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Michael Chang

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Scaling of Crop Diversity and Optimal Allocation of Foodshed Infrastructure

By

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B.A. Botany, University of Wisconsin, 2011

THESIS

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B.A., Botany, University of Wisconsin, 2011
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ABSTRACT

Food hubs are organizations that manage the aggregation and distribution of local products, and are a small, but growing means to satisfy high demand for diverse, healthy diets. However, economic barriers inhibit small producers and distributors from developing mainstream, local consumer alternatives to industrial-scale products. To build a foodshed, distribution hubs could help overcome these challenges by reducing costs through shared refrigeration, processing, and transportation infrastructure. However, there is no theory to help plan them. I present and test theory to allocate foodshed infrastructure based on insight by Dunn, *et al.* (2011) that Shannon diversity measured relative to a whole set of sites, rather than site-by-site, reveals law-like scaling behavior. I accessed the US Dept of Agriculture's 2011 Cropland Data Layer (CDL) for 40 crop cover types at 30 m resolution in New Mexico. I tested two competing hypotheses: 1) a site-specific and 2) a whole-system normalization of crop probabilities interpretable as the information experienced by producers versus a distributor, respectively. Directly edible and marketable crops were differentiated from forage crops for livestock because of the different destinations and infrastructure they require. A distributor with information about the whole foodshed experiences law-like increase in uncertainty with increasing observation scales. Since the distributor uncertainty about an area's crop

inventory is an order of magnitude lower than the producers', a distributor should plan infrastructure at a scale that maximizes reduction of a producer's uncertainty. For all crops, I compared their relative contribution to total diversity per unit area so as to compare areas on the landscape with the highest capacity to diversify the foodshed as a whole. Development of a diverse foodshed will require knowledge of which products affect local diversity. This work grounds whole-foodshed planning in ecological theory, and contributes to understanding about how the conventional food system has allocated crop diversity.

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INTRODUCTION

“...the term foodshed becomes a unifying and organizing metaphor for conceptual development that starts from a premise of the unity of place and people, of nature and society.”

Kloppenburg et al. (1996)

Humans need a diverse diet to satisfy nutritional requirements, and thus diverse food systems to meet that need. High caloric yields are important, but as a singular focus of a food system, they obscure both direct external costs to consumer health from high calorie, low-nutrient foodstuffs (Tillotson, 2004; Conard and Ackerman 2010) and a web of indirect health costs to the environment: greenhouse gas emissions (GHG) from energy use (Weber and Matthews 2008), chemical-resistant pests (Owen and Zelaya 2005, Tabashnik *et al.* 2005), and soil degradation and runoff (Tilman *et al.* 2002, Pimentel *et al.* 2008, Patzek 2008). Today, food sustainability is contingent on building resilience into economically robust local systems within foodsheds that minimize or even mitigate these accumulating external costs, meanwhile retaining economic and environmental value (Kloppenburg 1996, Holling 2001, Folke 2006, Norris *et al.* 2008, Speth 2012). Across the nation, increasing demand for healthy, sustainable, and local products exceeds supply (Peters *et al.* 2009a, Conard 2010, USDA 2011a, USDA 2011b, Matson 2013). Food hubs—organizations that aggregate and manage the distribution of local products—are identified by the US Department of Agriculture (2011a) as a promising means to satisfy demand (Matson 2013). Unmet demand is not an issue of local supply capacity. Rather, Peters *et al.* (2009b) suggest that the land in New York State could support all the nutritional requirements of either: most of its smaller cities, or 55% of New York City.

Connecting supply and demand requires strategies to recruit farm labor into new markets, as 30% of the agricultural workforce is above age 65 (USDA 2007). However, multiple foodshed stakeholders capable of filling this gap face economic barriers in a market dominated by infrastructure that incentivizes large-scale agriculture. The National Young Farmers Coalition (Shute 2011) identifies lack of capital as the biggest obstacle to small, beginning farmers.

Also lacking is local infrastructure for shipping, storing, and processing the goods from small and midscale farms (Matson 2013). According to the Wallace Center (Dreier & Taheri 2008, 2009), distribution hubs can provide infrastructure that anchors small farmers to demand, thereby reducing both farmers' and distributors' costs via shared capital infrastructure. Hubs also have potential to be valuable community spaces and to improve food security in less-connected rural areas (Conard & Ackerman 2010, USDA 2011a).

Theory is lacking for where best to locate hubs and at what scale to build foodshed hub infrastructure that links concentrated urban demand to diffuse rural supply (USDA 2011b). Of about 200 identified food hubs, most of which have emerged in the last decade, roughly half are economically viable (Matson 2013) which presents a challenge and opportunity to facilitate hub growth by applying theory of ecological diversity. Ultimately, all stakeholders in a local food system—consumers, producers, and distributors – rely on each other for health and prosperity. Thus, I offer tools to help allocate investment for hubs in a given foodshed by leveraging uncertainty in crop production to the mutual advantage of local food distribution.

I innovate and test theory to allocate local food infrastructure based on recent theories of scaling and diversity (e.g. Harte *et al.* 2005, Harte, Zillio *et al.* 2008, Dunn *et al.* 2011). On a landscape, food producers experience uncertainty for lack of information about foodshed-wide demand and production by competitors. Meanwhile, distributors who develop economies of scale by aggregating local supply benefit from foodshed-wide information. Information about transportation costs and production schedules contextualizes their experience of uncertainty to collective advantage.

The producer's perspective of uncertainty is familiar to ecology, which classically identifies relative species abundance site by site to measure diversity. There are many ways to quantify diversity, all of which have been shown to be statistical variants of Shannon diversity (Shannon *et al.* 1949, Hill 1973, Jost 2006). Dunn *et al.* (2011) adopted a framework to normalize Shannon diversity (better understood as 'uncertainty', Pielou 1977) across all stream sites of a given Horton-Strahler order (Horton 1945, Strahler 1952), rather than along each individual stream. Adoption of such an approach that hierarchically considers parts of the system in relation to the whole (Allen and Starr 1982) can elucidate a description of how a distributor experiences uncertainty on the landscape. Distribution hubs, sized and located on the basis of whole-system information, can provide many producers the benefit of reduced uncertainty about inventory. This effect is maximized at an optimal scale where the numerical difference between producer and distributor diversity is greatest.

I sought to identify law-like behavior underlying the relationship between crop diversity and spatial scale and thereby identify an optimal areal extent for hub investment. I hypothesized that spatial patterns of crop diversity are governed by self-

similar scaling laws since at broad scales, many self-similar geophysical factors constrain land occupancy: surface water, topography, soil composition, and weather patterns (Brown *et al.* 2002). More generally, agriculture feeds cities, which have recently been likened to organisms (Bettencourt *et al.* 2007, 2010, Samaniego and Moses 2008), based on earlier theory of space-filling fractal networks that support the metabolism and growth of all life (West *et al.* 1997, 1999). I investigate the implications of whole-system diversity for the producers of specific crops of different crop classes. Some crops enter the human food supply directly, while others are fed to animals first. Planners of infrastructure need to know how different crops within these classes affect diversity so that producers can respond adaptively. The theory presented here of optimal hub scale and location may help optimize the allocation of infrastructure in a cost-effective manner, based on mutual benefit, while informing strategies and policies to accelerate the development of local, resilient alternatives to the global food system.

METHODS

Study area

The study area was drawn entirely within the state boundaries of New Mexico, USA. The state (pop. 2,059,180) covers 31,491,531 ha (US Census 2010) between 37° N and 31° 20' N latitude, with elevation ranging from 867 to 4013.3 m (USGS 2001). Over the years 2000-2012, mean statewide annual temperature was 12.6 C and the mean statewide annual precipitation 32.59 cm, ranging from the hottest and driest year (13.2 C, 20.75 cm in 2012) to the coolest and wettest (12 C, 45.09 cm in 2004) (NOAA 2013). New Mexico hosts 8 Level III ecoregions of 84 in the conterminous United States (Omernik 1987, USEPA 2006) and a continuum of USDA Hardiness Zones 4b through 9a (USDA 2012). The NM growing season varies substantially based on elevation and terrain, but typically ranges from April/May to October/November (NOAA 2010a, 2010b). Agricultural lands total 17,497,800 ha, 5.40% of which are crops, 86.95% pasture, 6.64% timber production, and 1.01% other, producing a total market value of \$2,175,080,000 (USDA 2007). Although mean farm size in NM is 836 ha, it is worth noting that this mean reflects a bimodal distribution of farm sizes. Of 20,930 farms, 9,311 are cropland, and roughly as many are larger than 100 ha as are smaller than 4 ha (USDA 2007). There are 10,167 irrigated farms (335,908 ha), split between 8,492 cropland farms (262,346 ha) and 2,918 pastureland and other farms (73,562 ha) (USDA 2007).

Crop Spatial Data

The Cropland Data Layer (CDL) provides geographical information about agricultural land cover in the continental US (Boryan et al. 2011, Han et al. 2012).

