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Research paper

Identifying, quantifying and classifying agricultural opportunities for land use planning

Daniel L. Erickson[a,c,*], Sarah Taylor Lovell[b], V. Ernesto Méndez[c]

[a] Food Systems Research Institute, PO Box 1141, Shelburne, VT 05482, USA
[b] Department of Crop Sciences, Plant Science Laboratory, University of Illinois, Urbana, IL 61801, USA
[c] Plant and Soil Science Department, University of Vermont, Jeffords Hall, 63 Carrigan Drive, Burlington, VT 05405, USA

HIGHLIGHTS

- Geospatial analyses identified a wide variety of agricultural opportunities.
- Automated cluster analysis was used to organize thousands of opportunities.
- Agricultural neighborhood analysis explored creating larger spaces for farming.
- Spaces exist to expand local food production, even into residential areas.

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ABSTRACT

Worldwide, urbanization is causing a loss of agricultural land as residential and commercial development expands. In many parts of the US, this land use conversion has in some cases resulted in subdivision of farms into large residential parcels. Some of these residential parcels may retain sizeable areas of undeveloped prime agricultural soil. In an uncertain future challenged by population growth, climate change, food insecurity, water shortages, and energy limitations, communities are beginning to explore their ability to feed themselves from local supplies. Addressing this issue will require additional tools for planning land use in a way that could support greater food self-sufficiency at the community level. In this study, a process was developed to identify, quantify and classify agricultural opportunities (AO). AO are simply open lands suitable for some level of agricultural production.

The methods outlined here were developed in Chittenden County, Vermont but they can be applied elsewhere. While individual ancillary datasets may be unique to each study area, the general process can be replicated as long as some basic datasets such as classified land cover imagery and prime soils are available. The tools described herein, if employed by planners or geospatial analysts, can generate actionable information. The results of the analyses, as well as the associated participatory community discussions, can aid decision makers when drafting new or revising old policies. Because of their widespread applicability, these tools can serve as decision support aids for policy makers and planners tasked with developing strategies to increase food self-sufficiency.

1. Introduction

1.1. Loss of farmland

Agricultural lands have been converted to residential and commercial uses worldwide (Boudjenouia, Fleury, & Tacherift, 2008; Fazal, 2001; Matteucci & Morello, 2009; Yan, Liu, Huang, Tao, & Cao, 2009), and often this conversion results in a net loss in prime agricultural land. In the United States, for example, development led to the conversion of 3,527,486 ha (8,716,600 acres) or 3% of prime agricultural land to other uses during the 25 year period between 1982 and 2007 (AFT, 2010; USDA, 2009). Two types of growth have played a major role in this conversion. The first simply involves expansion at the fringe of existing urban areas. The second involves the development of large residential lots, usually greater than 0.4 ha (1 acre), well beyond the urban fringe and often located in rural counties (Heimlich & Anderson, 2001). In the United States, the latter form of development seems to have peaked during the period 1992–1997, and in recent years (2002–2007) it has slowed by 29% (Dempsey & Ferguson, 2010). This reduction in agricultural land development may be attributed to more compact housing developments and smart growth policies

* Corresponding author at: Food Systems Research Institute, PO Box 1141, Shelburne, VT 05482, USA. Tel.: +1 802 448 2403.
E-mail addresses: derickson@foodsri.com (D.L. Erickson), stlovell@illinois.edu (S.T. Lovell), emendez@uvm.edu (V.E. Méndez).

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(Dempsey & Ferguson, 2010) or simply to the recent economic crisis and an associated declining rate of new home construction. Regardless of the recent trend, significant areas of agricultural land have already been lost to large-lot development, so in effect these areas are currently unavailable for food production.

Land use conversion at the fringes of urban areas creates a serious issue for existing and new farmers who want to engage in agricultural activities located near the population centers that host many consumers. These agricultural entrepreneurs are forced to compete with residential homeowners, commercial developers, and other interests on the same land market (Cavailhes & Wavresky, 2003). As a result, farmers seeking land to farm close to urban markets face at least two challenges. First, there is simply less land available for them to farm, and second, agricultural land within an exurban landscape is often valued based on its potential development as non-agricultural uses (Plantinga & Miller, 2001; Plantinga, Lubowski, & Stavins, 2002). However, farmers operating within this dynamic, mixed-use landscape do benefit from proximity to urban consumers and local markets because of reduced transportation costs.

