the Midwest and mid-South.

Colorado, and on into the Mountain Northwest and Sierra Nevada regions. Many counties in Arizona and California would also be pictured as intensive water use areas, however their SMSA status eliminates them from this analysis.

To check the validity of these findings, we correlated ERS (2004) and appropriate Beale Code (2003) classifications with the factor scores that share the same characteristics. Significantly, ERS and

Beale Codes are dichotomous classifications while the factor scores are continuous variables. Despite the differences in measurement, a correlation coefficient gives a valid indication of the extent to which these measures overlap. In addition, we also report the correlation between McGranahan's Amenities Scale (1999) and non-scenic to scenic amenities factor score. Table 3 shows that the correlations are at around the 0.25 level or above. The negative correlations in the

Fig. 2. Darker shades of red represent counties that have a high degree of population change, migration, and population growth. Darker shades of blue represent agricultural counties with higher levels of healthcare employment.
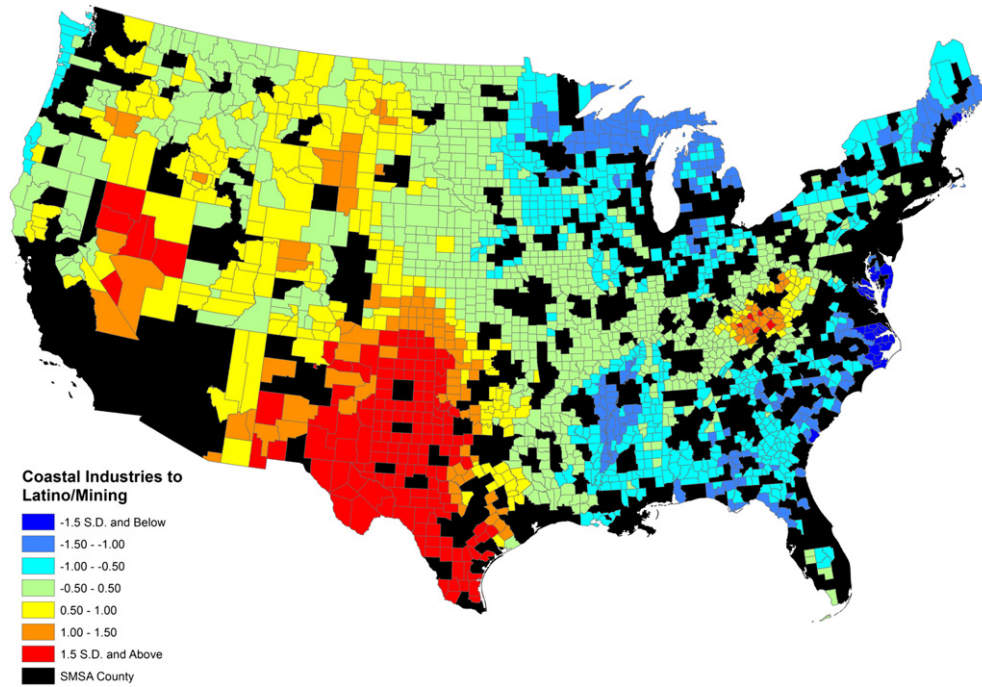
Fig. 3. Darker shades of red represent counties with a high level of Hispanics and low July humidity coupled with mining and agricultural employment located mostly in the Southwest. Darker shades of blue represent counties that couple African Americans and water area with manufacturing employment located mostly in the east half of the U.S.

table simply reflect the coding direction of the components. All reported correlations are significant at the 0.01 level.

Fig. 5 summarizes the findings of these analyses. In this figure, we highlight counties that are ±1.5σ from the mean on each of the factor scores. We label these counties as "exemplar" because they most vividly display the characteristics of each of the coupled-systems. The advantages of our coupled-systems approach over previous classification systems come from the added depth of the description. For example, instead of having one classification for