The CDL is derived from several sources of satellite imagery and made available at 30-m resolution in Albers Equal Area Conical projection (USDA 2013). I used 39 food-related cover types (of 53 total) reported for New Mexico in the CDL for the 2011 growing season and assigned types to one of two classes: (1) crops directly edible by humans and therefore of interest to stakeholders in the local food system; (2) forage commodities supportive of the livestock and dairy industry, generally harvested and distributed or consumed *in situ* (Table 1). I assigned crop types of ambiguous composition to both edible and forage classes by splitting abundance 50:50 between the two classes. Areas of double crop categories of an edible and fiber (or forage) crop were classified as half edible and half forage. Fallow/idle cropland was assigned to edible and forage categories. These included fallow/idle and double crop categories, i.e., a succession of two crops in the same cell during 2011 of an edible crop and cotton or an edible crop and a forage crop. Classes $k = 1$ and 2, and combined as class 3 were used experimentally to examine composition and diversity of a number, $S(k)$, of crops from perspectives of different stakeholders. Total crop type richness $S_o = S(k=3) = 48$ was subset to 33 types in the edible class and 15 types in the forage class.

Overall classification accuracy of row crops and annual fruit and vegetables is 70.8% trending upwards of 85-95% for major crop-specific land cover categories (USDA 2013). Accuracy rates below 70% are exclusive to minor crops such as triticale, watermelons, and onions, and for locations that hosted two crops in a year. Calculations were applied to 76% (24,159,191 ha) of the state's area within a square lattice of length $L = 2^{14} = 16,384$ 30-m wide cells occupied by $A_o = 8,099,291$ ha of CDL types in this study (Figures 1 & 2). Crop areas were tallied in a hierarchical log base-4 series of nested square blocks

starting with unit cells at order $\omega = 0$ and progressing to $\omega = 14 = \Omega$, the highest order.

Thus individual blocks at each order were composed of 30-m cells that covered areas $900 \times 2^{2\omega} \text{ m}^2$.

Producer and distributor crop diversity

The goals were to identify an optimal order and locations of proposed food hubs that could serve clusters of producers and simultaneously reduce transportation costs of a centralized distributor at an annual time scale. I assumed producer's precise knowledge is restricted to their own inventory. In contrast, distributors enjoy a complete inventory of crops across the study area. Thus, I normalized crop areas within and among blocks differently for producers and distributors, calculated respective entropies to characterize diversity and equivalently uncertainty, and compared mean entropies by order to identify an optimal hub scale at which a distributor's uncertainty is lowest compared to producers'.

Conceptually, producers were occupants of individual $2^6 = 64 \times 64$ cell blocks (368.64 ha each, $n = 65,536$) and defined the state of each block, $i = 1, 2, \dots n(\omega)$, as the vector of areas occupied by CDL categories $j = 1, 2, \dots S(k)$. For producers, proportions of crop areas

$$p(\omega, k)_{i,j} = a(\omega, k)_{i,j} / \sum_j^{S(k)} a(\omega, k)_{i,j} \quad [1]$$

where $\sum_j^{S(i)} p(\omega, k)_{i,j} = 1$ for each block. For distributors, proportions of crop areas

$$p(\omega)_{i,j} = a(\omega)_{i,j} / A_o \quad [2]$$

where $A_o = \sum_i \sum_j a_{i,j}$ and obeyed the conservation law $\sum_i \sum_j^{n(\omega) S_o} p(\omega)_{i,j} = 1$ (Dunn *et al.*

2011). Probabilities were used to calculate Shannon entropy

$$H(\omega, k)_i = - \sum_j^{S(k)} p(\omega, k)_{i,j} \log p(\omega, k)_{i,j}$$

with the notable property that distributor entropies

$H_d(\omega, k)_i$ from distributor probabilities (Eq. 2) were additive across the set of blocks and classes within each order while producer diversities $H_p(\omega, k)_i$ were additive within each block for any subset of $S(i)$. By design, producer and distributor diversities were necessarily equal at $\omega = \Omega$, thereby giving closure (*sensu* Giampietro 2004) for a system constrained by total richness S_o and area A_o (Harte *et al.* 2008).

I hypothesized that for a class k the hierarchical partitioning of crop areas among orders would produce mean values of distributor diversity that obey a Horton

$$\text{law } \bar{H}_d(\omega) = \exp(c + b\omega) \text{ where } R_c = \log b = \frac{\bar{H}_d(\omega+1)}{\bar{H}_d(\omega)}, \text{ the Horton ratio of diversity}$$

(Dunn *et al.* 2011). To find potential hub locations, I sought ω^* , the solution to

$$\frac{d}{d\omega} (\bar{H}_p(\omega) - \bar{H}_d(\omega)) = 0, \text{ where the maximum deviation between expected producer}$$

diversity and distributor diversity indicated the hub's greatest power to reduce uncertainty among blocks. I found ω^* for the edible class, the forage class, and the combination of edible and forage classes (Table 1) to represent perspectives of local food system stakeholders in the first case, livestock producers in the second, and the entire

agricultural community in the third.

Scripts were written in the Python (v. 2.7) arcpy module to summarize the raster image so it could be interpreted by MATLAB (v.8) on a computer with 8 GB RAM.

Multi-scale crop composition and fractal scaling

I used principal components analysis to characterize relative crop abundance simultaneously in all blocks of orders 9 through 13. For each order, areas were normalized to proportions that summed to unity across blocks. Respective variances and covariances were added across orders before eigenanalysis so that blocks of any order could be assigned scores on each PCA axis. Eigenvectors for PCA axis 1 were used to score blocks as linear functions of crop proportions. A novel “glass blocks” visualization was used to examine variation in crop composition among locations and orders.

I estimated box-counting fractal dimensions to characterize how crops filled space in the limit as box length, $L = 900 \cdot 2^{\omega} \text{ m}^2$, goes to zero (Mandelbrot 1983). Under the null hypothesis a fractal dimension $D = 2.0$ was expected where crops fill space in wall-to-wall fashion or as a randomly distributed subset of the plane (Milne 1992). Dimensions less than 2 were diagnostic of environmental constraints or management practices that limit crop distribution. Blocks were tallied if one or more crop types were present, visualized as a count of orders (Milne et al. 1996) that registered an occupation. Tallies were fit as a power of box length to estimate the fractal dimension, D , the absolute value of the slope of log-log transformed counts and box length. The Akaike Information Criterion, AICc, for small sample sizes (Hurvich and Tsai 1989) determined the upper limit, ω_u , to the orders used to estimate D , with $\omega_u = 13, 12$, and 12 for edible, forage,

and combined classes, respectively.

RESULTS

Multi-scale crop composition and fractal scaling

I examined crop composition for orders 9 through 13 by displaying PCA axis 1 scores of individual blocks in geographical space (Figure 3). Scores were obtained from distributor probabilities to make blocks at various scales directly comparable. Axis 1 represented 97-99% of the variance in separate analyses of edible, forage, and combined crops. Edible crop composition was most differentiated in the eastern portion of the study area. Conspicuous nesting of boxes indicated concentrations of influential crop types as block size decreased. Extreme negative PCA scores were due to winter wheat and fallow/idle cropland in the edible class with relatively large abundances and extreme values in the eigenvector (Table 1). High PCA scores for forage crops were attributed to grassland which comprised 93% of forage area. Grassland dominated in the analysis of combined specialty and forage crops and produced patterns at all scales that were indistinguishable from the PCA of forage crops alone.

The box-counting fractal dimension of edible crops ($D = 1.798$, s.e. 0.05452, $p < 0.001$) was significantly lower than 2.0 ($t = -9.06$, $p = 0.0038$) and significantly lower than that of the forage class ($D = 1.876$, s.e. 0.044, $p < 0.001$; $t = -3.86$, $p = 0.02$). Thus, for any quadrupling of land area, forage crops exhibited 5.5% greater occupied area than edible crops, commensurate with the more spatially saturated forage cover (Figure 2). Considering all crops together ($D = 1.876$, s.e. 0.044, $p < 0.001$, Figure 4), the space-filling tendency was dominated by grassland which induced a dimension equal to that of forage crops alone yet significantly less than 2

($t = -214.72$, $p < 0.001$). All three classes were restricted to subsets of the 2-dimensional plane.

Scaling of crop diversity

Distributor probabilities with the constraint $\sum_i^{n(\omega)} \sum_j^{S_o} p(\omega)_{i,j} = 1$ gave total diversities at each order

$$H_T(\omega) = - \sum_i^{n(\omega)} \sum_j^{S_o} p(\omega)_{i,j} \log p(\omega)_{i,j} . \quad [3]$$

which I compared to diversities obtained from the producer probabilities (Eq. 1). Striking differences in diversity were found in comparisons that involved stakeholder perspective, spatial scale, and class of crop. Figure 5 shows the quartile distribution of diversity for producers and distributors at each order. Mean values at each order were fitted via linear regression. Distributor diversity of edible crop types exhibited clear Hortonian behavior across scales ($b=1.26$, $R^2 = .9997$, $p < 0.001$). Forage did not reveal as clear of a relation as for the distributor. For both edible and forage cover type classes, distributor diversity tended to be an order of magnitude lower than producer diversity at each order. This allowed the identification of the optimal hub scale ω^* , for edible ($\omega^*=12$) and forage ($\omega^*=10$) classes (Figure 6).