While the development of large residential lots in the US and elsewhere has taken agricultural land out of production, not all of this land has been completely paved over or built on. In fact, the trend for large residential lots has created a situation in which only a portion of the parcel may contain buildings, while the remainder is managed as lawn or other habitat.

In our study area, Chittenden County, Vermont, USA, the practice of subdividing large parcels, often farms, into 2.02 and 4.04 ha (5 and 10 acre) parcels due to local zoning regulations (minimum lot sizes of 2.02 ha in rural zones and exemption from septic permitting for lots greater than 4.04 ha) has resulted in many parcels with open spaces still suitable for agriculture. This farmland fragmentation prohibits the traditional economies of size that support conventional agricultural systems. Because of this situation, we investigate pooling these suitable spaces, in this and a related study (Erickson, Lovell, & Méndez, 2011 masked for blind review). As Chittenden County begins to explore opportunities for increasing local food production to meet the growing demand, several important questions arise, such as: (1) how much land is available? (2) how much food can be produced on that land? and (3) can the region reach a higher degree of food self-sufficiency from local sources?

1.2. Land inventories and organizing frameworks

Knowing *where* and *how much* land is available will be essential for coordinated, community efforts to set and meet local food and biofuel production goals. To this end, several cities in North America have conducted land inventories including Cleveland, OH (Taggart, Chaney, & Meaney, 2009), Oakland, CA (McClintock & Cooper, 2010; McClintock, Cooper, & Khandeshi, 2013), Portland, OR (Balmer et al., 2005; Mendes, Balmer, Kaethler, & Rhoads, 2008), Seattle, WA (Horst, 2008), Vancouver, BC (Kaethler, 2006; Mendes et al., 2008) and Toronto, ON (MacRae et al., 2010). Two common threads amongst these inventories are the focus on publically owned land and the manual visual assessments of suitable parcels with the aid of aerial imagery and some ground-truthing. Also, at the city scale, Kremer and DeLiberty (2011) used Geographic Information Systems (GIS) and remote sensing to determine the space available for urban agriculture within residential yards of Philadelphia, PA. Grewal and Grewal (2012) considered portions of residential lots within Cleveland, OH as part of scenarios developed to determine the potential level of food self-reliance. At a regional scale, many areas in the US have begun food systems assessments. One such assessment, The Philadelphia Food System Study (DVRRPC, 2010) investigated the agricultural land base using classified, remotely sensed imagery and data of prime agricultural soils.

In another part of the world, Thapa and Murayama (2008) conducted a GIS-based land evaluation on the peri-urban region around Hanoi, Vietnam, to consider suitability for transitioning from conventional agriculture to the production of perishable, directly consumable foods. The evaluation relied on input data layers for soil, land use, roads, water, and markets. The output was a map of varying levels of suitability, each of which might be used for different purposes (Thapa & Murayama, 2008). While this previous work is quite relevant to our study, we are unaware of any studies at the regional scale that have identified agricultural opportunities on land classified as residential, although we do recognize the growing body of remote-sensing literature on lawns that is relevant to our methods (Giner, Polsky, Pontius Jr, & Runfola, 2013).

Land cover studies done in urban areas to inventory and quantify urban tree canopies could also offer methodologies applicable to inventorying agricultural opportunities, including the use of high resolution, remotely sensed imagery and associated geospatial processing (Galvin, Grove, & O'Neil-Dunne, 2006a; Galvin, Grove, & O'Neil-Dunne, 2006b; Grove, O'Neil-Dunne, Pelletier, Nowak, & Walton, 2006). To organize these inventories and facilitate planning, urban forestry programs have used a forest opportunity spectrum (FOS) which provides a framework for organizing data (Raciti et al., 2006). An opportunity spectrum represents all of the places where trees can be grown in urban areas. Further, an opportunity spectrum moves beyond assessing what is simply biophysically possible, to analyzing the potential (economically likely) and preferred (socially desirable) phases of planning. As noted by Raciti et al. (2006), a foundation of biophysical and social data is necessary to inform landscape planning, management, and policymaking when working with a spatially heterogeneous landscape.

