

SELF-PATTERNING OF PIÑON-JUNIPER WOODLANDS IN THE
AMERICAN SOUTHWEST

by

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Abstract

Plant-scale water processes are increasingly well understood in U.S. drylands, but the links between plant-level dynamics and landscape-level outcomes are not as well established. Local facilitation of the establishment of new individuals by existing vegetation and the patch-scale diversion of surface water are identified as driving the landscape-level phenomenon of emergent self-organization in conspicuously patterned landscapes in semi-arid systems worldwide, and these plant-level mechanisms are well documented in the American southwest. This form of self-patterning, theorized to be associated with climate sensitivity, has not previously been proposed as an explanation for the observed grouping of individuals into aggregate vegetative patches in U.S. drylands. Using piñon-juniper woodlands in Arizona and New Mexico as a study system, I tested for self-patterning at 5 sites by measuring the spatial correlation of vegetated patch shape complexity with terrain-based estimates of surface water conditions. Maps of vegetated patches were extracted from aerial imagery, and the degree of spatial structure present in vegetation configuration was measured. Hydrological models of surface flow and soil water content were derived from a digital elevation model (DEM), and spatial regression analyses were conducted to test the correlation of vegetation pattern and modeled hydrological character across each site. The measured relationships suggested close linkages between surface water conditions, vegetation pattern, and vegetation density. Key spatial correlations support the presence of self-patterning for sites in Arizona, where low values of the *Wetness Index (WI)* of surface water flow were associated with high values of *Mean Shape Index (MSI)* of spatial structure of patches (*pseudo-R*² 0.67, *p*<0.01). The *Relative Stream Power (RSP)* index of surface water flow was also spatially correlated with *MSI*, although in a positive relationship (*pseudo-R*² 0.67, *p*<0.01). A second measure of spatial pattern, *Area Weighted Mean Patch Fractal Dimension (AWMPFD)* was also tested with and yielded similar results. These analyses are consistent with the presence of a self-patterning dynamic not previously identified in American semi-arid ecosystems and linked with threshold sensitivity to climate change.

1 Introduction

1.1 Background

The semi-arid ecosystems which cover much of the American southwest are increasingly understood to show non-linear sensitivity to changes in climate (Breshears et al., 2005). Substantial research has described the individual-scale dynamics affecting plant-water relations in these ecosystems, but the linkages between plant-scale processes and landscape-level response to precipitation are less well understood. Significant changes in the amount and variability of precipitation are predicted to continue to occur in the American southwest, and the response to these changes will be at the landscape level. There is a compelling interest in improving understanding of the links between plant-scale mechanisms and landscape-level processes. Documented individual-scale mechanisms in U.S. drylands include local self-facilitation of species and patch-mediated distribution of runoff, processes which are associated with the phenomenon of vegetative self-organization in conspicuously patterned landscapes in other parts of the world, but no examples of water-limited self-patterning of American drylands have been previously identified.

The phenomenon of surface water induced self-organization of semi-arid vegetation has been described in several dryland regions of the world. Examples include "tiger striping" of bush in

the African Sahel (White, 1970), "mazing" of woody vegetation in the West African savanna (Couteron and Kokou, 1997) and banding of chenopod shrubland in Australia (Dunkerley and Brown, 1995). In these systems, established plants modify their immediate environment, creating a zone of litter layer, soil accumulation, modified soil structure, increased soil organic content, increased ground water retention, and temperate micro-climate. Seedlings establishing in these "organic shadows" are more likely to be successful. As these plant-scale mechanisms of spatially differential growth aggregate over time and across landscapes, structured patterns of plant presence emerge, composed of chains of vegetation linked by contiguous areas of biotic modification (Figure 1 depicts mazing of savanna in Mali and vegetative arcs in Somalia). Depending on the region-specific details of interactions of surface water, soil water, litter accumulation, and seedling response in each ecosystem, these emergent mosaic structures may take the form of linear bands or interlocking curves, or multi-forked maze complexes, or an intermediate variation (Rietkerk et al., 2002). These systems are described as self-organized, in the sense that exogenous forces acting on the system are not sufficient to explain the observed spatial outcome, but rather the patterns which emerge are principally the result of individual-to-individual interactions. In this case, those interactions are the spatially differentiated facilitation of the establishment of new vegetation by existing vegetation. The type and degree of patterning which emerges is mediated by the presence of surface water that enters the system extrinsically as precipitation. The organization is thus intrinsically self-organized, but mediated by precipitation.

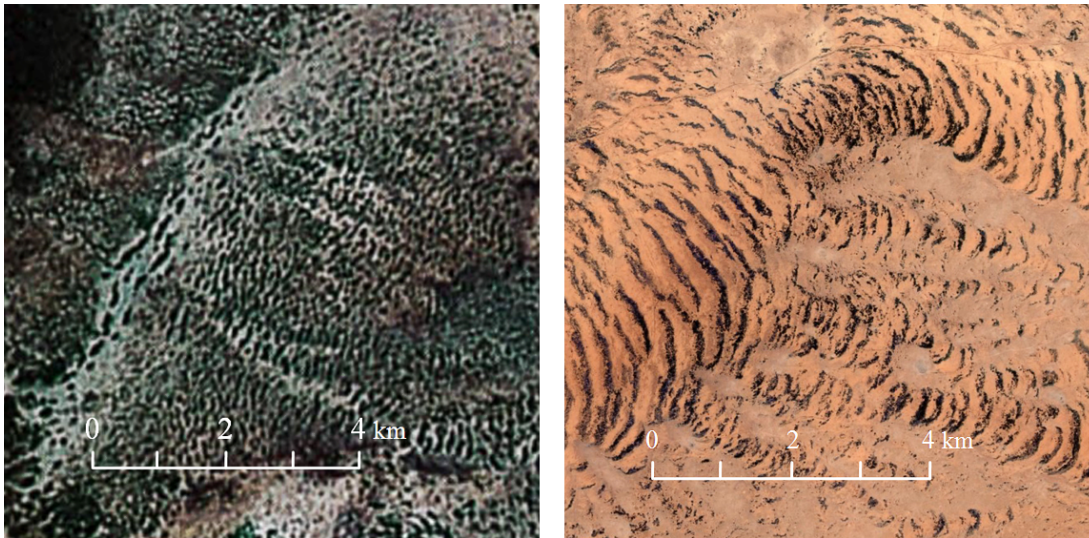


Figure 1: **Mazing of savanna in Mali; Vegetative arcs in Somalia.**

In recent years, modeling has been used to formalize and explore this conceptual model of vegetative self-organization, to test the plausibility of the proposed plant-level mechanisms underlying it, and to make predictions about the functional response of such systems to variation in the controlling driver of precipitation. Modeling approaches typically involve lattice representation of space, with mechanisms encoded using cellular automata (Thiery et al., 1995; Dunkerley, 1997; Esteban and Fairen, 2006) or differential equations (Couteron and Lejeune, 2001; Rietkerk et al., 2002; Kefi et al., 2007; Saco et al., 2007; Zeng and Zeng, 2007).

Self-organized semi-arid landscapes are understood to be more efficient at retaining rain water than would random spatial plant distribution, facilitating infiltration by slowing surface water flow and channeling it over greater area. (Tongway and Ludwig, 2001; Ludwig and Tongway, 1995; Puigdefabregas, 2005). Emergent pattern may therefore allow plants to exist at lower levels of precipitation than would otherwise be possible, mitigating the amount of vegetation lost if precipitation is reduced. However, recent dynamic simulation of these systems using formal models suggests that such systems may exhibit sudden and total loss of vegetation below some threshold of precipitation. In these scenarios of catastrophic shift, gradual reduction of vegetation in response to changes in rain availability eventually cross a lower limit of vegetation cover, under which the drought-mitigating effects of pattern are abruptly diminished, at which point vegetation disappears. Furthermore, re-vegetation may not be possible even if rainfall amount subsequently surpasses what was present at the time of the catastrophic transition, as no one first plant can be a rain-efficient pattern unto itself. Consequently, the presence of vegetation self-patterning may be a predictor of hysteretic response in landscape distribution of vegetation, and may mask impending regional mortality (Rietkerk et al., 2002). In cases where available rainfall varies outside previously observed limits, it would therefore be crucial to know if self-patterning of vegetation was occurring in a system of interest, in order to predict possible threshold sensitivity and calibrate management response.

I used publicly available aerial imagery to survey a variety of semi-arid ecosystems in the American southwest, and noted what appeared to be contiguous bands of vegetation in several ecotypes, ranging from montane forest to grasslands. In all cases, the observed aggregations of individuals were less defined and spatially extended than in the archetypal landcovers associated with self-patterning vegetation. This suggested the possibility that a form of self-patterning might be occurring in these systems that was less constrained than in more conspicuously banded systems, but which, if present, might still have an effect on spatial organization and system-level response to variation in precipitation.