Distributor and producer diversities, viewed at their respective optimal hub orders, were radically different both in magnitude and spatial distribution (Figure 7). Magnitudes of distributor diversities were necessarily lower because the sum of probabilities for any given block was much less than unity, while every vector of

producer probabilities was, by design, equal to unity. For the same reason the spatial pattern of diversity differed between distributors and producers. For distributors, peak diversity of edible crops centered over Roswell, New Mexico on the eastern border of the study area. For producers it reached a maximum near Las Cruces on the southern border. Comparing distributor to producer diversities of forage crops showed a westward shift of peak distributor diversity away from the northeast corner, accompanied by a latitudinal bifurcation that favored higher producer diversity north and south.

Part-to-whole diversity relations and leverage

For the study area as a whole ($\omega = \Omega$), the contribution of crop j to total diversity simplified to

$$H_j = -p(\Omega)_j \log p(\Omega)_j \quad [4]$$

such that $H_T(\Omega) = \sum_j^{S(k)} H_j$. I examined per-area contributions of crops to total

diversity by relating cumulative diversity $H_t = \sum_{j=1}^{t \leq S(k)} H_j$ to cumulative area

$A_t = \sum_{j=1}^{t \leq S(k)} A_j$ (Figure 8). Within each class, crops were sorted from highest to lowest

“leverage” ratio, $\eta_j = H_j / A_j$ to consider two null hypotheses. One, that mean ratios of individual crops equaled the respective class-wide ratio, (i.e.,

$$H_0: \bar{\eta}(k) = \frac{1}{S(k)} \sum_i^{S(k)} \eta_j = \sum_j^{S(k)} H_j / \sum_j^{S(k)} A_j$$

which were rejected for edibles ($t = 12.03$, $df =$

32, $p < 0.0001$) and forage crops ($t = 8.17$, $df = 14$, $p < 0.0001$). Two, that mean ratio

for crops of class k equaled the ratio for all crops combined, $H_0: \bar{\eta}(k) = H_T / A_o$. Among edible crops, cherries and the double crop Durum wheat/sorghum led a majority of edible crops with numerically greater leverages than expected ($t = 23.11$, $df = 32$, $p < 0.0001$; solid green boxes, Figure 8). Two remaining edibles (i.e., fallow/idle and winter wheat) had leverage values below expected for edibles, thereby resulting in closure across the class. Nine of 15 forage crops put the mean forage leverage above expected overall ($t = 8.03$, $df = 14$, $p < 0.0001$) in the following order: double Durum wheat/sorghum, lettuce/cotton, barley/sorghum, oats/corn, millet, winter wheat/cotton, barley/corn, and winter wheat/corn. These evaded visualization as minute solid red boxes in the lower left corner of the blue forage box (Figure 8), while grassland (97% of forage area) with the lowest impact on diversity per area of all types, constituted the long horizontal box in the upper right corner.

To display the spatial distribution of leverage among potential hubs, the sum of type areas weighted by leverage ratio, η_j , was divided by the sum of areas weighted by the expected leverage, $\eta(k)$, so that small areas of high-leverage crops would be amplified ($\eta_j / \eta(k) > 1$), and large areas of low-leverage crops would be diminished ($\eta_j / \eta(k) < 1$). This exercise was repeated for the three different leverage ratios for edible, forage, and combined cover types (Figure 9 a, b, & c, respectively) to reveal cells at the hub scale along the western side of the study area whose areal composition of crop cover contributed more to the diversity of the whole foodshed relative to other blocks of the same scale.

DISCUSSION

The identified asymmetry of producer and distributor perspectives is a useful comparison in that it reflects both real-world experience and underlying economic capacity to invest in foodshed infrastructure. Generally, food distributors are more tightly connected to demand than producers and thus to income, but producers supply the diversity of food to meet demand.

The New Mexico foodshed is fractal, with spatial organization governed by law-like statistical behavior across scales. The maximum extent of inventory considered represents the context of both producer and distributor knowledge. From a producer's perspective of uncertainty, only nearby inventory is considered. A distributor perspective integrates that knowledge of nearby inventory in the context of the whole foodshed, to the privilege of lower uncertainty. With a whole-system contextualization a distributor can expect an immutable logarithmic increase in uncertainty about supply inventory as hub infrastructure broadens its scope of aggregation. Across the same range of scales, producer uncertainty about inventory is much higher on average because it is based on information only from a local domain. This difference in uncertainty defines an optimal hub scale because of asymmetrical semantics of uncertainty and diversity that emerge from the producer and distributor perspectives.

Distributors seeking to aggregate diverse local supply can offer producers access to demand and reduced overhead costs via shared hub infrastructure. Investment in foodshed infrastructure entails risk, which is far more complicated than can be discussed here, but is nonetheless a function of uncertainty, scale, location, and perspective. If infrastructure is built on the premise of a distributor's information, all users benefit

from lowered whole-system uncertainty. Specific aspects of planning a hub (i.e. refrigeration, storage space, processing equipment, packaging equipment, etc.) require anticipation of what inputs are received. The average diversity of those inputs is a predictable function of scale for a distributor, but not for producers.

A distributor offers producers efficiency and lower uncertainty. Producers offer a distributor resilience, and higher diversity. Ergo, these mutually exploitable asymmetries of capacity and information can be leveraged for mutual benefit.

In a world where the dominant means of food production are global and driven by a need for ever-increasing industrial efficiency, prudent communities will satisfy demand for food by investing in resilient local infrastructure as a complement to industrial strategies. The theory and analysis presented here can be a tool for distributors to take a whole-system view of diversity and identify optimal scale and location of infrastructure to maximize impact on foodshed development. The CDL has data of the same 30-m resolution used in this study for every year 2003-present. Further research about the temporal patterns of spatial diversity would provide a clearer picture for long-term infrastructure after assessing temporal variation in ω^* . Some cover types in the CDL, like winter wheat and fallow/idle, represent an ecological aspect of food production that can help restore soil biota stressed by intensive chemical use. Since the industrial revolution, diverse landscapes have been subject to non-diverse practices to sidestep differences in location and achieve economies of scale in food production (Leach 1975). The incorporation of fossil energy to increase labor efficiency increased yields, but decreased energy efficiency is the precarious focus of today's food system. According to resilience theory (Holling 2001; Ulanowicz *et al.* 2009), efficient systems emerge through the

expenditure of adaptive capacity, or resilience, and become adapted; resilience is thus in a trade-off with efficiency that sustainable systems seek to balance. Maize monoculture is an example of a system where exceptional production efficiency compromises its sustainability (Patzek 2008). In contrast to efficiency, diversity and redundancy of functional elements may be inefficient in labor or time, but these qualities of a system can diffuse the capacity of an external shock to disrupt flows of energy and matter essential to sustain it. From a thermodynamic standpoint, all enterprises of human civilization produce wealth by virtue of infrastructure that dissipates highly concentrated energy from fossil fuel and other sources to sustain economic growth (Schneider and Kay 1994, Garrett 2011). It is imperative to consider how energy and wealth are allocated to food infrastructure that sustains human society.

The whole-system approach to define state-variables (Harte 2008) has its roots in statistical mechanics of physical systems and touches on a future pathway to consider how physical constraints shape the diversity of biota. Rosen (1989) posits a general renormalization to render equivalent patterns of “behavioral” state-variables (i.e. phenotypic or crop diversity) to “control” state-variables, i.e. environment.

The clear difference between edible and forage crop classes lends weight to the relationship of diet and land use, adding a novel perspective on how agricultural land is partitioned among a diversity of crop types. Differences in diet, in relation to a foodshed’s capacity, have been examined in cities in New York State (Peters *et al.* 2009b). Consumer flexibility in the context of local ecology matters for sustainability: livestock displace vegans in an omnivorous population if those livestock compete for

land. Animal products differ dramatically from vegetables, fruits, and grains, insofar as most of their carbon and energy costs are accrued prior to direct transport, suggesting layered complexity in the flows of energy that produce food (Weber & Matthews 2008). The trophic-dynamic concept of ecosystems is the theoretical lens through which space, energy, and food biomass can be seen as convergent. Trophic-dynamics state that as energy and matter flow through a hierarchical food-chain, energy is degraded by an order of magnitude at each step (Lindeman 1947). Crops grown for a local vegetarian diet are the first trophic level of human consumption, whereas grains and pasturelands feed livestock that are the second trophic level. This theory predicts that for a given animal's body size, its diet affects its spatial range and population density by an order of magnitude (Damuth 2007). New Mexico, whose rangelands occupy ten times as much space as croplands and yield ~95% of the net agricultural income (USDA 2011), exemplifies an agricultural landscape advantageously suited for the growth of local animal products. Livestock, especially ungulates, are the means through which humans transform diffuse solar energy (stored in cellulose) to concentrated food energy such as meat, dairy, and eggs. Knowledge of diet and nutritional differences is necessary to help make sensible decisions to plan diversity and capacity of foodsheds on the basis of local ecology.