To our knowledge, an agricultural opportunity spectrum (AOS), akin to a FOS has yet to be developed. Borrowing from the FOS work of Raciti et al. (2006), an AOS can be used to: (1) inventory existing agricultural opportunities; (2) link the desires of community stakeholders with local food production goals; (3) identify and assess the impact of alternative agricultural opportunities on other community initiatives; and (4) develop inter-organizational partnerships. Higher food and fuel prices are provoking proactive communities and municipalities to begin to address the potential for increasing local food and biofuel production, as a strategy to achieve higher regional sustainability. There is still academic debate on whether local food sourcing is more sustainable for a region, in terms of ecological (i.e. energy efficiency of food production and transport), and economic factors (cost to consumers; Edwards-Jones et al., 2008; Risku-Norja, Hietala, Virtanen, Ketomaki, & Helenius, 2008). However, the state of Vermont has taken the position to support this notion at several levels, including the development of Farm to Plate a 10-year strategic plan for the Vermont food systems (VSJF, 2011). This justification is based on research by the "Farm to Plate" initiative that showed how investing in regional food systems would generate jobs and revitalize the state's economy (VSJF, 2011).

Planning efforts would benefit from having an organizational framework like an AOS. To this end, as part of this study, we have begun to develop a classification of agricultural opportunities within the county to aid planning and decision making. A spatially explicit classification can facilitate decision making by providing planners or policy makers with an empirical, data-driven basis by which to prioritize and target specific areas for coordinated regional planning efforts (e.g. trans-town agricultural districts).

1.3. Can Chittenden County feed itself?

Several previous studies offer some insight into the potential for Chittenden County to supply the food to meet the local

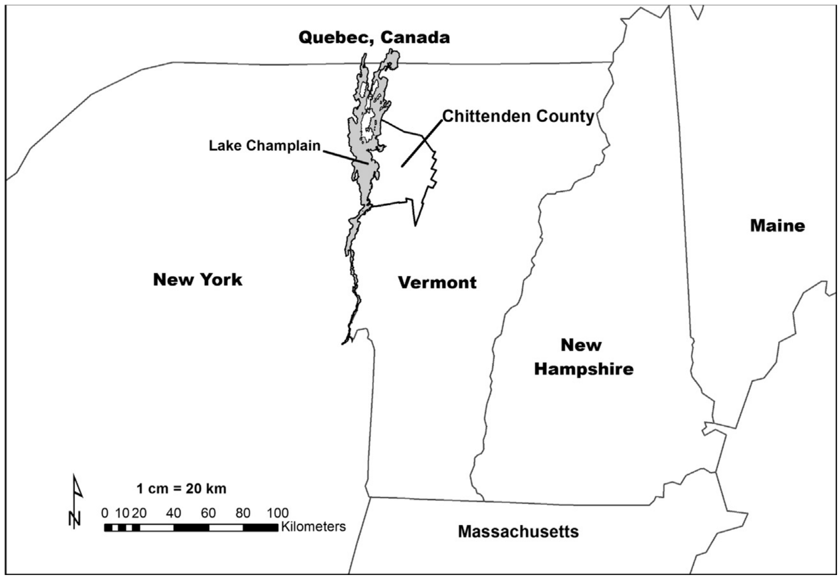

Fig. 1. Regional location of the study area.

needs. One study found that Toronto, Canada, a city with a simlar climate to Burlington's, would need 2317 ha of land (if all production is organic) to produce 10% of the annual fresh vegetable needs for its 2.5 million residents (MacRae et al., 2010). A study conducted locally by McKellips (2009) estimated that Chittenden and its five neighboring counties needed additional land to supply the demand for local foods: 572 ha of additional vegetable production, 2064 additional hectares of hard wheat, and 11,509 ha of land dedicated to fodder crops for local beef and pork production. The study also noted that Chittenden and its surrounding counties have 78,934 dairy cows and 449 ha of apple orchards beyond what is needed for local demand (McKellips, 2009). These studies suggest that there is some potential for Chittenden County to become more food self-sufficient, but they offer little in terms of planning goals to make that happen.