1.2 Research approach

Using piñon-juniper woodlands as a focal system for study, I used remote sensing, landscape pattern measurement and hydrological modeling methods to test the possibility that emergent water-limited self-organization might be occurring in these landscapes. I derived maps of vegetation presence from aerial imagery for five sites in Arizona and New Mexico, USA. From those maps of vegetation patch distribution, I calculated metrics of patch shape, specifically *Mean Shape Index (MSI)* and *Area Weighted Mean Patch Fractal Dimension (AWMPFD)*. For the same sites, I used digital elevation model (DEM) data to develop topographical models of surface and ground water hydrology, using the *Wetness Index (WI)* and *Remote Stream Power (RSP)* index to estimate local available ground water and erosive force of surface water, respectively. According to the conceptual models of vegetation self-patterning in semi-arid ecosystems, I expected to find that areas with less available surface water would be more likely to undergo greater spatial self-organization of vegetation, yielding higher *MSI* and *AWMPFD* values. I also expected to find a spatial correlation of higher estimated stream flow with greater spatial structuring of vegetation. I also anticipated that greater density of vegetation would result in increases in aggregation of individual plants into contiguous groups, yielding higher values of *MSI* and *AWMPFD* in areas of higher vegetative density regardless of the presence or absence of the self-patterning dynamic.

Finally, I anticipated that if vegetative patterning does mitigate the effects of precipitation limitation, there should be a relationship between spatial structure of vegetation and vegetation density. I therefore tested the spatial correlation of vegetation density (measured using the *Class Area (CA)* metric) with the *MSI* and *AWMPFD* metrics, and with the *WI* and *RSP* hydrological indices.

The benefit of a remote-sensing and modeling approach such as this is that it allows for efficient utilization of extensive landscape-level data to assess the plausibility of an ecological process that might be expected to be difficult to apprehend using individually validated ground-level data. A drawback of this approach is that it is necessarily limited to testing if the landscape-level patterns thus measured are consistent with expectations drawn from plant-level understanding of the ecological mechanisms of interest, rather than directly observing those mechanisms.

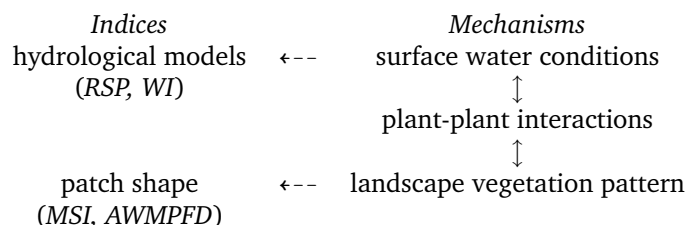


Figure 2: **Indices and hypothesized mechanisms.** Specific indices are defined in 2.4.2.

Specifically, I hypothesize that surface water conditions will mediate the degree to which plant-level mechanisms of patch-inter-patch dynamics will result in the aggregate emergence of spatial structuring of vegetation. Thus a link between the two measured classes of phenomenon—hydrology and landscape pattern—is expected to be made by third class of mechanism: plant-plant interactions. Even if the specific statistical relationships that follow from the hypothesis are found to exist in the landscapes of study, it would still be possible that some non-hypothesized plant-level mechanism was mediating those relationships. I have attempted to choose a study system for which the relevant plant-level mechanisms are well-described, and to select remote-sensing and modeling based measurements which are plausibly linked to the hypothesized mechanisms, such that ecologically meaningful inferences might be drawn from observed relationships among those measurements. Nonetheless, this approach can only assess the possibility that water-limited self-patterning occurs in these ecosystems, rather than directly detect it.

1.3 Piñon-juniper woodlands

I chose piñon-juniper woodlands as a landcover type in which to investigate this phenomenon because of its spatial extent in the American southwest, because it is well suited to remote sensing of vegetation presence, and because the key plant-level mechanisms identified by conceptual models of emergent self-patterning have been identified by existing research on plant-environment relations in these landscapes.

Piñon-juniper woodlands are defined by the co-dominance of *Juniperus monosperma* and *Pinus edulis*, and occur extensively in American drylands regions. The common ecological dynamics

of piñon-juniper woodlands are well documented at the levels of individual plants and of plant-to-plant interactions (Van Auken, 2007), and considerable emphasis has been given to the understanding of these landscapes from a perspective of plant-water relations. A few documented ecological processes are of particular importance with respect to the possibility of self-patterning. Models of surface water mediated patterning vary in their details, but the key mechanisms common to most are:

- Improved growth conditions in the vegetative patch surrounding an existing plant.
- Diversion of surface water due to the physical obstruction of these patches.

Within piñon-juniper woodlands considerable differentiation has been observed between the vegetated patch areas below and around canopies and the barren or sparsely vegetated inter-patch area, in particular with regard to soil structure and organic content, water infiltration rates, solar radiation, and sediment erosion and transport (Wilcox and Breshears, 1994; Reid et al., 1999; Breshears, 2008). These ecophysiological characteristics are likely to affect establishment of new seedlings in resource limited semi-arid systems. This localized modification of the environment is typically evident as a zone of accumulated litter and soil around an established individual, often varying in color from the surrounding substrate and in many cases raised by several centimeters (e.g. Figure 3).



Figure 3: **Piñon-juniper woodland.** From left to right, an individual of *Juniperus monosperma*, an individual of *Pinus edulis*, and a dead *Pinus edulis*. Note the area of litter accumulation and soil accumulation and differentiation under and around the base of each individual.

With regard to surface water flow, Reid et al. (1999) demonstrated substantial differences in the runoff and runoff rates of bare inter-canopy, vegetated inter-canopy, and sub-canopy zones in an area close to one of the sites used in this study. While the Reid et al. study was not designed to test the lateral diversion of flow around vegetated patches, it clearly demonstrates that such patches represent substantively different hydraulic conditions, suggesting that downslope flow necessarily would have to be diverted to a significant degree. The authors note that “these features suggest. . . that runoff is usually routed around the canopy areas” (p. 1870).

In addition to possessing these plant-level mechanisms associated with self-patterning, piñon-juniper woodlands have the additional benefit of being well suited for remote sensing of vegetative presence. Individual canopies are typically more spatially separated than in some non-water-limited landcovers, with distinct areas of sub-canopy matrix apparent. The background matrix is commonly a mix of dry grasses and bare soil. The resulting contrast between the dark and green canopy and the bright background facilitates precise identification and extraction of vegetation location and shape.

2 Methods

2.1 Study sites.

Five sites were chosen for analysis; three in Coconino National Forest, Arizona, USA, and two in the mesas surrounding Los Alamos, New Mexico, USA (see Figures 4, 5 and 6).

Accurate mapping of vegetation required availability of color aerial photography of sufficient resolution. Size and shape of each study site were factors of the distribution of piñon-juniper landcover, and of position and size of the aerial photographs used for extraction of vegetation location. Aerial ortho photography is typically recorded as a series of discrete exposures. Each resulting image has different color and contrast response, necessitating that vegetation classification be executed for each independently, and that each study site be constrained to area of a single aerial image.

#	State	Size (hectares)	Location	Canopy Cover	Elevation (meters)
1	AZ	1150	35° 25' N, 111° 35' W	25%	1960 to 2230
2	AZ	2030	35° 29' N, 111° 30' W	16%	1680 to 1880
3	AZ	2500	35° 31' N, 111° 42' W	27%	1940 to 2260
4	NM	250	35° 47' N, 106° 14' W	52%	1900 to 2000
5	NM	450	35° 45' N, 106° 16' W	27%	1890 to 1990

Table 1: Study site details.

Site 1. (Bear Jaw Canyon and Sinagua Valley)

Site 1 is located in the Coconino National Forest, north of Flagstaff, Arizona, USA. Southern and south-western borders of the site are delimited by the foothills of San Francisco Mountain. Care was taken to shape the border to exclude areas of *Pinus ponderosa* (ponderosa pine) which dominate the higher-elevation foothills.

Site 2. (Cedar Ridge and Ball Court Wash)

Site 2 is also in Coconino National Forest, northwest of the Strawberry Crater formation. The site is a primarily flat plain with some low-relief ridges, and is bordered by areas of further juniper woodland and open grassland.

Site 3. (Missouri Bill Hill)

Site 3 includes the Missouri Bill Hill crater and surrounding irregular low-relief hills. The site is bordered on the north by open grazed grassland, otherwise by further hills and flats with scattered juniper woodland. Three high-relief areas with north aspect, which were in shade in the aerial imagery, were removed from analysis.