The fractal nature of crop diversity revealed by an hierarchical perspective is exciting for theoretical and practical reasons. Fractals are characterized by geometrical similarity between a whole system and its parts, which in nature emerges through self-organization. Hypothetically, the same scaling laws that apply to the agricultural landscape of New Mexico could be dilated to encompass the entire Southwestern United States. From a

practical perspective, shifting focus upscale and ‘downstream’ in the foodshed could aid in building regional networks of food hubs. Conversely, shifting focus to finer resolutions of crop diversity—polycultures, plant families, and population genetics—may very likely reveal the same stunning intricacies one finds in the infinitesimal folds of the Mandelbrot set. Imagine if instead of remotely-sensed, 30-m monoculture pixels there were a dataset built by a critical mass of small farmers cooperatively sharing their specific inventories on a smartphone app which could calculate drop-off locations for vegetable carpools to the local food hub, thereby streamlining the bulk delivery of fresh, healthy, diverse produce to nearby consumers. Though the scale of data presented here spans orders of magnitude, it is only a small part of the foodshed story waiting to be told by producers, distributors, and consumers alike.

Literature Cited

- Allen, T.F.H. and T.B. Starr 1982. *Hierarchy: Perspectives for Ecological Complexity*. University of Chicago Press. 310 pp.
- Bettencourt, L. M., J. Lobo, D. Helbing, C. Kühnert, and G.B. West. 2007. Growth, innovation, scaling, and the pace of life in cities. *Proceedings of the National Academy of Sciences* 104(17):7301-7306.
- Bettencourt, L. M., J. Lobo, D. Strumsky, and G.B. West. 2010. Urban scaling and its deviations: Revealing the structure of wealth, innovation and crime across cities. *PloS One* 5(11), e13541.
- Boryan, C., Z. Yang, R. Mueller, and M. Craig. 2011. Monitoring US agriculture: the US Department of Agriculture, National Agricultural Statistics Service, Cropland Data Layer Program. *Geocarto International* 26(5):341–358.
- Brown, J. H., V.K. Gupta, B.L. Li, B.T. Milne, C. Restrepo, and G.B. West. 2002. The fractal nature of nature: power laws, ecological complexity and biodiversity. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences* 357(1421): 619-626.
- Conard, M. and K. Ackerman 2010. Regionalizing the Food System for Public Health and Sustainability. NESAWG Conference. Albany, NY, Urban Design Lab.
- Damuth, J. 2007. A macroevolutionary explanation for energy equivalence in the scaling of body size and population density. *The American Naturalist*, 169(5), 621-631.
- Dreier, S. and M. Taheri 2009. Innovative Models: Small Grower and Retailer Collaborations, Part B - Balls Food Stores Perspective (pp. 1-10). Arlington: Wallace Center at Winrock International.

- Dreier, S. and M. Taheri. 2008. Innovative Models: Small Grower and Retailer Collaborations. Arlington: Wallace Center at Winrock International.
- Dunn, W., B. Milne, R. Mantilla, and V.K. Gupta. 2011. Scaling relations between riparian vegetation and stream order in the Whitewater River network, Kansas, USA. *Landscape Ecology* 26(7):983-997.
- Folke, C. 2006. Resilience: The emergence of a perspective for socio-ecological systems analyses. *Global Environmental Change* 16:253-267.
- Garrett, T. 2011. Are there basic physical constraints on future anthropogenic emissions of carbon dioxide? *Climatic Change* 104:437-455.
- Giampietro, M. 2004. Multi-scale integrated analysis of agroecosystems. CRC Press.
- Han, W., Z. Yang, L. Di, and R. Mueller. 2012. CropScape: A Web service based application for exploring and disseminating US conterminous geospatial cropland data products for decision support. *Computers and Electronics in Agriculture* 84:111–123.
- Harte, J., E. Conlisk, A. Ostling, J.L. Green, and A.B. Smith. 2005. A theory of spatial structure in ecological communities at multiple spatial scales. *Ecological Monographs*, 75(2), 179-197.
- Harte, J., T. Zillio, E. Conlisk, and A.B. Smith. 2008. Maximum entropy and the state-variable approach to macroecology. *Ecology* 89(10):2700-2711.
- Hill, M. O. 1973. Diversity and evenness: a unifying notation and its consequences. *Ecology* 54(2):427-432.
- Holling, C.S. 2001. Understanding the complexity of economic, ecological, and social systems. *Ecosystems* 4(5)5: 390-405 URL: <http://www.jstor.org/stable/3658800> .

- Horton, R.E. 1945. Erosional development of streams and their drainage basins; hydrophysical approach to quantitative morphology. *Geol. Soc. Am. Bull.* 56:275-370.
- Hurvich, C. M. and C.-L. Tsai. 1989. Regression and time series model selection in small samples. *Biometrika* 76:297–307.
- Jost, L. 2006. Entropy and diversity. *Oikos*, 113(2):363-375.
- Kloppenburg, J., Hendrickson, J., & Stevenson, G. W. 1996. Coming in to the foodshed. *Agriculture and Human Values* 13(3):33-42.
- Leach, G. 1975. Energy and Food Production. *Food Policy*, 1(1): 62-73.
- Lindeman, R. L. 1942. The trophic-dynamic aspect of ecology. *Ecology*, 23(4):399-417.
- Mandelbrot, B. B. 1983. *The Fractal Geometry of Nature*. W.H. Freeman. 468 pp.
- Matson, J., M. Sullins, and C. Cook. 2013. The Role of Food Hubs in Local Food Marketing. *USDA Rural Development Service Report 73*.
- Milne, B. T., A.R. Johnson, T.H. Keitt, C.A. Hatfield, J. David, and P.T. Hraber. 1996. Detection of critical densities associated with pinon-juniper woodland ecotones. *Ecology* 77:805-821.
- Milne, B.T. 1992. Spatial aggregation and neutral models in fractal landscapes. *American Naturalist* 139:32-57.
- NOAA National Climactic Data Center 2013. Climate at a glance. Accessed March 21, 2013, at <http://www.ncdc.noaa.gov/cag/>
- NOAA, 2010b. Spring Freeze Dates across New Mexico. Accessed March 21, 2013, from <http://www.srh.noaa.gov/abq/?n=springfreezetable>
- NOAA. 2010a. Fall Freeze Dates across New Mexico. Accessed March 21, 2013, from

<http://www.srh.noaa.gov/abq/?n=clifeature2010falfreezetable>

- Norris, F.H., S. P. Stevens, B. Pfefferbaum, K. F. Wyche, and R.L. Pfefferbaum. 2008. Community resilience as a metaphor, theory, set of capacities, and strategy for disaster readiness. *Am. J. Community Psychology*. 41:127-150.
- Omerik, J.M. 1987. Ecoregions of the conterminous United States (map supplement): *Annals of the Association of American Geographers*, 77(1):118-125.
- Owen, M.D.K. and I.A. Zelaya. 2005. Herbicide-resistant crops and weed resistance to herbicides. *Pest Management Science* 61(3):301-311.
- Patzek, T. W. 2008. Thermodynamics of agricultural sustainability: The case of US maize agriculture. *Critical Reviews in Plant Sciences* 27(4):272-293.
- Peters, C. J., N.L. Bills, A.J. Lembo, J.L. Wilkins, and G.W. Fick. 2009b. Mapping potential foodsheds in New York State: A spatial model for evaluating the capacity to localize food production. *Renewable Agriculture and Food Systems* 24(1):72-84.
- Peters, C. J., N.L. Bills, J.L. Wilkins, and G.W. Fick. 2009a. Foodshed analysis and its relevance to sustainability. *Renewable Agriculture and Food Systems* 24(1):1-7.
- Pielou, E. C. 1977. *Mathematical Ecology*. New York: Wiley.
- Pimentel, D., S. Williamson, C.E. Alexander, O. Gonzalez-Pagan, C. Kontak, and S.E. Mulkey. 2008. Reducing energy inputs in the US food system. *Human Ecology* 36(4):459-471.
- Rosen, R. 1989. Similitude, similarity, and scaling. *Landscape Ecology* 3(3):207-216.
- Samaniego, H. and M.E. Moses. 2008. Cities as organisms: Allometric scaling of urban road networks. *Journal of Transport and Land use* 1(1):21-39.