manufacturing dependent counties, there are three factors (F1: Manufacturing South, F2: Ag and Industry, and F6: Coastal Industries) that describe three different types of manufacturing based rural counties. Similarly, there are six coupled-systems that describe different types of extraction based on agriculture and ranching (F1: Aging Farms, F2: Ag and Industry, F3: Deep Rural, F4: Not Scenic Farm, F5: Rural Decline, F7: Intensive Water). These coupled-systems characterizations can be used in the same manner that the previous classification schemes; primarily as a tool to
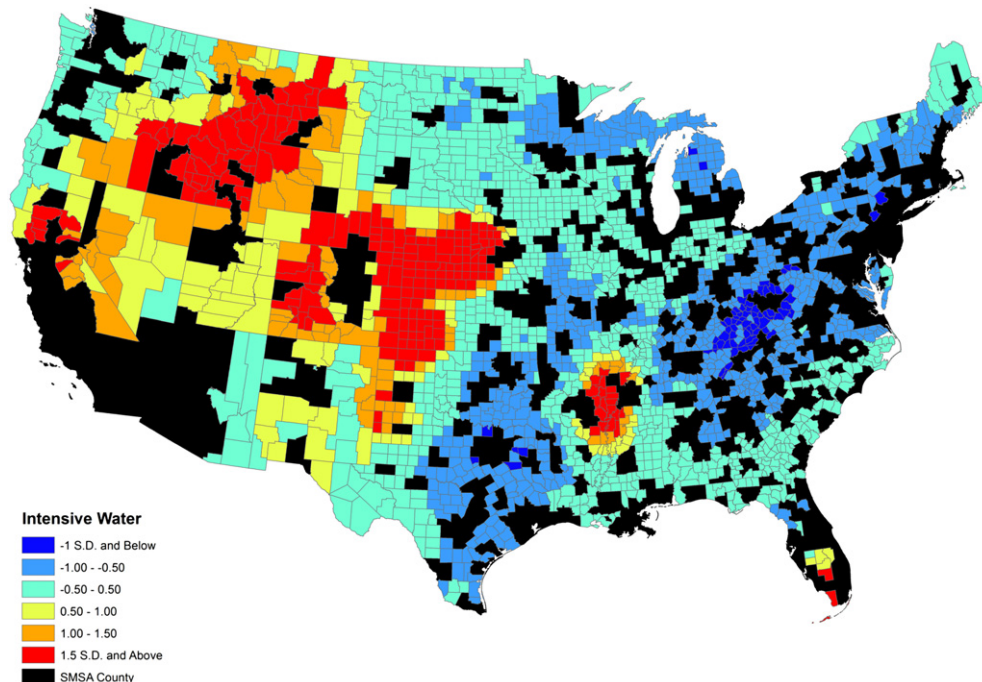

Fig. 4. Darker shades of red indicate heavy water usage on a per capita or per acre basis, in most cases the intensive water use is for irrigated agriculture.

Table 3
Correlations among factor scores and rural classifications.

	ERS dependencies (2004)				Beale code (2003)	McGranahan
	Farming	Manufacturing	Mining	Government	Adjacent (Codes 4, 6, 8)	Amenity scale
Description						
F7: Water Intensive	0.381					
F2: For/Govt to Ag/Indust		−0.297		0.131		
F6: Coastal Industries to Latino/Mining		0.398	−0.308			
F1: Aging Farm to Manufacturing South	0.248	−0.321				
F4: Non-Scenic Ag to Scenic	0.273					−0.419
F3: Adjacent to Deep Rural					0.347	

understand the socio-economic-resource contexts of rural counties, which in turn can be used to help explain rural development and sustainability issues.