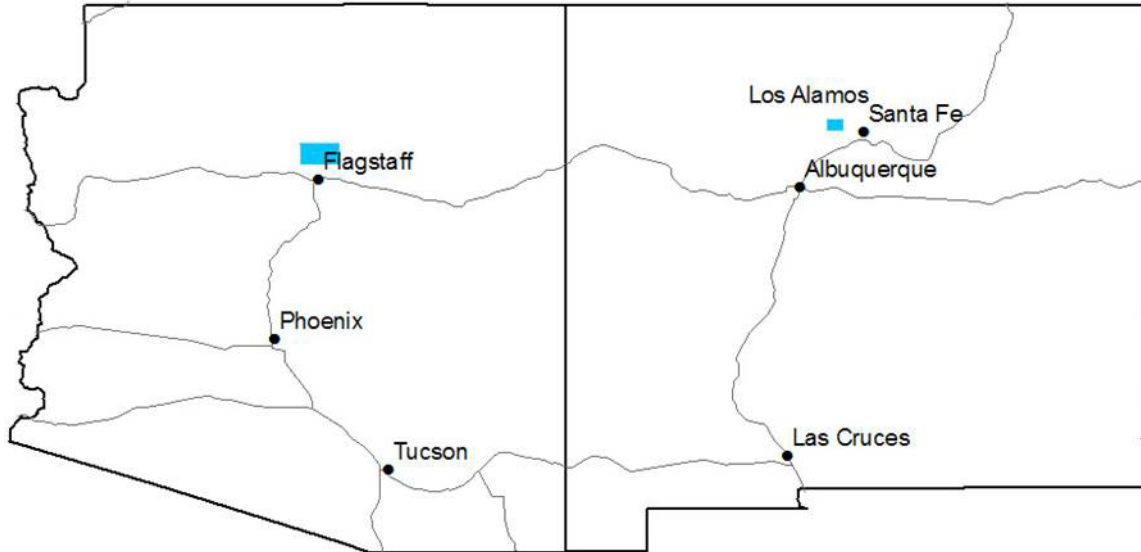


Figure 4: Regional context of study sites locations.

Site 4. (Doe Springs Mesa)

Site 4 is located on a small mesa south of Los Alamos, New Mexico, USA. The complicated topography of this area limits the size of contiguous areas of juniper woodland, and consequently both sites 4 and 5 are smaller than the Arizona sites. Site 4 is bordered on the west by a highway and otherwise by small spring-fed canyons.

Site 5. (Frijole Canyon Mesa)

Site 5 is located on a small mesa south of Los Alamos, in Bandolier National Monument, and is bordered on all sides by small canyons.

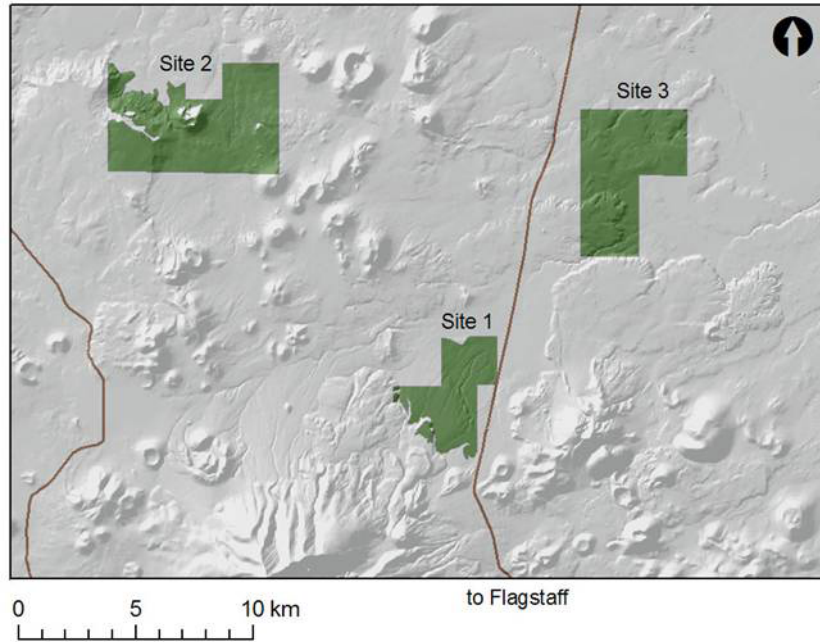


Figure 5: Arizona sites.

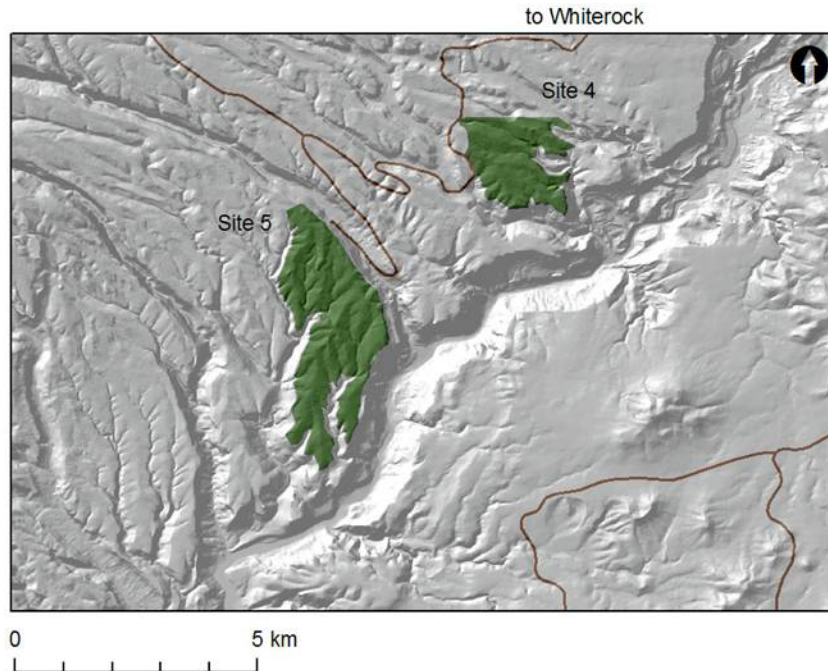


Figure 6: New Mexico sites.

2.2 Vegetation mapping

A map of vegetated patches was extracted from aerial photography using unsupervised pixel classification. US Geological Survey High Resolution State Orthoimagery was used as a basis for classification. This imagery has 1 m resolution and is in natural color, with positional artifacts due to sensor orientation and ground topography removed prior to distribution. An ISODATA classification algorithm was applied to the imagery in ERDAS Imagine (ERDAS Inc, Atlanta GA). The ISODATA algorithm identifies groups of pixels in an n-dimensional phase space defined, in this case, by their red, green and blue reflectance values. Groups of pixels that appear to share similar RGB values are assigned by the algorithm to arbitrary classes. I varied the number of classes generated for each image based on the degree of heterogeneity of the reflective characteristics of vegetation and bare ground apparent in each image; as few as 25 and as many as 40 initial classes were used as a base for classification. The final map output was composed of 2 classes, patch and inter-patch. ISODATA-generated classes that appeared to consist of canopy were included in the “patch” output class. Those that appeared to consist of the area of litter and soil accumulation, which typically extends laterally from under the edge of an individual canopy, were also included in the “patch” output class. Those that appeared to consist of bare or grassy areas were included in the “inter-patch” class.

Figure 7 presents a representative area of piñon-juniper woodland and the derived map of vegetated patches. In some cases, a discrete “patch” area represents a single canopy and its associated zone of litter and soil accumulation. In other cases, a patch will represent two or more individuals joined by contiguous areas of organic accumulation. These areas of litter and soil accumulation are typically well developed at the base of *Pinus edulis* and *Juniperus monosperma* individuals, and according to the self-patterning hypothesis act as zones of facilitation for new vegetation. In some instances there was ambiguity as to whether a particular ISODATA class consisted of this type of organically modified ground, or of particularly grassy inter-patch. These ambiguous classes represented a small proportion of the area classified as vegetated patch, typically located at the outer edge of the organically modified zone surrounding an individual canopy. Choice of assignment of these marginal ISODATA classes was therefore important in determining whether nearby areas of vegetative patch would remain separate in the generated map or would be joined into a single discrete patch. Since this grouping of vegetation into contiguous patches was one of the primary phenomenon under measurement (see 2.3), care was taken to apply a consistent standard across sites for making this assignment, based on relative differences in color, brightness, and shape. Assignment was however necessarily subjective, and given the variation in contrast and color response among aerial images, more true patch may have been assigned as “patch” class for some sites relative to others. This represents a possible source of inter-site pattern measurement discrepancy. The spatial extent of sites was specifically limited to a single aerial image, such that this source of error should be minimized with regard to within-site comparisons of locations.