- Schneider, E. D. and J.J. Kay. 1994. Life as a manifestation of the second law of thermodynamics. *Mathematical and Computer Modelling* 19(6):25-48.
- Shannon, C. E. and W. Weaver. 1949. *The Mathematical Theory of Communication*. Urbana: University of Illinois Press.
- Shute, L. L., A. Anderson, H. Bernhardt, T. Creech, S. vT. Fleming, E. Oakley, B. Shute, and B., Jackson. 2011. *Building a Future with Farmers: Challenges Faced by Young, American Farmers and a National Strategy to Help Them Succeed*. National Young Farmers' Coalition, NY.
- Speth, J. G. 2012. *America the Possible*. Yale University Press.
- Strahler, A.N. 1952. Hypsometric (area altitude) analysis of erosional topography. *Geol Soc Am Bull* 63:1117-1142.
- Tabashnik, B. E., J.B.J. Van Rensburg and Y. Carrière. 2009. Field-evolved insect resistance to Bt crops: definition, theory, and data. *Journal of Economic Entomology* 102(6):2011-2025.
- Tillotson, J. E. 2004. America's obesity: conflicting public policies, industrial economic development, and unintended human consequences. *Ann. Rev. Nutr.* 24:617-643.
- Tilman, D., K.G. Cassman, P.A. Matson, R. Naylor, and S. Polasky. 2002. Agricultural sustainability and intensive production practices. *Nature* 418(6898):671-677.
- U.S. Census Bureau 2010. *State & County Quickfacts: New Mexico*. Accessed March 21, 2013, from <http://quickfacts.census.gov>.
- U.S. Environmental Protection Agency. 2006. *Level III ecoregions of the continental United States* (revision of Omernik, 1987): Corvallis, Oregon, USEPA – National Health and Environmental Effects Research Laboratory, Map M-1, various scales.

- U.S. Geological Survey 2001. Elevations and Distances in the United States (online edition). Accessed Mar 21, 2013, at <http://egsc.usgs.gov/isb/pubs/booklets/elvadist/elvadist.html#Highest>.
- Ulanowicz, R. E., S.J. Goerner, B. Lietaer, and R. Gomez. 2009. Quantifying sustainability: resilience, efficiency and the return of information theory. *Ecological Complexity* 6(1): 27-36.
- USDA 2011a. Food Hubs: Viable Regional Distribution Solutions. Sustainable Agriculture & Food Systems Funders Forum. US Department of Agriculture.
- USDA 2011b. Know Your Farmer Know Your Food. Retrieved 10/2011, from <http://www.usda.gov/wps/portal/usda/usdahome?navid=KNOWYOURFARMER>.
- USDA National Agricultural Statistics Service 2007. U.S. Census of Agriculture 2007.
- USDA National Agricultural Statistics Service 2013. USDA, NASS Marketing and Information Services Office, Washington, D.C. <http://nassgeodata.gmu.edu/CropScape/NM>
- USDA Plant Hardiness Zone Map 2012. Agricultural Research Service, U.S. Department of Agriculture. Accessed from <http://planthardiness.ars.usda.gov>.
- Weber, C. L. and H.S. Matthews. 2008. Food-miles and the relative climate impacts of food choices in the United States. *Environmental Science & Technology* 42(10):3508-3513.
- West, G. B., J.H. Brown and B.J. Enquist, B. J. 1997. A general model for the origin of allometric scaling laws in biology. *Science* 276(5309):122-126.
- West, G. B., J.H. Brown and B.J. Enquist. 1999. The fourth dimension of life: fractal geometry and allometric scaling of organisms. *Science* 284(5420):1677-1679.

Table 1: Cropland Data Layer types for the 2011 New Mexico growing season. Crop areas are expressed as total area with accuracies according to USDA, National Agricultural Statistics Service (2013). Relative abundances are with respect to areas occupied in total (A_o), exclusively by edible types (A_e) and forage types (A_f). Eigenvectors are from separate principal component analyses for each class; absolute values of 0.00 occur where the vector element was less than 0.01. Forage crops are indicated by dark shading and ambiguous crops that were split between edible and forage classes by lighter shading.

Cover Type	Cover Area (ha)	Accuracy (%)	% Abundance relative to:			PCA axis 1 eigenvector		
			A_o	A_e	A_f	All	Edible	Forage
Corn	17930.34	79.87	0.22	0.00	0.23	0.00	n/a	0.00
Sorghum	29280.96	76.32	0.36	0.00	0.37	0.00	n/a	0.00
Peanuts	927.27	65.61	0.01	0.41	0.00	0.00	-0.01	n/a
Pop or Orn Corn	22.68	88.93	0.00	0.01	0.00	0.00	0.00	n/a
Barley	1797.84	50.92	0.02	0.79	0.00	0.00	-0.01	n/a
Durum Wheat	815.67	64.14	0.01	0.36	0.00	0.00	0.00	n/a
Spring Wheat	279	0.00	0.00	0.12	0.00	0.00	0.00	n/a
Winter Wheat	130228.29	83.10	1.61	57.28	0.00	0.02	-0.94	n/a
Rye	680.85	62.72	0.01	0.30	0.00	0.00	0.00	n/a
Oats	1558.71	52.66	0.02	0.69	0.00	0.00	0.00	n/a
Millet	427.41	72.42	0.01	0.00	0.01	0.00	n/a	0.00
Alfalfa	67525.38	91.06	0.83	0.00	0.86	0.00	n/a	0.00
Dry Beans	1520.28	91.73	0.02	0.67	0.00	0.00	0.00	n/a
Potatoes	228.42	99.62	0.00	0.10	0.00	0.00	0.00	n/a
Other Crops	105.03	0.00	0.00	0.05	0.00	0.00	0.00	n/a
Watermelons	51.93	23.53	0.00	0.02	0.00	0.00	0.00	n/a
Onions	966.06	63.18	0.01	0.42	0.00	0.00	0.00	n/a
Fallow/Idle Cropland	135658.26	71.85	1.67	29.83	0.86	0.01	-0.33	0.01
Cherries	12.6	n/a	0.00	0.01	0.00	0.00	0.00	n/a
Apples	232.47	n/a	0.00	0.10	0.00	0.00	0.00	n/a
Grapes	27	n/a	0.00	0.01	0.00	0.00	0.00	n/a
Pecans	9847.26	85.85	0.12	4.33	0.00	0.00	0.00	n/a
Grassland Herbaceous	7661183.85	n/a	94.59	0.00	97.13	1.00	n/a	1.00
Pasture/Hay	21297.96	n/a	0.26	0.00	0.27	0.00	n/a	0.00
Pistachios	333.54	98.06	0.00	0.15	0.00	0.00	0.00	n/a
Triticale	1361.7	50.22	0.02	0.60	0.00	0.00	0.00	n/a
Peppers	1792.17	73.47	0.02	0.79	0.00	0.00	0.01	n/a
Apricots	15.3	n/a	0.00	0.01	0.00	0.00	0.00	n/a
Dbl Crop WinWht/Corn	3316.77	56.54	0.04	0.73	0.02	0.00	-0.03	0.00
Dbl Crop Oats/Corn	215.19	72.60	0.00	0.05	0.00	0.00	0.00	0.00
Lettuce	64.44	96.76	0.00	0.03	0.00	0.00	0.00	n/a
Pumpkins	151.29	66.77	0.00	0.07	0.00	0.00	0.00	n/a
Dbl Crop Lettuce/Cotton	25.38	n/a	0.00	0.01	0.00	0.00	0.00	0.00
Dbl Crop Durum Wht/Sorghum	5.67	n/a	0.00	0.00	0.00	0.00	0.00	0.00
Dbl Crop Barley/Sorghum	212.04	19.39	0.00	0.05	0.00	0.00	0.00	0.00
Dbl Crop WinWht/Sorghum	4058.91	62.33	0.05	0.89	0.03	0.00	-0.03	0.00
Dbl Crop Barley/Corn	3097.8	76.09	0.04	0.68	0.02	0.00	-0.02	0.00
Dbl Crop WinWht/Cotton	2001.69	39.90	0.02	0.44	0.01	0.00	-0.02	0.00
Cabbage	34.11	57.41	0.00	0.02	0.00	0.00	0.00	n/a
Total area A_o :	8099291.52	% of A_o :	100.00	2.81	97.19			