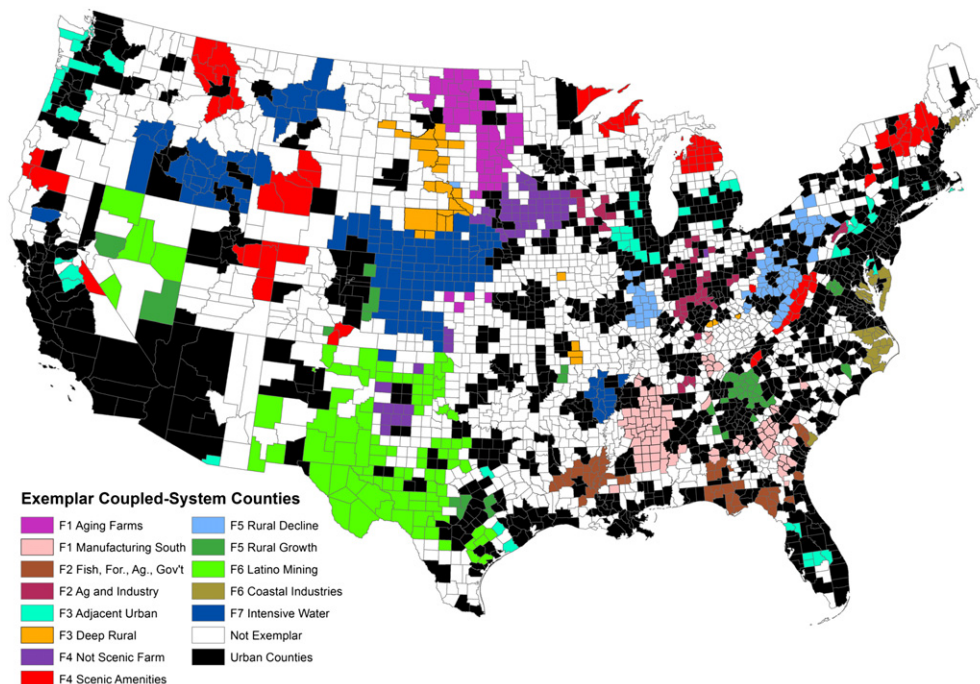*The intersection among components: hyper-extractive counties*

Perhaps the real advantage of this methodology is that it allows one to look at the intersection among components to move beyond the dichotomous taxonomy schemes that have dominated the classification literature up to this point. Indeed, our efforts seek to understand the complex patterns that are associated with coupled-systems using a land and resource use perspective. Specifically, we wish to find the extent to which other regions in the U.S. have characteristics that resemble the hyper-extractive counties in Southwest Kansas.

We defined hyper-extractive communities as being rural in character, dependent on the extraction of natural resources for employment, experiencing a recent history of population growth and in-migration, with perhaps a strong Hispanic/Latino ethnic flavor. As one examines the components, there is no single component or set of components that can be brought together to perfectly match the exemplar case of Southwest Kansas. However, we can bring together those components that come closest to matching our theoretical thrust.
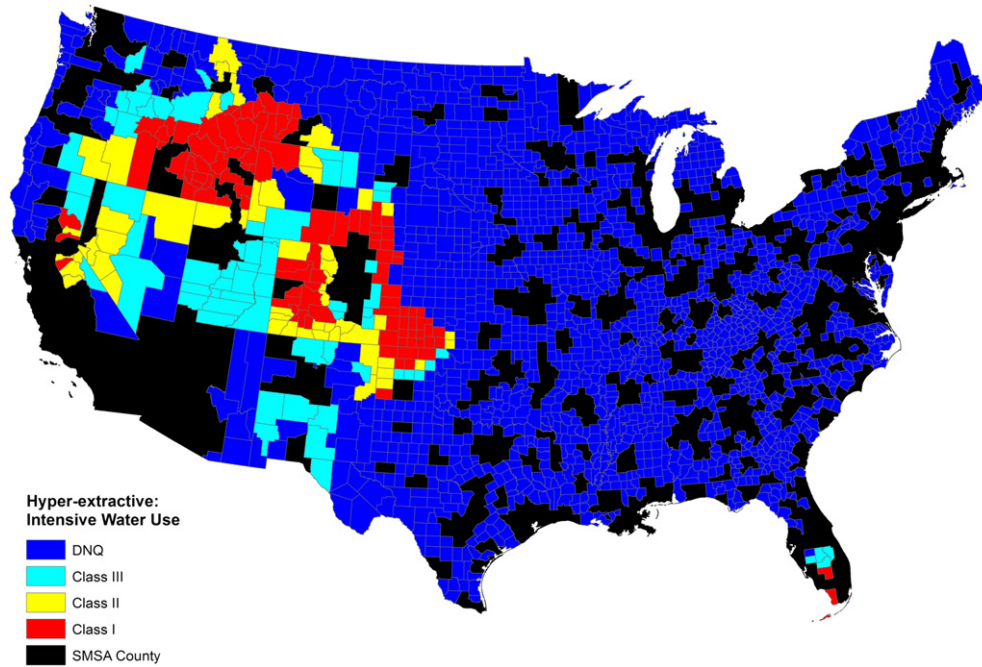
The driving force of our hyper-extractive theory points toward the extraction of resources above and beyond the norm coupled with a pattern of positive population change and in-migration. These are the counties that have escaped the rural decline path dependence. With this in mind, we revise our focus to be on counties that are 0.5σ above the mean on factor 5: Rural Growth (or approximately in the 70 percentile or higher) and that score 0.5σ or above the mean on factor 7: water intensive counties, factor 6: Latino mining counties, or factor 2: forestry, fishing, and agricultural services and government employment.