1.4. Purpose of study

In an uncertain future challenged by climate change, food insecurity, water shortages, and energy limitations, communities are beginning to explore their ability to feed themselves from local supplies. Addressing this issue will require additional tools for planning land use in a way that could support greater food self-sufficiency at the community level. To this end, the primary goal of this research was to develop a process by which to identify, quantify and organize (classify) agricultural opportunity (AO) spaces in order to facilitate regional planning efforts concerned with increasing local food self-sufficiency. An AO is simply any open land suitable for some level of agricultural production. The methods outlined here were developed in Chittenden County, Vermont, but they can be applied elsewhere. While the individual ancillary datasets may be unique to each study area, the general process can be replicated as long as some basic datasets, such as classified land cover imagery and agricultural soils are available. The tools described herein, if employed by planners or geospatial analysts, can generate actionable information. The results of the analyses, as well as the associated community discussions, can aid decision makers when drafting new or revising old policies.

2. Methods

2.1. Study area

Our study was conducted in Chittenden County, located in the Champlain Valley of Vermont. The county extends east from the shores of Lake Champlain to the foothills and ridgelines of the Green Mountains, and is home to the City of Burlington, Vermont's most densely populated and built-up urban area (Fig. 1). The total estimated county population is 156,545 (USCB, 2011), and the population density is 112 per km^2 (291/mi^2). The median household income in 2011 was $62,260, with 10.9% of county residents living below the poverty line. The 2010–2011 2-year averages in Vermont and the US were $54,777 and $50,443 respectively (USCB, 2013). Within the Burlington School District, 46% of enrolled students qualified for free or reduced price meals, while 26% qualify within the county as a whole (VTDoE, 2012). There are 66,345 housing units with a median value of owner occupied units of $263,200 (USCB, 2011). The landcover of the county consists of mostly natural, pervious surfaces. Despite the presence of Burlington and its immediate neighboring surburban towns, only about 10.6% of the land area of the county is truly developed (i.e. occupied by buildings and other impervious surfaces). The surrounding towns are still largely rural in character with a heterogeneous landscape of town centers, suburban housing developments, farms and forests. The majority of the undeveloped area in the County is forested (61.5%), with the balance a mix of open land–lawns and agricultural fields (22.5%). The remainder consists of water, wetlands and barren sites. In 2008, Chittenden County had 39,573 land parcels (totaling 54,083 ha) with residential use, as classified by the Chittenden County Regional Planning Commision (CCRPC). Their classification was based on the American Planning Association's Land-Based Classification Standards (APA, 2010).

2.2. Geospatial database development

A geographic information system (GIS) was assembled with freely available spatial data layers acquired from the Vermont Center for Geographic Information (VCGI), the University of Vermont Spatial Analysis Lab (UVM-SAL), the Chittenden County Regional

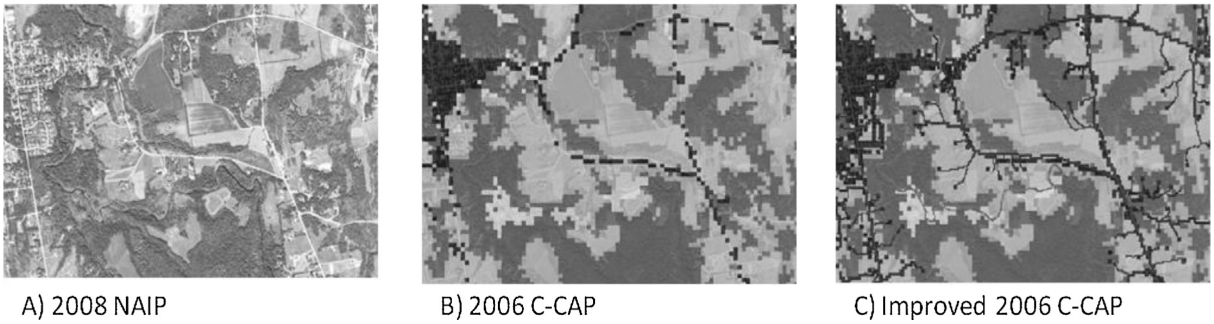

Fig. 2. Comparison of (a) NAIP orthoimage, (b) original C-CAP image and (c) improved C-CAP image.