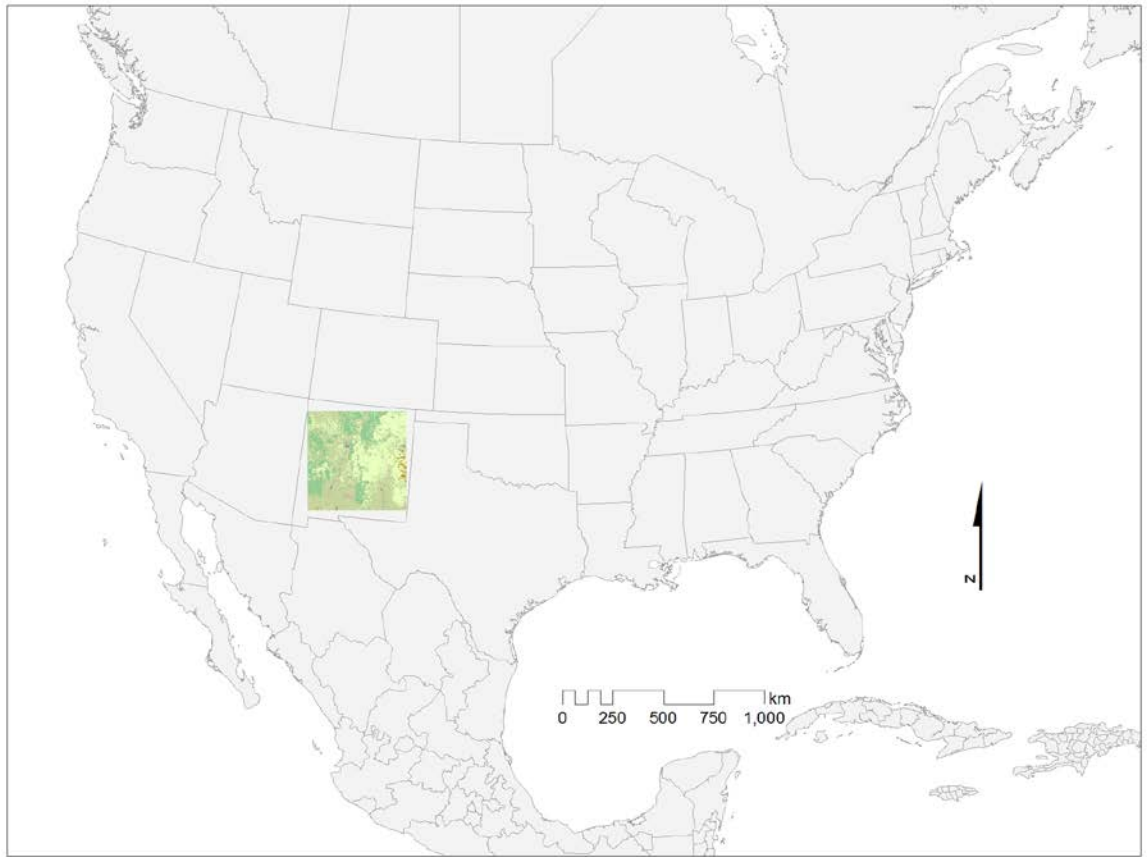


Figure 1. New Mexico study area (24,159,191 ha) and orientation. Colors correspond to Cropland Data Layer types in the 2011 growing season.

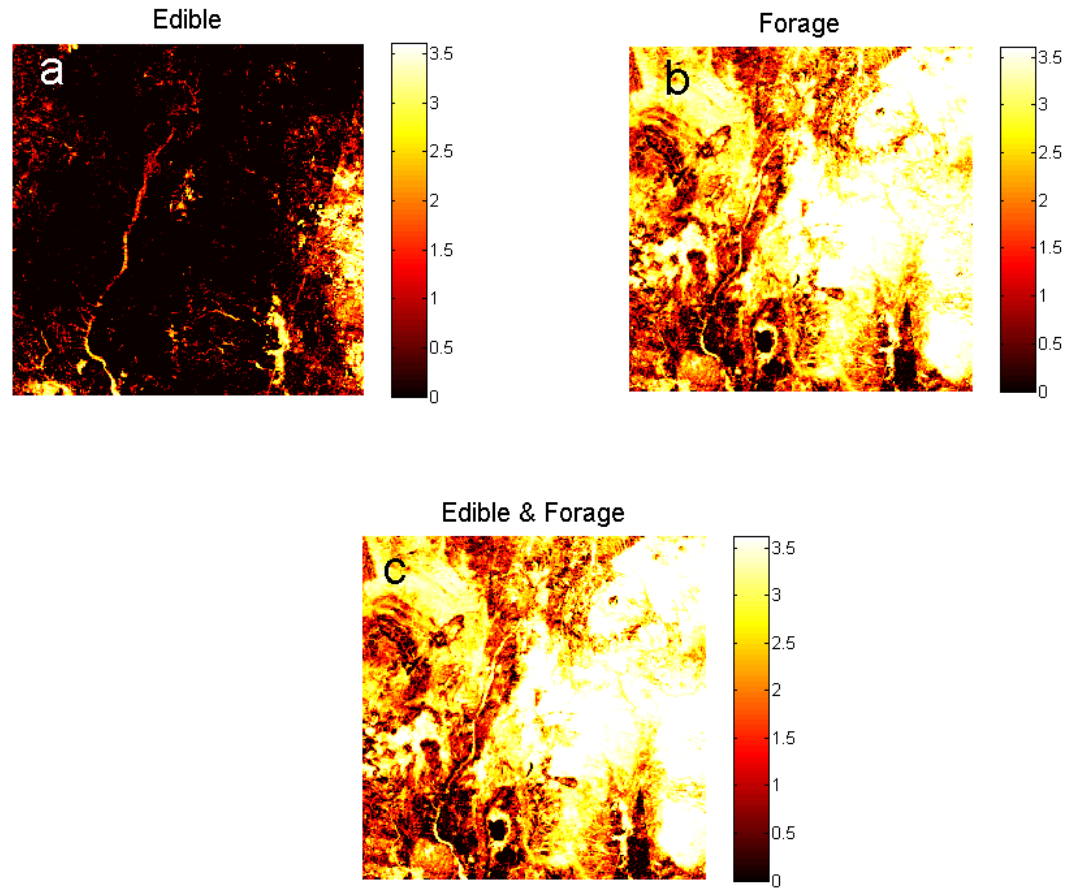


Figure 2. Densities (\log_{10}) of 30-m cells within 1474.56 ha blocks sampled from the USDA Cropland Data Layer occupied by: (a) combined edible crops, (b) forage crops including highly prevalent grassland, and (c) combined edible and forage for the 2011 New Mexico growing season within the 24,159,191 ha study area.

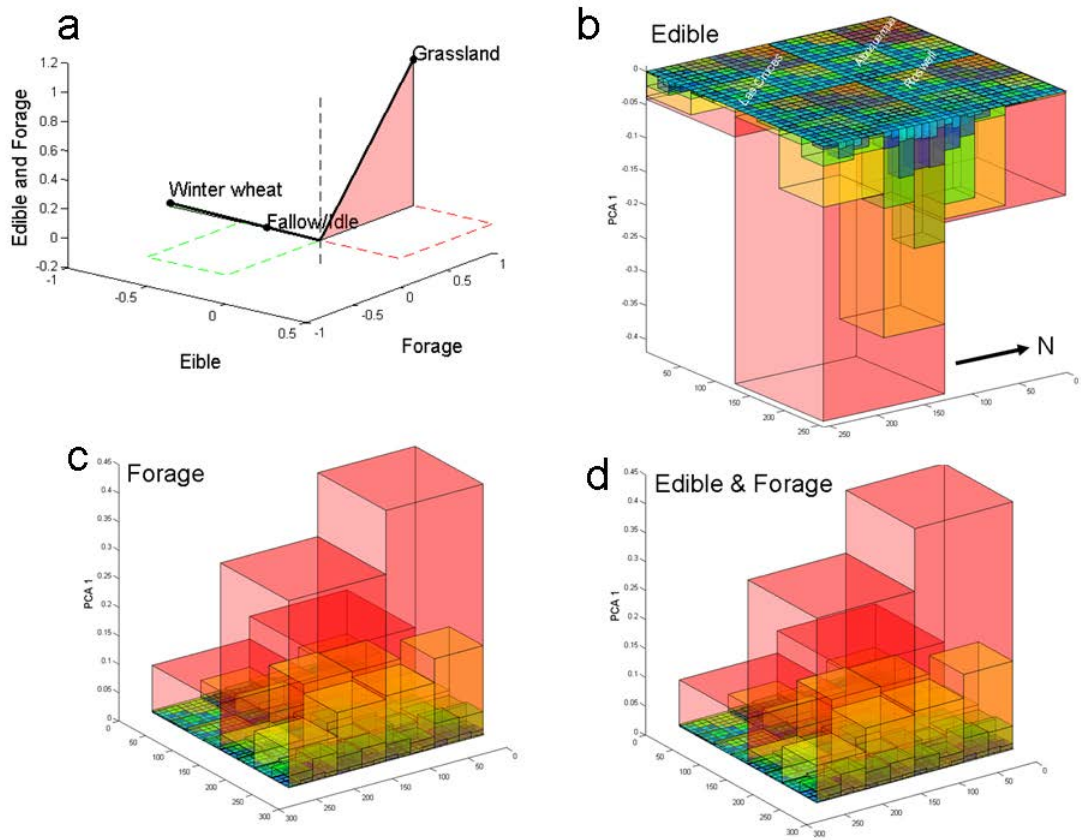


Figure 3. Crop composition represented by: (a) principal component analysis axis 1 eigenvectors and (b, c, d) PCA scores for blocks of orders 9-13 in analyses of edible, forage, and combined edible and forage classes, respectively. Color spectrum from blue to red corresponds to box lengths short to long.