Even though these factor scores are continuous variables, we nonetheless want to provide readers with some sense of the extent to which counties in the U.S. are hyper-extractive. With this in mind, if a county scores at least 0.5σ above the mean on the rural growth factor and scores greater than or equal to 1.5σ above the mean (or 93rd percentile or above) on the coupled-systems factor in question (factors 2, 6 or 7), we classify them as Class 1 cases of hyper-extraction; they are the most extreme examples. We classify counties that are between 1.49σ and 1.0σ (between the 92nd and 84th percentile) on the coupled-systems factor in question as a Class II hyper-extractive case. For those counties that are between 0.99σ and 0.5σ (83rd and 71st percentile) on the coupled-systems factor in question we classify as a Class III hyper-extractive case. We consider these counties as "approaching" hyper-extractive. Any county that is below 0.5σ on the coupled-systems factor in question and rural growth factor are coded 0 for Did Not Qualify (DNQ).

Exemplar Coupled-System Counties

- F1 Aging Farms
- F1 Manufacturing South
- F2 Fish, For., Ag., Gov't
- F2 Ag and Industry
- F3 Adjacent Urban
- F3 Deep Rural
- F4 Not Scenic Farm
- F4 Scenic Amenities
- F5 Rural Decline
- F5 Rural Growth
- F6 Latino Mining
- F6 Coastal Industries
- F7 Intensive Water
- Not Exemplar
- Urban Counties

**Fig. 5.** Depicted are counties that are exemplars of each type of coupled-system.

Fig. 6. Hyper-extractive intensive water use counties. These counties are 0.5σ or more on the rural growth factor and 0.5σ or greater on the irrigation factor. Where class I are counties 1.5σ or more on irrigation factor, class II are between 1.49σ and 1.0σ, and class III are counties between 0.99σ and 0.5σ.

Fig. 6 shows coupled-systems counties that use water intensively and that are 0.5σ above the mean on rural growth component. Compared to Fig. 4, most of the counties east of the Mississippi River are not shown in Fig. 5 because their growth levels are below +0.5σ. Rather, hyper-extractive water use counties tend to be located from the High Plains of Oklahoma and Southwest Kansas through Colorado, Montana, Idaho, and Nevada. We classify 102 counties as Class I examples hyper-extractive water use counties, another 52 counties as Class II counties and 66 counties as Class III

or approaching hyper-extractive water use. Southwest Kansas counties, which composed our exemplary cases for hyper-extractive theory, qualify as Class I in Fig. 6.