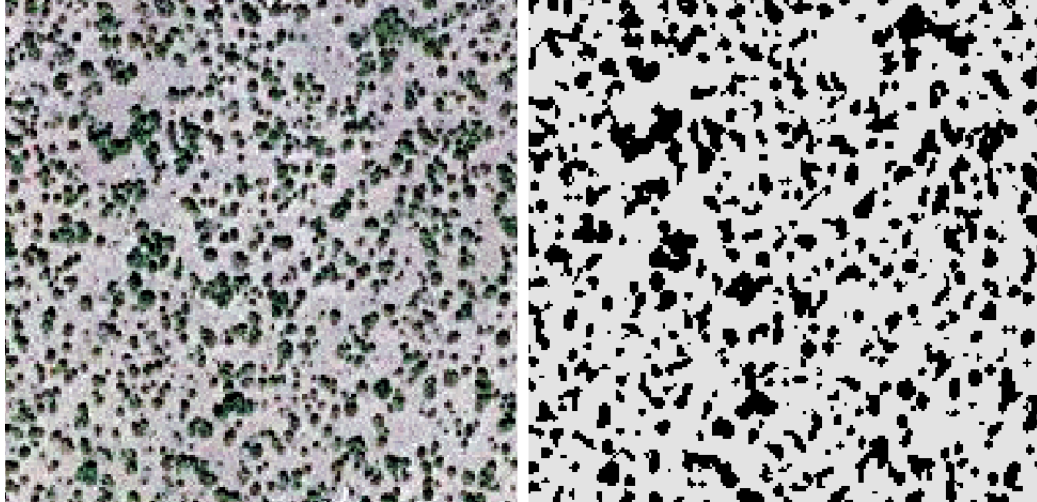


Figure 7: Woodland aerial photo and derived map of vegetated patches.

2.3 Pattern measurement

In the regions of study, observed spatial structuring of vegetation is characterized by curved or straight groups of contiguously linked vegetative canopies and their associated area of biotic modification. These contiguous groups of vegetated patch extend from a few meters to a few tens of meters. In areas of lower density they tend to be shorter and share a common orientation with neighboring bands. In more densely vegetated areas, canopy groups are typically more curved and may form complexes with little common orientation. This type of pattern can be considered as midway between the mazing of the West African savanna (Couteron and Kokou, 1997), and the more common banding of the African Sahel (White, 1970) and of Australian chenopod shrublands (Dunkerley and Brown, 1995), albeit substantially less consistent and spatially extended than either archetype.

The Patch Analyst (Rempel, 2008) implementation of the FRAGSTATS software package (McGarigal et al., 2002) was used to measure the degree of spatial structure present in the spatial distribution of vegetation. FRAGSTATS reports a number of common landscape indices based on the shape and distribution of patches of landcovers across a landscape. The FRAGSTAT-generated indices most likely to resolve contiguously structured vegetation were:

2.3.1 Mean Shape Index (MSI)

The *Shape Index* is a measure of the degree to which a given raster patch deviates from being a simple square, calculated by a perimeter-area comparison (Forman and Godron, 1986). *Mean Shape Index* is the mean average *Shape Index* of a group of patches.

$$MSI = \left(\frac{\sum_{j=1}^n \frac{0.25 p_{ij}}{\sqrt{a_{ij}}}}{n_i} \right)$$

Where i is a patch class (there being only one class of patch in this case, *i.e.* vegetation), n is the number of patches of class i , j is the number of patches of all classes, p is the perimeter of patch ij , and a is the area of patch ij .

2.3.2 Mean Patch Fractal Dimension (MPFD)

The *Patch Fractal Dimension* is similar to the *Shape Index* in that it contains a comparison of the perimeter and area of each shape, but goes further by testing the exponent of that relationship (Milne, 1988). Fractal dimension is a measure of the complexity of shapes. The *Mean Patch Fractal Dimension* is the mean average *Patch Fractal Dimension* of a group of patches

$$MPFD = \frac{\sum_{j=1}^n \left(\frac{2 \ln (0.25 p_{ij})}{\ln a_{ij}} \right)}{n_i}$$

2.3.3 Area-Weighted Mean Patch Fractal Dimension (AWMPFD)

The *Area-Weighted Mean Patch Fractal Dimension* is a version of the *MPFD* that weights larger patches more heavily in calculating the index of shape.

$$AWMPFD = \sum_{j=1}^n \left[\left(\frac{2 \ln (0.25 p_{ij})}{\ln a_{ij}} \right) \left(\frac{a_{ij}}{\sum_{j=1}^n a_{ij}} \right) \right]$$

All of these indices are measures of the irregularity of the shape of the landscape patches being assessed, with *MSI* having an emphasis on degree of compactness, which could be interpreted as indicating elongation of patches, and *MPFD* and *AWMPFD*, having an emphasis on complexity of form.

2.3.4 Class Area (CA)

Class area is simply the summed area of all patches of a class of interest, in this case vegetated patch. It was used to measure local vegetation density.

$$CA = \sum_{j=1}^n a_{ij}$$

2.3.5 Initial tests of pattern metrics.

Mean Shape Index's focus on simple perimeter:area ratio seems likely to capture any linear patterning of vegetation. This represents both an advantage and a disadvantage for this study. The likely robustness of the metric to a range of pattern types, including simpler and less distinct patterns, makes it suitable for capturing any degree of patterning present, including the range of linear to more complex patterns plausibly created by surface water mediated self-organization. On the other hand, the lack of specificity of the metric means that it may also respond to any

form of shape present due to any organizing force, such as simple channeling alongside stream beds, vehicle tracks, or ridges. An effort was made to choose sites which were relatively free from such structural features, and in a small number of cases, areas that included them were removed from analysis.

Self-organizing systems commonly result in complex spatial configurations, and *Area Weighted Patch Fractal Dimension* was also included in analyses to test if it could improve resolution of measurement of these types of patterns.

An initial assessment of the ability of these indices to resolve the patterns of interest was made by applying them to areas that were visually identified as spatially structured. Representative regions of between 20 ha and 60 ha were chosen from each site. For sites 1 and 4 visits to the locations chosen had also confirmed the presence of well developed vegetative patches of soil and litter accumulation below and around canopies of individual plants, and indications of surface water movement (e.g. washes of size-sorted detritus, small channels in notably sloping areas of exposed soil) throughout the area. An average *MSI* and *AWMPFD* was generated for each region of identified spatial structure and also for the entirety of each site, and those averages were entered into a paired-sample T test. *MSI* values for the representative regions were significantly different than for their respective sites overall ($p=0.01$). *AWMPFD* values were likewise differentiated ($p=0.02$).

2.4 Hydrological modeling

The goal of hydrological modeling was to create a realistic, spatially explicit estimate of the state of ground water and surface water flow as experienced by vegetation on the landscape. The estimate was produced by applying established spatial models of surface water aggregation, movement, and distribution to available elevation data.

2.4.1 Elevation data.

The National Elevation Dataset (NED) was used as the basis for topographical analyses. The NED is a product of the U.S. Geological Survey, and is a standardized compilation of best-available elevational data from a number of sources. Spatial resolution of the NED version used here was $1/3$ arc-second (approximately 10 m). Vertical and horizontal accuracy of the data is dependent on the original source. A disadvantage of using the NED is the lack of estimates of vertical and horizontal accuracy for any particular subset of the data, but ± 7 m is suggested as a common degree of horizontal error. Note that horizontal error will typically apply to an entire region, with adjacent pixels sharing the same offset from the true elevation, which reduces the impact of error for purposes of hydrological modeling. The NED is processed to remove artifacts prior to distribution, and I additionally executed a depression-filling procedure (Planchon and Darboux, 2002) using the Topographic Analysis System (Lindsay, 2005) prior to all hydrological calculations.

2.4.2 Hydrological indices.

I applied several indices of hydrological character to the areas under study. All modeling processes are cell-based computations using the cellular digital elevation model (DEM) provided by

the NED.

Wetness Index (WI)

If self-patterning is occurring, I would expect that spatial structure of vegetative would be more pronounced in areas of lower available soil moisture. In semi-arid systems, water is a primary limiting resource. All other things being equal, the presence of sufficient ground water would reduce the necessity of growing near a facilitative vegetated patch. With this constraint loosened, seedlings would be likely to establish without regard to existing vegetation, and spatial structuring would be reduced. We would therefore expect to see a negative relationship between estimated ground water content and the non-compactness of vegetation patches. The *Wetness Index* was used to estimate local ground water availability.

Wetness Index is one of the most commonly used hydrological indices derived from topographical data. *WI* will be highest in locations which receive high runoff but are relatively flat. This encodes an assumption that surface water which is moving more slowly will have more time to infiltrate into the soil, increasing local soil moisture. Versions of the *WI* have been demonstrated to correlate with observed surface soil wetness conditions (e.g. Beven and Kirkby, 1979; Moore et al., 1988).

$$WI = \ln \left(\frac{A_s}{\tan S} \right)$$

Where A_s is specific catchment area and S is slope. The specific catchment area for each pixel is the modeled rainshed for that cell: how much up-slope area is expected to be passing precipitation through that location. Specific catchment area is determined by first creating a flow direction surface, which algorithmically determines direction of surface water flow from each cell based on the previously computed slope and aspect of the cell, then using the resulting flow patterns to determine how many cells are “upstream” of a given cell, and adjusting for area relationships.

The output of these calculations is dependent on the flow routing algorithm used. There are several algorithms available (Wilson et al., 2008). The *FDS* algorithm (Quinn et al., 1991; Freeman, 1991) was chosen as a basis for all flow-based modeling tasks. The *FDS* algorithm allows for a portion of surface water to flow into each downslope cell, on a slope-weighted basis. This produces a somewhat more diffused flow model, particularly in areas of lower slope. This was consistent with observations that surface water flow in both the Arizona and New Mexico sites appeared to be distributed across several tens of meters in areas of lower slope. A slope weighting parameter (p) of 1.1 was used, *per* Freeman, 1991. The Topographic Analysis System was used to calculate *WI* and *RSP*.