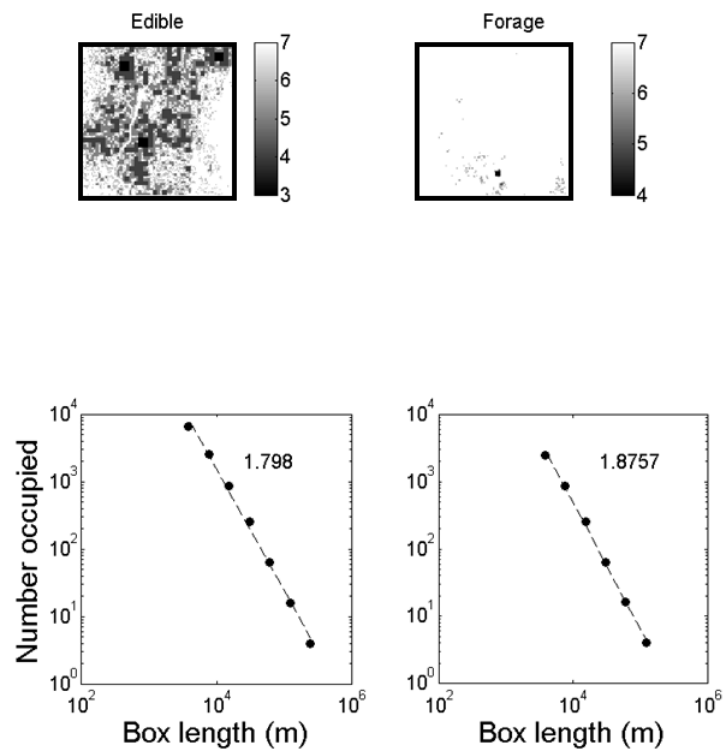


Figure 4. Box-counting fractal scaling relations of edible and forages crop classes. Top row: maps at $\omega = 7$ resolution of the number of orders 7-13 that included the cell within an occupied block. Bottom row: Power law relations with box-counting fractal dimensions for each crop class.

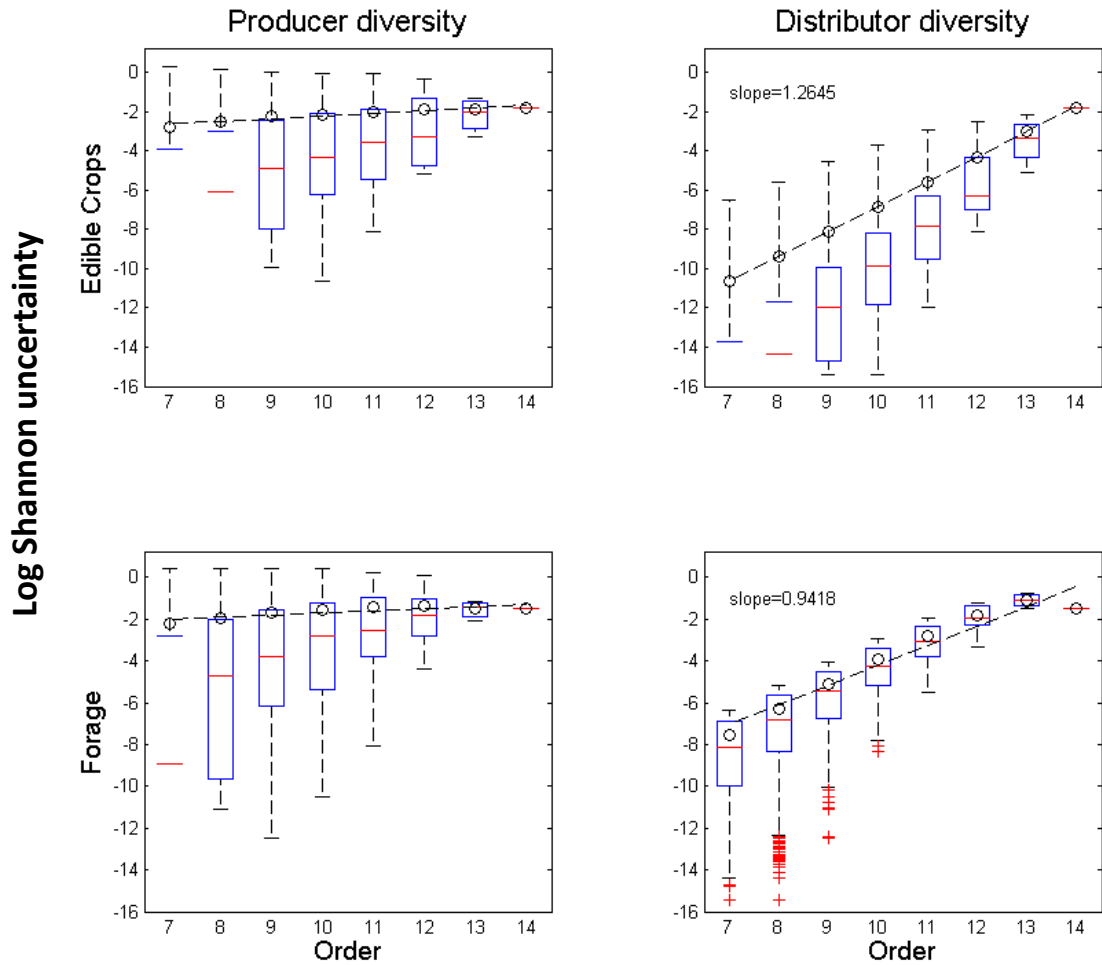


Figure 5. Quartiles (boxes) and mean values (open circles) of Shannon uncertainty at each order $\omega = 7, 8, 9 \dots \Omega$ organized by crop type and accounting schema. Identical axis scaling emphasizes differences between distributions. For both edible (top) and forage (bottom) crops, the difference between producer (left) and distributor (right) diversities show Hortonian behavior for distributors. Dashed lines are linear regressions of mean uncertainty values on order.

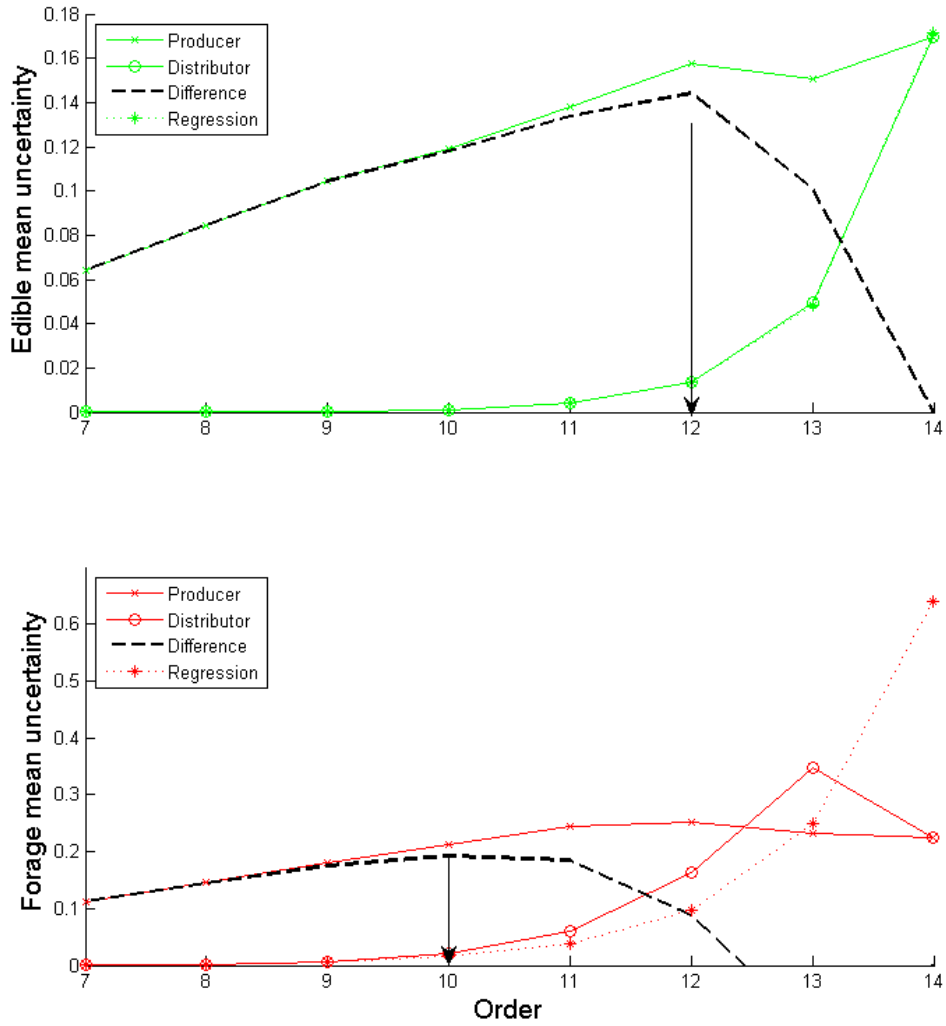


Figure 6. Optimal hub orders for edible (top) and forage (bottom) classes based on the difference between producer and distributor uncertainty (dashed line). Arrows indicate ω^* at the maximum difference. Top: Producers' mean edible crop uncertainty is higher than distributor's mean uncertainty across all orders < 14 , and observed distributor mean uncertainty indistinguishable from the regression curve. Bottom: Distributor uncertainty for forage does not show perfect Hortonian scaling. As is the case with the edible crops, forage distributor and producer uncertainty reach closure at order $\Omega = 14$.