Fig. 7 shows Latino/mining intensive counties that are 0.5σ above the mean on rural growth. They are located primarily in the western half of the U.S. stretching from Texas and New Mexico in the South, up through Southwest Kansas, and west through Colorado and Nevada. Fifty-four counties represent the most extreme cases of hyper-extractive Latino/mining intensive counties (Class I),
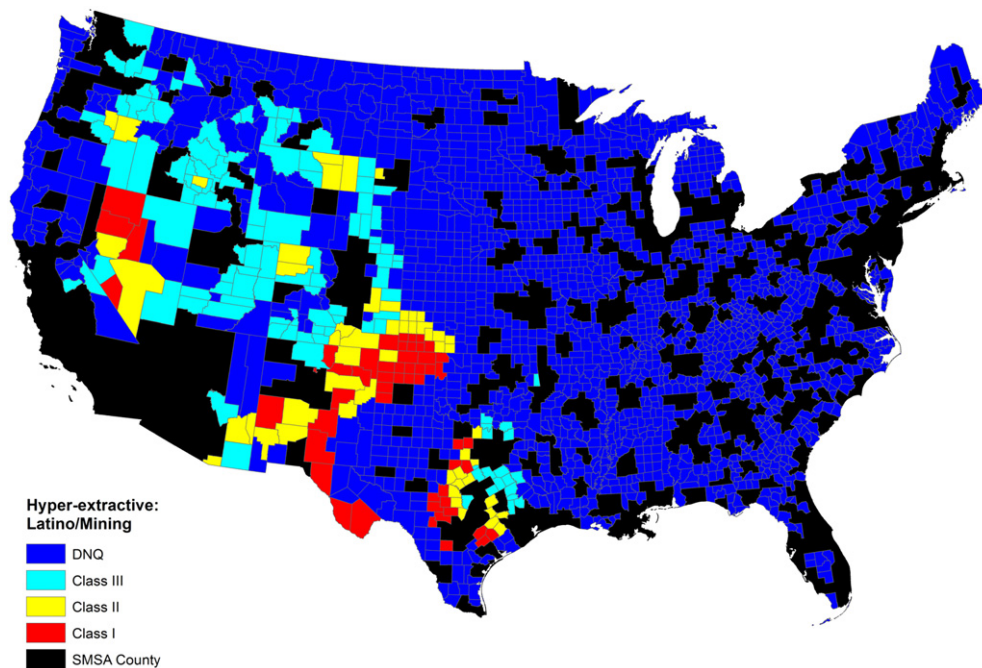
Fig. 7. Hyper-extractive Latino/mining counties. These counties are 0.5σ or more on the rural growth factor and 0.5σ or greater on the Latino/mining factor. Where class I are counties 1.5σ or more on Latino/mining factor, class II are between 1.49σ and 1.0σ, and class III are counties between 0.99σ and 0.5σ.
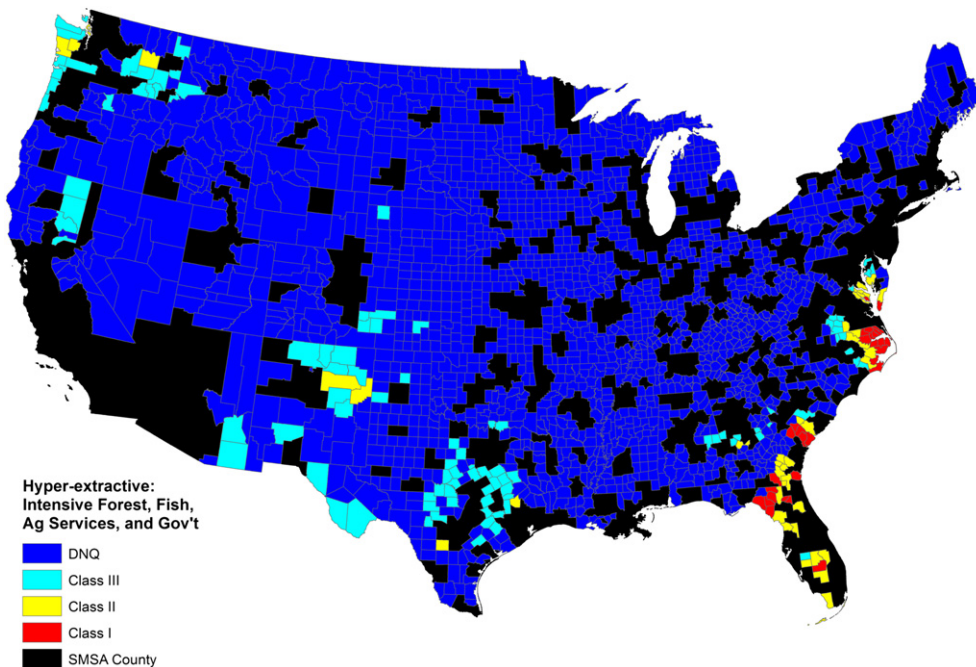
Fig. 8. Hyper-extractive forestry/fishing/agriculture support counties. These counties are 0.5σ or more on the rural growth factor and 0.5σ or greater on the forestry/fishing government factor. Where class I are counties 1.5σ or more on forestry/fishing government factor, class II are between 1.49σ and 1.0σ, and class III are counties between 0.99σ and 0.5σ.

with another 55 counties classified as Class II hyper-extractive, and 117 counties in Class III or approaching hyper-extractive status. Interestingly, some counties of Southwest Kansas score highly on this version of hyper-extraction as well.