Planning Comission (CCRPC), the National Oceanic and Atmospheric Administration's Coastal Change Analysis Program (NOAA C-CAP) and ArcGIS Online. These data sets were assembled, analyzed, and processed in ESRI® ArcMap™ 9.3.1 and later 10.0.

2.2.1. Geospatial analysis

A 2006 NOAA C-CAP land cover image, with a 30 m^2 resolution was downloaded from the NOAA C-CAP web site. The C-CAP data product is developed to have an overall accuracy of 85% (NOAA, 2011). The image was visually cross checked against 0.16 m^2 orthoimagery from 2004, but no formal accuracy assessment was conducted. We believe the accuracy and resolution of the imagery used is suitable for this 'first pass' analysis. However, ground truthing and/or the use of higher reolution imagery is warranted before enacting new land use policies.

To facilitate subsequent processing, the land cover image was clipped to the study area and reclassified from 19 classes to six: (1) built; (2) open-agriculture-lawns; (3) forested; (4) wetlands; (5) water; and (6) barren/bare earth. The image cell size was converted from 30 to 10 m^2. This was done to improve the image with respect to the addition of features not captured at the 30 m^2 resolution. This change in *storage* resolution was done to facilitate updating the source image with ancillary vector GIS datalayers. However, to be clear, this change in cell size did not change the 30 m^2 resolution of the land cover data. Thus, with the exception of some of the additional data layers added to the image, as described below, the image resolution in effect remained 30 m^2.

The following vector data layers were incorporated into the source image using standard raster overlay procedures: surface water, roads, driveways and buildings. Thus, any pixel in the C-CAP image that corresponded with a road or driveway pixel was reclassified as built. The cell size of the raster versions of the vector data varied: driveways were 10 m^2, local roads 20 m^2 and major roads 30 m^2. Buildings, originally represented as points, were converted to a 30 m^2 raster. This cell size was chosen because it was assumed that for small buildings such as residences, even if they had a smaller footprint, their structure and surrounding lawn or parking area would influence an area of about 30 m^2. It was also assumed that larger buildings were correctly classified as built in the source image and would thus be larger than one 30 m^2 cell. We acknowledge that these assumptions and the use of the 30 m^2 land cover imagery may lead to the unintended consequence of removing possible arable land from consideration. Thus, if available, the use of land cover data generated from higher resolution imagery is encouraged. Fig. 2 illustrates the improvement of the source C-CAP image. A 2008 National Aerial Imagery Program (NAIP) orthoimage with a 1 m^2 resolution is also included as a reference for comparison purposes. Driveways and buildings are now clearly visible in the center of the improved image (Fig. 2C), and roads are now connected and no longer segmented.

The improved land cover image was eventually reduced to a binary image of possible agricultural land. The built, forested, wetlands, water and barren/bare earth were combined into one class and coded zero (0) and the open-agriculture-lawns was coded as one (1). While we chose not to include forested land in our analysis, users of this approach in other locales may opt to include this land cover type because of its potential for agroforestry and the growing of shade tolerant crops. A percent slope raster was generated from a 10 m^2 hydrologically correct digital elevation model acquired from VCGI. The resulting raster was reclassified into the following 3 classes, based on the USDA slope class definitions (http://soils.usda.gov/technical/manual/contents/chapter3.html): (1) nearly level (0–3%); (2) gently to strongly sloping (3–16%); and (3) steep (>16%). Polygons of prime agricultural soil (defined here and throughout the rest of the paper as USDA prime soils and those soils of statewide importance for agriculture) were converted to a raster. The binary image of possible agricultural land, the slope and prime agricultural soils raster layers were all merged using standard raster overlay procedures. The resulting agricultural opportunity raster had six classes: (1) open-nearly level, (2) open-moderate slope, (3) open-steep slope, (4) open-nearly level – with prime soil, (5) open-moderate slope – with prime soil and (6) open-steep slope – with prime soil. We acknowledge that such classifications of land may lead to rigidity in using the data. Further, such a simplified classification, meant for a 'first pass' analysis should not dictate how a farmer should use a given piece of land.