Relative Stream Power (RSP)

In semi-arid systems, water inputs are commonly in the form of infrequent but intense rainstorms, such that surface water flow may reach levels of significant physical intensity over short time periods. Studies have shown that the presence of patches may affect erosion (Reid et al., 1999), but has not made explicit inferences about possible effect of erosive flows on patches. The lack of specificity regarding the effects of physical flow on vegetation patches is also reflected in theories

regarding known self-patterning systems. Models of pattern emergence tend to focus on water as a state variable assigned to a given location, but are not typically formulated to explicitly include physics concepts such as weight, speed, and force (although see Saco et al., 2007). More commonly, formal models account for surface flow in terms of direction only, typically modifying the predicted degree of facilitation of new vegetation depending on their orientation around existing vegetation with respect to direction of flow, e.g. new vegetation is modeled to have the highest success when it is near existing vegetation, but positioned perpendicularly to the modeled direction of flow, rather than up-slope of the existing vegetation (Thiery et al., 1995; Dunkerley and Brown, 1995). The aggregate outcome of this directionally differentiated influence on growth is to increase the linearity of contiguous bands of vegetation.

While the directionality of surface water flow is not obviously tied to the force of the flow, it is reasonable to suppose that the degree to which new growth is constrained relative to that direction may be tied to the flow strength. A more specific conceptual model of how direction constrains growth would help to inform this supposition, but it generally seems reasonable that vegetation patch shape may be induced to aggregate into more complex, or at least more linear shapes, in the presence of stronger surface flow.

Relative Stream Power is explicitly designed to be an estimate of the physical force of flowing water, and in particular erosive force. *RSP* is a composite index which incorporates the specific catchment area of each cell as well as the slope. *RSP* and several comparable indices are commonly used to model the erosive power of flowing water (Moore et al., 1993).

$$RSP = A_s \times \tan S$$

In contrast to the *Wetness Index*, which will be higher for cells which are less sloped, the construction of *RSP* is such that the cells with highest values will be those which are both receiving substantial up-slope runoff and also are themselves substantially sloped. This is intended as a measure of the physical force of the water passing across the cell.

2.4.3 Limitations of the modeled hydrology.

The digital elevation models used to construct the flow networks for both *RSP* and *WI* do not incorporate vegetation presence. Central to the hypothesized self-patterning of vegetation is the capacity for vegetation patches to adjust the flow of surface water across the landscape. However, the NED elevation values are “bare-ground” data, that is, they are measure the elevation of the substrate surface only. The flow networks modeled from this data may then be thought of as potential networks, and if vegetation patches do alter distribution of surface water, then it must be assumed that realized surface water flow deviates from these models. The realized flow network is likely to be more diffuse, as it percolates throughout the more complex landscape of vegetative channeling. This is anecdotally reflected in on-site observations of fields of relatively intense water flow across tens of meters. The capacity to model these wider flow fields is in part why the FD8 algorithm for flow routing was chosen. This flow routing algorithm created more diffuse models of flow, and to some extent this may have reduced the disparity between modeled and real-world water distribution.

2.5 Regression Analysis

The degree of association between the measured pattern and estimated hydrological conditions was measured using spatial regression techniques.

2.5.1 Spatial summarization.

In order to correlate the patch-based pattern information with the cellular hydrological characteristics, a common method of summarization was required. A common framework of 1 ha hexagonal grid cells was used to summarize all variables across the landscape. The hexagonal grid is recommended by the authors of the Patch Analyst implementation of FRAGSTATS as the stacking shape which, being closest to a circle, minimizes corner effects. Hexagonal grid size was chosen to encompass the scale of meaningful variation of the ecological and hydrological mechanisms under analysis, minimizing informational redundancy and maximizing computational efficiency (Rempel and Kushneriuk, 2003). Semi-variogram analysis of several variables was conducted, as well as experimental regression analyses using several grid sizes (0.25 ha, 0.5 ha, 1 ha and 2 ha) and variables.

A further consideration was the effect of grid size on the calculation of shape metrics. Grid cell borders would in some cases fall across contiguous groups of vegetated patch. The effect on shape indices would be difficult to predict, depending on the distribution of length classes, but would presumably be to artificially reduce the number of high-shape-value patches while increasing the number of medium-shape-value patches, by including sections of spatially extended patches in the averaging of multiple grid cells. While it was difficult to verify the presence of this effect in the analyses, it was assumed that by using a larger grid cell size, this effect could be reduced.

A 1 ha hexagon size was chosen to balance these considerations of precision, error, and redundancy. The resulting hexagonal grid was the basis for averaging used in the shape metrics, *e.g.* *Mean Shape Index* was computed as the mean *Shape Index* value of all vegetated patch and groups of contiguous patches falling inside a given hexagon. Likewise, each hexagon was assigned the averaged value of the *slope*, *RSP*, and *WI* values of all cells within that hexagon. The hexagons then became the unit of analysis in the regression analyses, such that the *N* of a given site analysis was the number of hexagons overlaying that site.

2.5.2 Spatial regression.

Classic regression tests of statistical correlation depend on the independence of each sample entered into the regression. Data collected across an un-partitioned landscape necessarily violate this condition, as the value of two neighboring locations are almost certain to be more similar to each other than two samples drawn at random from the pool of all samples (Tobler, 1970). This spatial autocorrelation problem has led to the development of a number of statistical approaches to spatial data.

Geographically weighted regression models (Fotheringham et al., 2002) are more flexible statistical constructions that explicitly allow for the possibility that neighboring locations are under the influence of similar forces. Second-order causal influences are accounted for in the spatial lag

and spatial error models, which allow for the possibility that in addition to sharing extrinsic influences, neighboring locations may interact with each other in ways which influence their state. The spatial lag model includes a lag term which quantifies the interactive effects of neighbors; the spatial error model includes an error term which measures the interactivity of the sample-specific errors produced by the regression (Anselin, 1988).

Residuals of geographically weighted spatial regressions were highly spatially correlated for all sites and all variables tested, indicating the appropriateness of a regression model that incorporated spatial interactive effects. Spatial lag terms were typically (although not always) positive and significant. Spatial error terms were significant for some regressions and not for others. The statistical power of spatial error regressions was in many cases slightly higher than respective spatial lag regressions, but not in all cases, and only by small margins. For the key regressions described in the Results, the average change in the *pseudo-R*² value between the two methods was 0.01. It was desirable to use a single regression model to allow for more meaningful comparisons. The spatial lag model was chosen as being more parsimonious, and more generally supported by the statistical indicators. All reported regression results are, unless otherwise noted, of the spatial lag type. All spatial regressions were conducted using the GeoDa software package (Anselin et al., 2006).

3 Results

Results of the spatial lag regressions indicate linkages between three ecosystem characteristics: patch shape (*Mean Shape Index*, *Area Weighted Mean Patch Fractal Dimension*), patch density (*Class Area*), and modeled water conditions (*Relative Stream Power*, *Wetness Index*). Figure 8 summarizes key relationships among them.

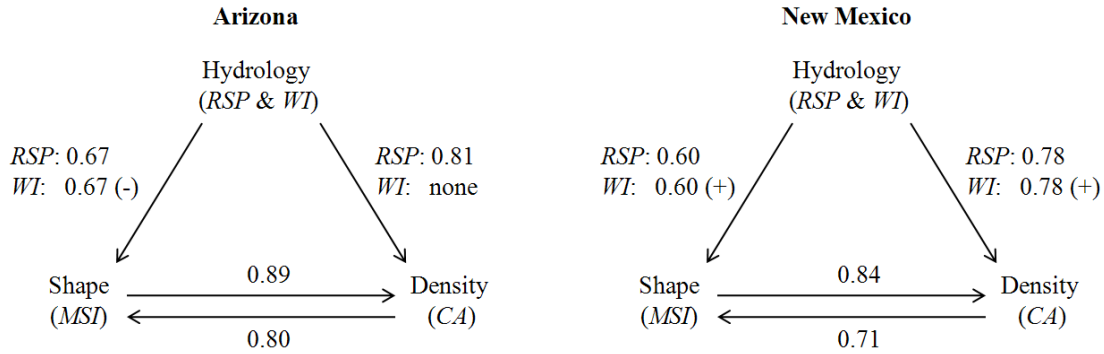


Figure 8: **Key interactions of vegetation density, vegetation shape, and hydrology.** All values are spatial regression *pseudo-R*² results, all reported relationships are significant at $p=0.05$ or better. Arrows indicate independent and dependent roles of variables, *i.e.* *independent* \rightarrow *dependent*. Negative relationships (high values of independent variable associated with low values of independent variable) are marked (-), otherwise all reported relationships are positive.