Fig. 8 shows forestry, fishing, agricultural services and government counties that are 0.5 standard deviations above the mean on rural growth. Hyper-extractive forestry, fishing, agricultural services and government counties are mostly located in the Southeast quadrant of the U.S. in states like North Carolina, South Carolina, and Georgia. There are some marine fishing dominated coastline rural counties also represented, while forestry dominates interior counties. Only 32 counties represent a Class I example of this type of hyper-extractive coupled-systems. Another 40 counties qualify as Class II hyper-extractive, while another 100 counties are in Class III, approaching hyper-extractive. The smaller number of counties that fit Class I status may reflect a life-cycle effect for hyper-extractive counties. We suspect that historically, there were many more counties that would fall into Class I for these types of hyper-extractive activities. However, as woodlands and marine fisheries became more depleted (Schlager, 1994; Ostrom et al., 1994), the number of thriving counties based on this type of extraction may have also declined.

The boomtown literature is a strong influence on our hyper-extractive theory. Thus, a natural question to ask is whether social externalities are more likely to afflict hyper-extractive counties compared to other rural counties in the U.S. Even though there are a number of ways to assess social externalities, we choose the violent crime rate and property crime rate for the year 2000. Each type of hyper-extractive coupled-system is divided into counties that qualify as Class I, Class II, Class III, and DNQ. We conducted a difference of means T-Test. For two of the three hyper-extractive coupled-systems, Intensive Water and Latino/Mining, the findings are insignificant and if anything, the opposite of the expected relationship. That is the level of property and violent crimes were lower in these hyper-extractive counties than the overall mean level for rural counties (results not shown in a table). We did find that both property and violent crimes are double the

rate in hyper-extractive Forestry, Fishing, Agricultural Services and Government coupled-systems compared to all other rural counties. Given that most of these counties in the Southeast, where violent and property crimes tend to be higher than other regions of the U.S., these findings suggest that these two types of social externalities are not prominent features of hyper-extractive coupled-systems.

Conclusion

Coupled natural and human systems are inherently complex and those built on extractive resources are vulnerable because usually they mostly use only one particular resource that is often non-renewable. Such conditions resemble the phenomenon of boomtowns that are going bust once the natural resource is depleted. Hyper-extraction, however, is more complex because of the vertical concentration of industries that masks the original relationship with extraction and provides a false picture of economic security. Therefore, the issue of hyper-extraction is not simply an issue of extraction, but rather a symptom of a coupled-system that is unsustainable in the long run, albeit this unsustainability is difficult to recognize. Our theoretical and methodological purpose is to contribute to the understanding of such systems, help local decision makers to recognize the pitfalls of hyper-extraction and plan local development accordingly.

For this reason, the focus of this research is on the development of theoretical and methodological framework for identifying and understanding hyper-extractive coupled human–natural systems in rural areas of the U.S. To accomplish this purpose, we develop a multidisciplinary coupled-systems approach using hot spot and factor analyses methods to analyze 35 variables measuring a wide variety of social-demographic, employment, natural resource, environmental and land-use characteristics.

The findings show a breadth and depth of description for rural counties previously not depicted in any other classification system. For example, Fig. 5 illustrates that there are multiple ways to think about agriculturally dependent counties or manufacturing dependent counties, depending on social-demographic, land use and

resource use patterns. These coupled-systems characterizations can be used by practitioners in the same manner as previous classification schemes; primarily as a tool to understand the socio-economic-resource contexts of rural counties, which in turn can be used to help explain rural development and sustainability issues.

We also found support for a revised version of our hyper-extractive theory, which focuses on the extraction of resources above and beyond the norm coupled with a pattern of positive population change and in-migration. This classification method helps state and local decision makers recognize and identify where hyper-extractive systems are present, which in most cases indicates unsustainable development patterns. With this coupled-system classification method, it may be easier for state and local decision makers to identify the problem and act accordingly while there is still time to put the county on a more sustainable development trajectory.

This research moves the classification of rural counties to a more nuanced and complex understanding of development and sustainability patterns. Together, the theory and methods used here open the door for new ways to explore the development and evolution of rural counties in the U.S. and other countries around the world.

Acknowledgments

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