A polygon data set of land parcels acquired from CCRPC was used to tabulate the agricultural opportunity classes within each parcel. Each parcel had been coded by the CCRPC using the American Planning Association's Land Based Classification System (LBCS) (APA, 2010). The APA website defines these dimensions as follows:

- "Site" refers to the overall physical development character of the land. In general physical terms, it describes what is on the land.
- "Structure" refers to the type of structure or building present on the land.
- "Activity" is concerned with the actual use of land based on its observable characteristics.
- "Function" refers to the economic function or type of establishment that is using the land.

Two Euclidean distance rasters were also generated. The first was distance from center of Burlington, specifically City Hall. The second was distance from the center of other towns located within the county. These distance rasters were generated for inclusion in one of the cluster analyses described below.

2.3. Residential development index

A residential development index was also calculated to visualize residential neighborhood development patterns. In addition to providing a visual aid, this index was included in both of the cluster analyses described below (Section 2.5). This variable was included because it gives a sense of the degree to which residential activity is occurring in a given area. Following the methodology of Polimeni (2005), the residential development index was calculated as the total number of residential parcels in a census block group divided by the sum total of undeveloped and residential parcels within the census block group.

2.4. Agricultural opportunity neighborhood analysis

We conducted a 'neighborhood' analysis of each prime agricultural opportunity (PAO) to quantify the total sum of prime agricultural opportunities (i.e. nearly level land containing agriculturally important soil) occurring within neighboring land parcels. This was done to identify those areas where several PAO could possibly be pooled to create a larger 'parcel' that was potentially suitable to engage in larger scale agricultural production across parcels. The logic behind pooling land is twofold. For existing farmers, a series of PAO 'neighborhoods' may allow them to expand, for example, their existing rotational grazing operation. For new and/or landless farmers that do not live on the land they are farming, it makes practical and economic sense for them to commute to one or two large 'farms' they lease from non-farming landowners (potentially residential), instead of many smaller ones. For example, an individual PAO 'neighborhood' consisting of 4 ha of land located on several adjacent residential parcels may be suitable for a new, landless farmer to begin (e.g. a vegetable farm or a pastured poultry operation).

To begin the 'neighborhood analysis', a subset of agricultural opportunity polygons containing prime soil with slopes $\leq$16% were selected to create a PAO data layer. While we acknowledge that small plots less than 0.10 ha (0.25 acres) have the potential to be a viable farm, particularly in urban areas, we removed them from consideration as part of this larger regional scale study. If we had access to land cover data generated from high-resolution (1 m^2 or less) imagery for the whole study area, or we were focused on a smaller scale (e.g. City of Burlington), we most certainly would have included these smaller AO plots in the neighborhood analysis. Further, it was assumed that 0.10 ha was a suitable minimum AO size for intensive vegetable production. The decisions on what to include and exclude were made by us as researchers and local 'experts', independent of local community involvement. If time and resources permit, however, a preferable approach would be to engage in a more transparent community process to arrive at these decisions.

The remaining polygons (>0.10 ha) were then associated with their respective land parcel via an intersection. This geoprocessing step divided up large trans-parcel PAO by their parcel boundaries. Doing this allowed the polygons to be coded as residential or agricultural (existing farm) based on their associated parcels LBCS codes. A Python script was written to automate the processing of each parcel having a PAO in order to add up the total amount of PAO occurring within neighboring parcels. Again, based on the notion of economies of size, it made logical sense to identify where PAOs could be pooled to create larger farmable 'parcels'.