Although most of the measured relationships were similar between the Arizona sites 1 – 3 and New Mexico sites 4 and 5, there were region-specific differences for correlations involving the *Wetness Index* of ground water. In Arizona, areas of low *WI* were spatially correlated with areas of spatially structured vegetation; in New Mexico this relationship was inverted, with structured vegetation correlated with high estimated ground water. This relationship is particularly important to assessing the possibility of vegetative self-patterning. Given that the measured relationships were statistically significant in both cases, it seemed that separate inferences should be drawn from the two regions, and they are addressed independently in the discussion.

3.1 Hydrology-shape regressions

3.1.1 Shape Index regressions.

Regressions were conducted using data from each site; using data pooled from all sites from a given state (Arizona or New Mexico); and using data from all sites in a single regression.

Explanatory power of spatial regressions varied according to site and hydrological variable. Results are presented in Table 2. *Relative Stream Power* accounted for as much as 75% of observed variance in *Mean Shape Index* and as little as 41%. This indicates that areas with greater stream

site	RSP		WI			slope	
	R ²	p	R ²	±	p	R ²	p
1	0.74	<0.01*	0.74	-	0.53	0.75	<0.01*
2	0.53	<0.01*	0.53	-	0.78	0.54	<0.01*
3	0.63	<0.01*	0.62	-	0.18	0.63	<0.01*
AZ pooled	0.67	<0.01*	0.67	-	<0.01*	0.67	<0.01*
4	0.41	<0.01*	0.42	+	<0.01*	0.39	0.04*
5	0.42	<0.01*	0.43	+	<0.01*	0.42	<0.01*
NM pooled	0.60	<0.01*	0.60	+	<0.01*	0.60	<0.01*
all pooled	0.69	<0.01*	-	-	-	0.69	<0.01*

Table 2: **Mean Shape Index (MSI) regressions.** ± column indicates direction of relationship; “-” indicates high values of WI are associated with low values of MSI, “+” indicates high values of WI are associated with high values of MSI. Where direction of relationship changes between states, results from all-site pooled regressions are not reported. Significant relationships are marked*. Sites 1 – 3 are in Arizona, 4 and 5 in New Mexico.

power were associated with patches with greater perimeter relative to area, *i.e.* more irregularly shaped, suggesting greater pattern. When all sites were included in a single regression analysis, resulting *pseudo-R*² of RSP vs. MSI was 0.69. Correlation of Slope with MSI was tightly linked to respective RSP vs. MSI relationships, with a pooled *pseudo-R*² of 0.69. All relationships of MSI with RSP and Slope were significant at the $p=0.05$ level or better. The relationship between MSI and Wetness Index inverted between Arizona and New Mexico sites. Although no site in Arizona showed a significant relationship, when pooled WI accounted for two-thirds of variation (*pseudo-R*² of 0.67) in MSI, with areas of low estimated ground water associated with areas of more compact vegetation patches. By contrast, regression of New Mexican sites indicated that high WI values were spatially correlated with high MSI values pooled *pseudo-R*² of 0.60.

3.1.2 Fractal Dimension regressions.

Correlation of hydrological indices with *Area Weighted Mean Patch Fractal Dimension* was somewhat weaker than for *Mean Shape Index* at individual sites, but when pooled yielded very similar results. Results are presented in Table 3. With the exception of WI for Site 5, all relationships were significant. Notably, WI was significantly related to *AWMPFD* for all but Site 5, in contrast to MSI results, for which no Arizona sites had significant relationships. These results confirm the results of pooled regressions using MSI as an indicator of pattern, that the relationships between estimated ground water and measured pattern are meaningfully reversed between Arizona and New Mexico.

3.2 Vegetation-density regressions

Regressions were also conducted to test the relationship of hydrology and vegetation density, and of vegetation density and spatial structure. In this case, variables were entered in both the dependent and independent role in analyses. *Class Area* is a measure of vegetation density, *Relative Stream Power* was selected as representative of relevant hydrological character. *Mean*

site	RSP		WI			slope	
	R ²	p	R ²	±	p	R ²	p
1	0.58	0.01*	0.57	-	0.02*	0.59	<0.01*
2	0.42	<0.01*	0.40	-	<0.01*	0.46	<0.01*
3	0.64	<0.01*	0.63	-	0.01*	0.64	<0.01*
AZ pooled	0.67	<0.01*	0.66	-	<0.01*	0.67	<0.01*
4	0.25	0.43	0.29	+	<0.01*	0.25	0.52
5	0.48	<0.01*	0.45	+	0.21	0.48	<0.01*
NM pooled	0.51	<0.01*	0.51	+	0.01*	0.51	<0.01*
all pooled	0.67	<0.01*	-	-	-	0.68	<0.01*

Table 3: **Area Weighted Mean Patch Fractal Dimension (AWMPFD) regressions.** ± column indicates direction of relationship; “-” indicates high values of *WI* are associated with low values of *MSI*, “+” indicates high values of *WI* are associated with high values of *MSI*. Significant relationships are marked*. Negative *pseudo-R*² values indicate a negative relationship between variables. Where direction of relationship changes between states, results from all-site pooled regressions are not reported. Sites 1 – 3 are in Arizona, 4 and 5 in New Mexico.

Shape Index was used as a measure of spatial structure. Results are presented in Table 5 for density and pattern, and Table 4 for density and hydrology.

independent: dependent: site	WI			RSP	
	R ²	±	p	R ²	p
1	0.89	+	0.90	0.89	<0.01*
2	0.76	+	0.82	0.76	0.02*
3	0.72	+	0.23	0.25	<0.01*
AZ pooled	0.81	-	1.0	0.81	<0.01*
4	0.55	+	<0.01*	0.52	<0.01*
5	0.55	+	<0.01*	0.56	<0.01*
NM pooled	0.78	+	<0.01*	0.78	<0.01*
all pooled	-	-	-	0.82	<0.01*

Table 4: **Density and hydrology regressions.** ± column indicates direction of relationship; “+” indicates high values of *WI* are associated with high values of *CA*, “-” indicates high values of *WI* are associated with low values of *CA*. Where direction of relationship changes between states, results from all-site pooled regressions are not reported. Significant relationships are marked*. Sites 1 – 3 are in Arizona, 4 and 5 in New Mexico.

Spatial regressions indicated that *Wetness Index* is a strong predictor of *Class Area* (i.e. vegetation density) in New Mexico (*pseudo-R*² of 0.78), but there was no relationship observed in Arizona. Relative Stream Power was strongly correlated with *Class Area* for both regions (*pseudo-R*² of 0.82). Taken together with the results of the hydrology-shape regressions (3.1, above), this indicates that there is hydrology, vegetation density and vegetation pattern are all closely linked in these landscapes.

Two-way correlations between *CA* and *WI* were not significant for sites in Arizona. For the New Mexican mesa sites however *Wetness Index* accounted for much of observed variation in *Class*

Area (pseudo- R^2 of 0.78). RSP explained a very substantial amount of the observed variation in Class Area (pseudo- R^2 of 0.82).

independent: dependent:	CA		MSI	
	MSI		CA	
site	R ²	p	R ²	p
1	0.83	<0.01*	0.94	<0.01*
2	0.65	<0.01*	0.83	<0.01*
3	0.82	<0.01*	0.87	<0.01*
AZ pooled	0.80	<0.01*	0.89	<0.01*
4	0.54	<0.01*	0.52	<0.01*
5	0.82	0.13	0.85	<0.01*
NM pooled	0.71	<0.01*	0.84	<0.01*
all pooled	0.79	<0.01*	0.89	<0.01*

Table 5: **Density and pattern regressions.** Significant relationships are marked*. Sites 1 – 3 are in Arizona, 4 and 5 in New Mexico.

Two-way correlations between CA and MSI were strong. Slightly greater explanatory power was yielded with *Mean Shape Index* as a driver than with *Class Area* in that role, although the difference is perhaps not sufficient to draw meaningful conclusions regarding cause and effect.

4 Discussion

The results provide support for the hypothesis that self-patterning of vegetation could be occurring in the Arizona sites. As predicted by this hypothesis, there is a significant spatial correlation in these landscapes between areas estimated to be strongly water limited (*i.e.*, having low *WI*) and the aggregation of vegetation into non-compact shapes. This relationship is strong enough to suggest an ecologically meaningful dynamic, with two-thirds of the measured variation in *MSI* and *AWMPFD* accounted for by variation in *WI*. This possibility is supported by the equally strong relationship between the estimated intensity of surface water, as measured by *RSP*, and vegetation shape. This relationship is also interesting in that it suggests that, if self-patterning is indeed the mechanism linking vegetation structure and hydrology, physical strength of water flow may be as important as water limitation in driving patterning.