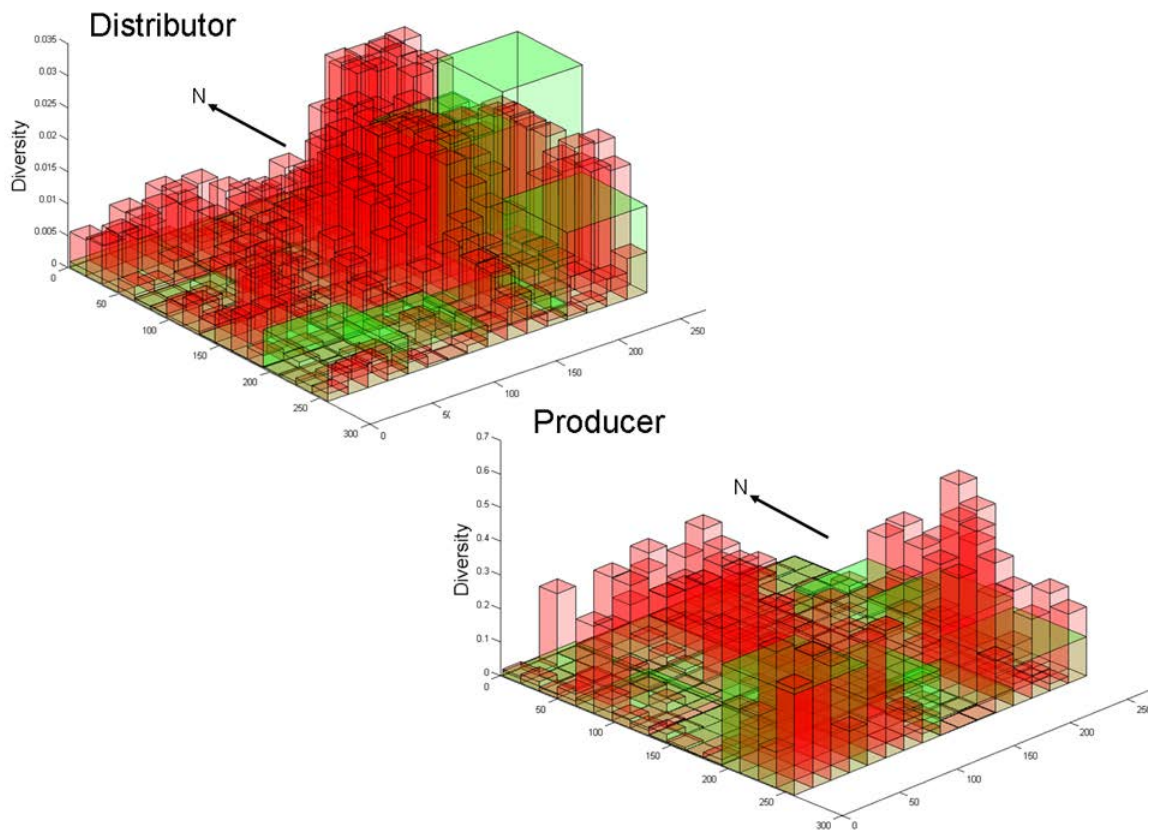


Figure 7. Distributor and producer diversities at optimal hub orders for edible (green, $\omega^* = 12$) and forage (red, $\omega^* = 10$) crop classes from the 2011 New Mexico growing season.

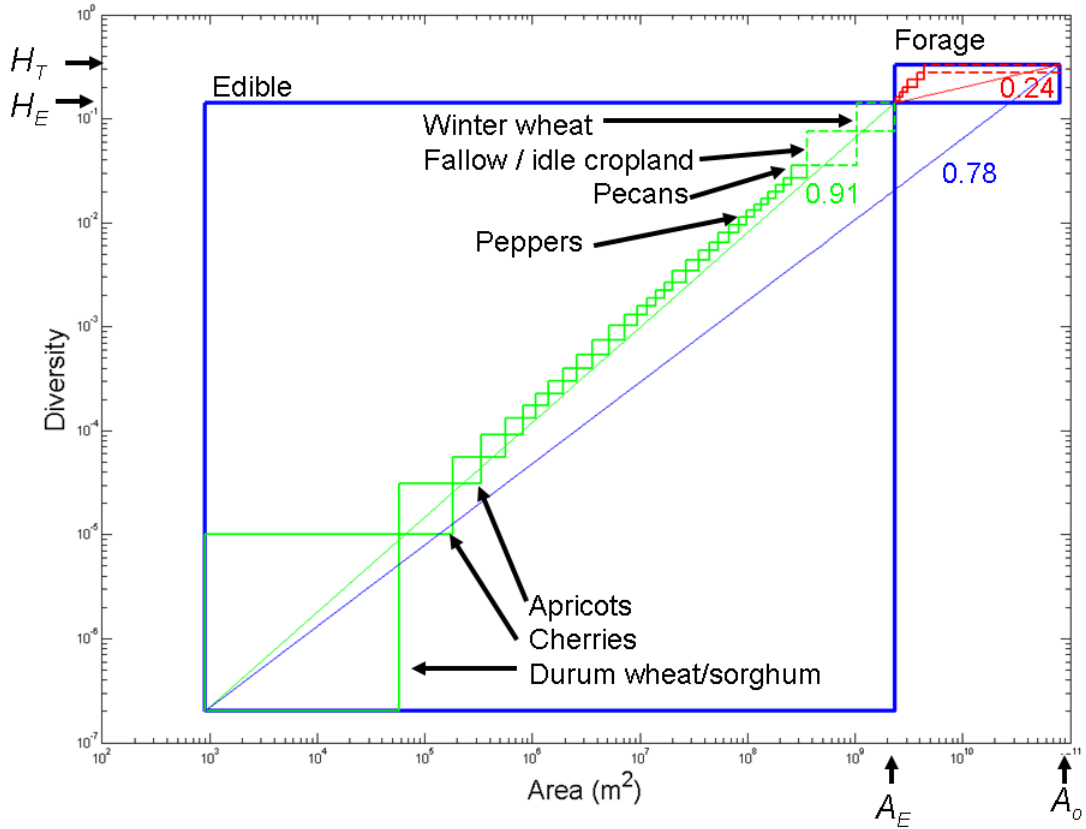


Figure 8. Part-to-whole relations of distributor diversity and area for edible and forage classes (blue boxes) and constituent crops (green and red boxes) for the 2011 New Mexico growing season. Blue diagonal line with slope 0.78 indicates the ratio of log diversity to log area under the null expectation that edible and forage crops contribute equally to diversity per unit area. Thin green and red diagonals indicate expected log-log diversity-to-area ratios for edible and forage classes, respectively. For individual crops, solid boxes indicate diversity-to-area ratio greater than expected for the class and dashed boxes the opposite.

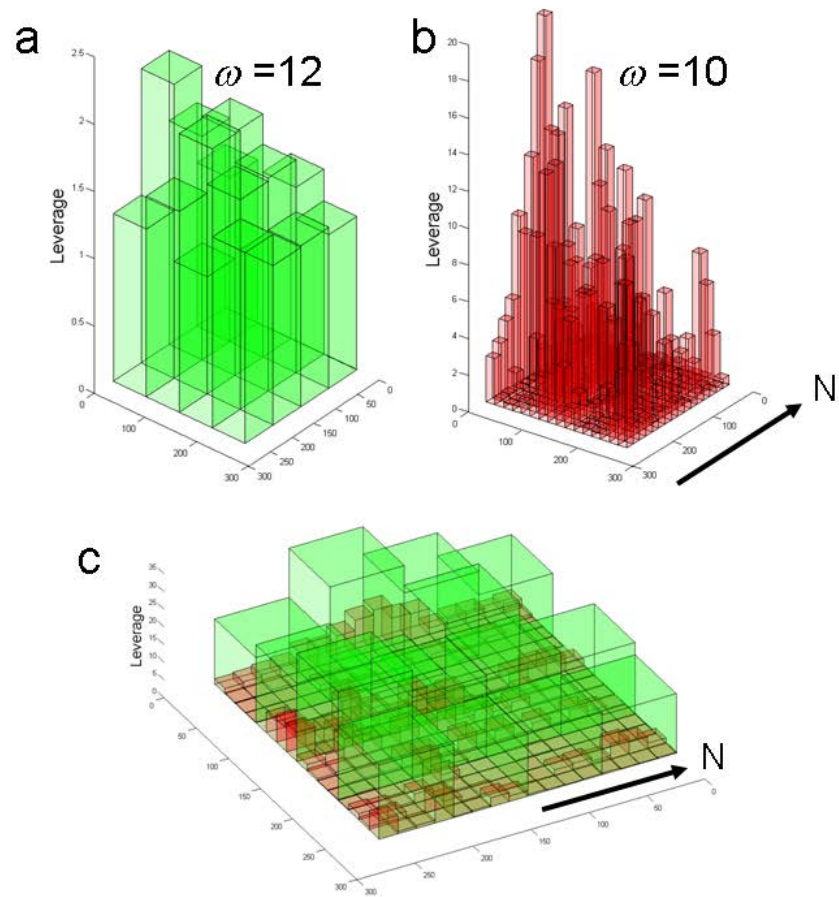


Figure 9. Spatial distributions of block leverages for: (a) edible (z-axis 0 – 2.5); (b) forage crops (z-axis 0 – 20) at optimal hub orders 12 and 10, respectively, based on within-class leverages; and (c) leverages of edible (green) and forage (red) crops on the common basis of leverage expected for all crops combined (z-axis 0 – 36).