2.5. Cluster analysis

Two-step cluster analyses were run using SPSS 19 to develop groupings of agricultural opportunities within Chittenden County. The clusters were assigned automatically using Akaike's Information Criterion (AIC), a strategy for selecting a statistical model from a set of models, based on relative goodness of fit. The purpose of the clustering was to organize the thousands of AOs. Two different approaches were used to cluster parcels. The first used a mix of demographic, physical and agricultural opportunity data to cluster AO on residential parcels only. We chose to focus on residential parcels because many large residential lots in the study area contain open areas with productive agricultural soils. Thus, our intent was to begin to organize these residential parcels to facilitate community discussions regarding embedding agriculture within them, in order to bring this underutilized land back into production. The cluster algorithm used the following six variables: distance to town center; distance to Burlington; mean residential development index (2008); average population density (2010); % of parcel that is open and nearly level with prime soil; and % of total agricultural opportunities. Because of limited resources, we opted not to involve the community in the selection of these variables. However, when feasible, community participation in cluster variable selection is encouraged.

The second cluster analysis used demographic, neighborhood PAO analysis and land use data to cluster both residential and agricultural parcels. The reason both residential and agricultural parcels were used during this clustering effort was to organize parcels for possible expansion of existing farms by utilizing land located witin residential parcels or for smaller farms operating within land pooled within backyards to 'scale-up'. The cluster analysis used the following four variables: mean residential development index (2008); mean population density (2010); parcel land use type (agricultural or residential); and neighborhood PAO area.

We note that some land characteristics of AO (e.g. soil quality, suitable crop types and potential yields) were not taken into account during this first phase analysis. While it was beyond the scope of our study, we acknowledge a 'second phase' analysis that includes this information is warranted.

A conceptualized view of the overall process of identifying, quantifying and classifying/organizing AO is visible in Fig. 3.

Table 1
Total area of agricultural opportunities (AO) within Chittenden County.

N = 110,078 (AO polygons)	Hectares	Mean size of AO polygon (ha)	Std. dev. of AO polygon (ha)
Total area of agricultural opportunities	31,637	0.29	2.03
Total of AO with prime soil[a]	24,254	0.36	2.55
Total of AO that are nearly level and have prime soil[a]	14,187	0.46	3.51

[a] USDA prime as well as soils of statewide importance.

3. Results

3.1. Agricultural opportunities

Our geospatial analyses determined that Chittenden County contains a total area of 31,637 ha in agricultural opportunities. Of this area, there are 24,254 ha of prime soil occurring on all slope types and 14,187 ha of prime soil occurring on nearly level land (Table 1). The agricultural opportunities are widely dispersed throughout the county with the majority occurring in the southwest quadrant, within the suburban towns of South Burlington, Shelburne, Charlotte and Hinesburg (Fig. 4). Additional high quality opportunities are visible along the Winooski River corridor which winds through the middle of the area from Bolton to Colchester and Burlington.

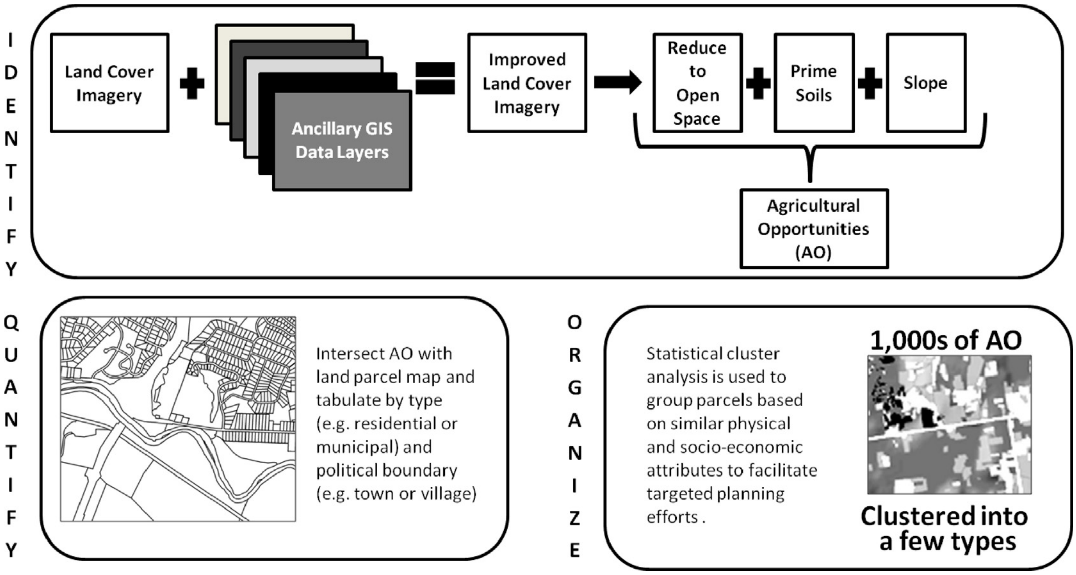

Fig. 3. Conceptual view of the methodological process: identify → quantify → organize agricultural opportunities.