The results for the New Mexico sites are not supportive of the self-patterning hypothesis. The relationship between *RSP* and vegetation shape is consistent with the Arizona sites, albeit slightly weaker (*pseudo-R*² of 0.60 for *RSP* vs. *MSI*), however the hypothesized relationship between *Wetness Index* and patch shape was not present. Rather, the inverse relationship was observed, such that areas in the New Mexico sites which had less compact vegetation patches were associated with higher available water. In the absence of any ecological explanation for this inconsistency, these results may be taken as suggesting that the hydrology–shape link may not be common across all piñon-juniper systems, or that there may be substantial limitations to the methodology used here to assess those relationships.

In both locations, the results clearly indicate that there is a strong relationship between vegetation density and the degree of spatial structure of contiguous vegetation shapes. This is to be expected: unless it grows on a regular grid, vegetation which is more densely packed will necessarily come into contact more frequently. Contiguous clumps of vegetation will be less compact than separate canopies, and pattern metrics such as *MSI* and *AWMPFD* will hence be higher for denser formations. This was reflected in the measured results, with strong observed relationship yielded by the spatial regression of *Class Area* and *MSI*, with *CA* in the independent role (*pseudo-R*² of 0.80 for Arizona sites, 0.71 for New Mexico sites).

It could be argued that the strength of this relationship is such that the effect of vegetation density on structure could be expected to overwhelm any potential self-patterning signal in these landscapes. Further, given that semi-arid vegetation density might be assumed to be higher in areas of greater available soil moisture, the observed statistical relationship between *WI* and vegetation shape might be a statistical artifact of the mechanistic mediating influence of density between hydrology and shape. There are several reasons why self-patterning is still supported by the observed results, even in the context of the strong ecohydrological relationship between density and shape of vegetation.

1. According to both field-based (Ludwig et al., 1997; Tongway and Ludwig, 2001; Schlesinger et al., 1999) and modeling based (Rietkerk et al., 2004) theory, spatial organization of vegetation structure should increase rainfall retention efficiency, an important factor for vegetation success in semi-arid systems. It is therefore reasonable to expect that, in addition to density increasing spatial structure, spatial structure may meaningfully increase vegetation density. With *MSI* entered in the independent role in the spatial regressions, the

statistical strength of the *MSI vs CA* relationships was somewhat higher than for the reverse relationship (*pseudo-R*² of 0.89 vs. 0.79, data pooled across all sites).

2. In the Arizona sites, which otherwise had relationships most consistent with the self-patterning hypothesis, there is no measured relationship between vegetation density and *Wetness Index*. This would appear to preclude the possibility that the observed hydrology–shape statistical link is an artifact of the hydrology–density and density–shape relationships. Given that we would normally expect to see a strong relationship between available water and vegetation success in semi-arid systems, the lack of this relationship does however raise the possibility of some other limitation to the methodology used.
3. The relationship between available water and self-patterning is theorized to be non-linear, such that even if this relationship were not the strongest determinant of vegetation shape at the levels of precipitation present in the sites observed, it might still be ecologically significant at other levels of precipitation.

Although the relative strengths of the density–shape and hydrology–shape relationships underscore the degree to which the ecological significance of any hydrology–shape mechanism is uncertain relative to other possible drivers of climate sensitivity in these drylands systems, it does not preclude the possibility that there is such a link. Neither does it preclude the possibility that the mechanism mediating that statistical link is indeed a form of self-patterning.

It should be emphasized that, while the observed relationships between estimated water distribution and vegetation spatial structure in the Arizona sites is consistent with self-patterning, it is possible that some other ecological mechanism may be responsible. Given the presence in the ecosystems of study of the plant-level mechanisms known to underlie self-organization in more explicitly patterned ecosystems, self-patterning does however seem to be a reasonable candidate to explain the observed relationships in these landscapes.

4.1 Banding by downslope forcing.

One alternative candidate to explain the observed relationships between shape and water conditions is a dynamic similar to hypothesized mechanism, but which would sufficiently diverge from the self-patterning mechanisms typically conceptualized as to warrant separate consideration.

If seedlings were less likely to establish in areas where strong downslope surface flows might wash them away, then we might expect to see bands of vegetation oriented downslope, such that in cases where a first plant managed to become sufficiently established to form a protective area behind it, a second plant would be likely to establish there, and so on. This would represent an alternate, simpler expression of emergent banding to the one hypothesized, or perhaps a variation on it, differentiated mechanically by a reduced physical resistance of establishing vegetation to surface flows. The key difference is that if this were the common outcome of banding, there would be little perpendicular diversion of surface water, and consequently less opportunity for ephemeral surface water to be fixed as available soil moisture.

This strongly linear configuration of banding would presumably be less likely to be captured by measurement of *AWMPFD*, but could have similar impact on *MSI* values as more lateral pattern. It is notable then that relationships between *AWMPFD* and *slope* were as strong or marginally

stronger than relationships between *AWMPFD* and *RSP* (note that *RSP* and *slope* are somewhat co-linear, with spatial regression of *RSP* vs. *slope* yielding *pseudo-R*² of 0.59, *p* < 0.01, see Tables 2 and 3). This could be taken to indicate that patterns on slopes are more complex, rather than more linear (although further work should be undertaken measuring the relative response of the two pattern metrics to different patch types).

It may be possible to construct a new metric to separate cross-slope from down-slope pattern, by converting the rasterized maps of canopy into discrete polygons, overlaying those on a direction-of-flow surface generated as an intermediate product in hydrological modeling, then measuring the degree of variance in the values of the pixels overlain by each polygon.

In the absence of this procedure, simple visual inspection was made of all sites to assess if banding was commonly oriented downslope. Continuums of orientation and linearity were observed, with straight vegetation phasing into areas of roughly semi-circular or more complexly curved vegetation. In areas with predominantly linear vegetation, some examples were found of downslope orientation, such as on the edges of scarps in Sites 2 and 5, but these appeared to be exceptions, with many more examples of non-downslope vegetation found on scarp and slope areas. At all sites, areas of higher slope commonly had relatively more complex, less linear pattern. Taken together, these quantitative and visual results suggest that patterning in these landscapes is commonly of a lateral type corresponding with the hypothesized driver of pattern.

4.2 Further research

4.2.1 Solar radiation as a predictor of pattern.

Ground water is not the only growth-facilitating character of canopies and associated vegetative patches. Additionally, they provide shade, organic content and a more temperate micro climate. In the same sense that pattern was expected to be more pronounced in areas with less available ground water, we might expect patterning to be stronger in areas of lower available organic content in the soils, or more intense sun or heat, where the facilitative influence of vegetated patches would therefore be more important to establishment and success. Unlike ground water, these conditions are less likely to be directional in nature, and so they may result in a different spatial configuration of emergent pattern, but they may still be expected to vary spatially with variations in aspect and soil type. Some portion of the observed variation in pattern which was not explained by hydrological conditions may be associated with these unmeasured variables.

A relatively simple enhancement to this study would be to model sun exposure and heat concentration from digital topography, and test the improvement in predictive power yielded by adding those variables into spatial regressions.

4.2.2 Separation of canopy from patch measurement.

Although 1 m color orthoimagery was chosen as a standard base for patch map creation, other remote sensing imagery and products were assessed. Among these were 0.2 m color orthoimagery recorded for Santa Fe County and a landcover classification derived from Quickbird (Digital Globe, Longmont, CO, USA) imagery. Both classifications allowed for the canopy of an individual plant to be accurately distinguishing from ground-level zone of litter and soil accumulation, both

of which were incorporated into the “patch” class in this study. These products were not used because in each case they were only available for one sites, precluding inter-site comparisons. However, given the centrality of the location and state of litter and soil accumulation implied by conceptual models of pattern formation, spatial analysis based on more a sophisticated map of vegetation presence explicitly distinguishing this class might improve inferences regarding the system.

4.2.3 Improved methods of pattern measurement.

Landscape patch metrics such as *Mean Shape Index* and *Area Weighted Mean Patch Fractal Dimension* were used in this study because they are well documented and integrated into existing software packages. They are however constructed as measures of shape irregularity, rather than “pattern”, and their use was a first-order attempt to capture pattern. Identification of spatial patterns is a goal of the field of artificial intelligence. Application of artificial intelligence methods in a GIS context might be implemented through, for instance, neural network analysis, although selection of appropriate training data and definition of spatial characteristics of interest for such analysis would be non-trivial.

5 Conclusions

Working from landscape-level data of large spatial extent from multiple sites in semi-arid ecosystems, I have tested the spatial correlation of vegetation shape distribution with estimates of surface and ground water distribution, and demonstrated a measurable link between vegetation spatial structure and modeled hydrology. For sites in Arizona, the nature of those relationships is consistent with the phenomenon of water-limited self-patterning of semi-arid vegetation, a dynamic not previously identified in American drylands, but which is known to occur in ecosystems sharing underlying plant-scale mechanisms present in the piñon-juniper woodlands which were the focus of this study. Observing a hypothesized link between local hydrology and vegetation shape is not in itself a demonstration of self-patterning phenomenon, but taken in the context of those well-documented plant-scale mechanisms, that link represents first support for the possibility that self-patterning could be occurring in these landscapes.

The importance of patch structure for efficient utilization of scarce rainfall has been identified in southwestern systems, but the dynamics mediating the establishment and change of patch structure in these ecosystems are not as well identified; if emergent self-patterning were the mechanism, then existing theory of self-patterning derived from other arid systems could have implications for predicting how American drylands will respond to pending changes in climate. Static descriptions of ecosystems will be insufficient in a climate-change scenario where ecological drivers move outside of previously observed ranges, or exhibit greater variation than previously observed. Predicting how ecosystems will respond will require dynamic theory, grounded in mechanism but capable of scaling to the level of landscapes, the scale at which change is likely to occur. Catastrophic threshold response to precipitation change has already been observed in southwestern semi-arid systems, and this is consistent with the predictions of system behavior made by theory of self-patterning of vegetation.

This study supports the possibility that piñon-juniper landscapes, and possibly other systems not previously identified with self-organization, may be under the influence of this phenomenon, and that the theory of semi-arid self-patterning may contribute to understanding and prediction of the response of these landscapes to pending changes in precipitation.

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References

- Anselin, L., 1988. *Spatial Econometrics: Methods and Models*. Kluwer Academic Publishers, The Netherlands.
- Anselin, L., Syabri, I., Kho, Y., 2006. Geoda: An introduction to spatial data analysis. *Geographical Analysis* 38 (1), 5–22.
- Beven, K., Kirkby, M., 1979. A physically based, variable contributing area model of basin hydrology. *Hydrological Sciences Bulletin* 24 (1).
- Breshears, D., 2008. Structure and function of woodland mosaics: Consequences of patch-scale heterogeneity and connectivity along the grassland-forest continuum. In: Van Auken, O. (Ed.), *Western North American Juniperus communities: A dynamic vegetation type*. Vol. 196 of *Ecological Studies*. Springer Verlag, p. 58.
- Breshears, D., Cobb, N., Rich, P., Price, K., Allen, C., Balice, R., Romme, W., Kastens, J., Floyd, M., Belnap, J., et al., 2005. Regional vegetation die-off in response to global-change-type drought. *Proceedings of the National Academy of Sciences* 102 (42), 15144–15148.
- Couteron, P., Kokou, K., 1997. Woody vegetation spatial patterns in a semi-arid savanna of burkina faso, west africa. *Plant Ecology* 132 (2), 211–227.
- Couteron, P., Lejeune, O., 2001. Periodic spotted patterns in semi-arid vegetation explained by a propagation-inhibition model. *Journal of Ecology* 89, 616–628.
- Dunkerley, D., 1997. Banded vegetation: development under uniform rainfall from a simple cellular automaton model. *Plant Ecology* 129 (2), 103–111.
- Dunkerley, D., Brown, K., 1995. Runoff and runoff areas in a patterned chenopod shrubland, arid western new south wales, australia: characteristics and origin. *Journal of Arid Environments* 30 (1), 41–55.
- Esteban, J., Fairen, V., Jun 2006. Self-organized formation of banded vegetation patterns in semi-arid regions: A model. *Ecological Complexity* 3 (2), 109–118.
- Forman, R., Godron, M., 1986. *Landscape ecology*. John Wiley.
- Fotheringham, A. S., Brundson, C., Charlton, M., 2002. *Geographically Weighted Regression*. John Wiley & Sons, Chichester.
- Freeman, T., 1991. Calculating catchment area with divergent flow based on a regular grid. *Computers & Geosciences* 17 (3), 413–422.
- Kefi, S., Rietkerk, M., van Baalen, M., Loreau, M., 2007. Local facilitation, bistability and transitions in arid ecosystems. *Theoretical Population Biology* 71 (3), 367–379.
- Lindsay, J., 2005. The terrain analysis system: A tool for hydro-geomorphic applications. *Hydrological Processes* 19 (5), 1123–1130.
- Ludwig, J., Tongway, D., Freudenberger, D., Noble, J., Hodgkinson, K., 1997. *Landscape Ecology, Function and Management: Principles from Australia's Rangelands*. Commonwealth Scientific and Industrial Research Organization (CSIRO). Queensland (Australia).

- Ludwig, J. A., Tongway, D. J., 1995. Spatial organisation of landscapes and its function in semi-arid woodlands, australia. *Landscape Ecology* 10 (10), 51–63.
- McGarigal, K., Cushman, S. A., C., N. M., Ene, E., 2002. FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps. University of Massachusetts, Amherst.
URL www.umass.edu/landeco/research/fragstats/fragstats.html
- Milne, B., 1988. Measuring the fractal geometry of landscapes. *Applied Mathematics and Computation* 27, 67–79.
- Moore, I., Burch, G., Mackenzie, D., 1988. Topographic effects on the distribution of surface soil water and the location of ephemeral gullies. *Transactions of the American Society of Agricultural Engineers* 31 (4), 1098–1107.
- Moore, I., Grayson, R., Ladson, A., 1993. *Terrain Analysis and Distributed Modeling in Hydrology. Advances in Hydrological Processes.* John Wiley & Sons, Chichester, Ch. Digital terrain modeling: a review of hydrological, geomorphological, and biological applications.
- Planchon, O., Darboux, F., 2002. A fast, simple and versatile algorithm to fill the depressions of digital elevation models. *Catena* 46 (2-3), 159–176.
- Puigdefabregas, J., 2005. The role of vegetation patterns in structuring runoff and sediment in fluxes in drylands. *Earth Surfaces Processes and Landforms* 30, 133–147.
- Quinn, P., Beven, K., Chevallier, P., Planchon, O., 1991. Prediction of hillslope flow paths for distributed hydrological modelling using digital terrain models. *Hydrological Processes* 5 (1), 59–79.
- Reid, K., Wilcox, B., Breshears, D., MacDonald, L., 1999. Runoff and erosion in a pinon-juniper woodland: Influence of vegetation patches. *Soil Science Society of America Journal* 63 (6), 1869–1879.
- Rempel, R., January 17th 2008. Patch Analyst. Centre for Northern Forest Ecosystem Research (Ontario Ministry of Natural Resources), Thunder Bay, Ontario.
URL flash.lakeheadu.ca/~rrempe1/patch/
- Rempel, R. S., Kushneriuk, R. S., 2003. The influence of sampling scheme and interpolation method on the power to detect spatial effects of forest birds in ontario (canada). *Landscape Ecology* 18 (8), 741–757.
- Rietkerk, M., Boerlijst, M. C., van Langevelde, F., HilleRisLambers, R., van de Koppel, J., Kumar, L., Prins, H. H. T., de Roos, A. M., October 2002. Self-organization of vegetation in arid ecosystems. *The American Naturalist* 160 (4), 524–530.
- Rietkerk, M., Dekker, S., de Ruyter, P., van de Koppel, J., September 24 2004. Self-organized patchiness and catastrophic shifts in ecosystems. *Science* 305 (5692), 1926–1929.
- Saco, P. M., Willgoose, G. R., Hancock, G. R., 2007. Eco-geomorphology of banded vegetation patterns in arid and semi-arid regions. *Hydrology and Earth System Sciences* 11 (6), 1717–1730.

- Schlesinger, W., Abrahams, A., Parsons, A., Wainwright, J., 1999. Nutrient losses in runoff from grassland and shrubland habitats in southern new mexico: I. rainfall simulation experiments. *Biogeochemistry* 45 (1), 21–34.
- Thiery, J., D’Herbes, J.-M., Valentin, C., 1995. A model simulating the genesis of banded vegetation patterns in niger. *Journal of Ecology* 83, 497–507.
- Tobler, W. R., 1970. A computer movie simulating urban growth in the detroit region. *Economic Geography* 46 (2), 234–240.
- Tongway, D., Ludwig, J., 2001. Theories on the origins, maintenance, dynamics, and functioning of banded landscapes. In: Tongway, D. J., Valentin, C., Seghier, J. (Eds.), *Banded vegetation patterning in arid and semiarid environments: ecological processes and consequence for management*. No. 149 in *Ecological Studies*. Springer Verlag, pp. 20–31.
- Van Auken, O., 2007. *Western North American Juniperus Communities: A Dynamic Vegetation Type*. Springer, New York.
- White, L. P., 1970. Brousse tigrée patterns in southern niger. *The Journal of Ecology* 58 (2), 549–553.
- Wilcox, B., Breshears, D., 1994. Hydrology and ecology of pinyon-juniper woodlands: Conceptual framework and field studies. In: *Conference: Forest Service conference on pinyon-juniper*, Flagstaff, AZ (United States), 9 Aug 1994.
- Wilson, J. P., Aggett, G., Yongxin, D., Christine, S., 2008. *Advances in Digital Terrain Analysis. Lecture Notes in Geoinformation and Cartography*. Springer, Ch. Water in the Landscape: A Review of Contemporary Flow Routing Algorithms, pp. 213–236.
- Zeng, X., Zeng, X., NOV 2 2007. Transition and pattern diversity in arid and semiarid grassland: A modeling study. *Journal of Geophysical Research-Biogeosciences* 112 (G4).