With 5925 ha, Charlotte had nearly twice the area of total agricultural opportunities as the next three highest towns. Charlotte's prime opportunities slightly exceed the total agricultural opportunity areas of the next three towns (Hinesburg, Milton and Shelburne), each with approximately 3000 ha of total agricultural opportunities. These three towns have 1092, 1188 and 1503 ha of opportunities on nearly level land with prime soil, respectively (Fig. 5).

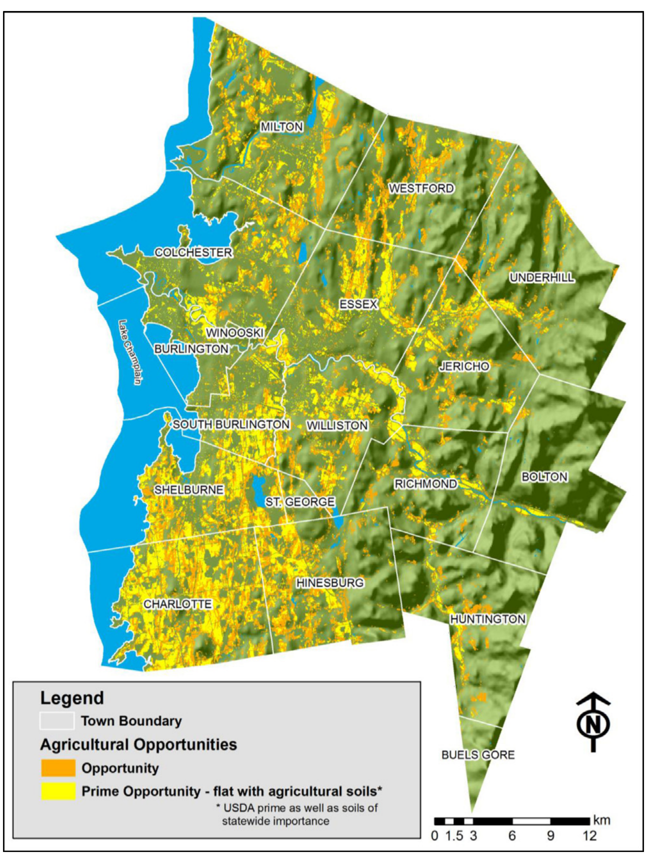

Fig. 4. Spatial distribution of all and prime agricultural opportunities within Chittenden County.

3.1.1. *Agricultural opportunities compared by site, structures, activities, and function*

Agricultural opportunities were compared at a parcel level based on site, structures, activity and function. Two LBCS site types were found to have the majority of agricultural opportunities, consisting of developed sites (code 3000 – crops, grazing and forestry) at 49% and developed sites with buildings (code 6000) at 38%. When the specific type of structure is considered, we found that parcels with residential structures had the highest amount of total agricultural opportunities, totaling 13,224 ha. Parcels with no structures totaled 10,328 ha, and parcels with farming-related buildings made up 5479 ha. If these two types were combined, they would exceed parcels with residential structures. As it turns out, however, the parcels with residential structures had the most high quality opportunities, totaling 5197 ha. When parcel activity was considered, natural resources related (e.g. agriculture and forestry) and residential were the two classes that dominated. Those parcels with natural resources related activity had the most AO with 15,590 ha and 7851 ha PAO. Parcels with residential activity had 10,203 ha AO with 3726 ha PAO. The next highest activity class was no human activity with 2249 ha AO and 899 ha PAO. Like parcel activity, parcel function was dominated by two functional classes, made up of agriculture, forestry and hunting and residence. Parcels coded as having a farming function provided 17,941 ha AO and 8732 PAO.

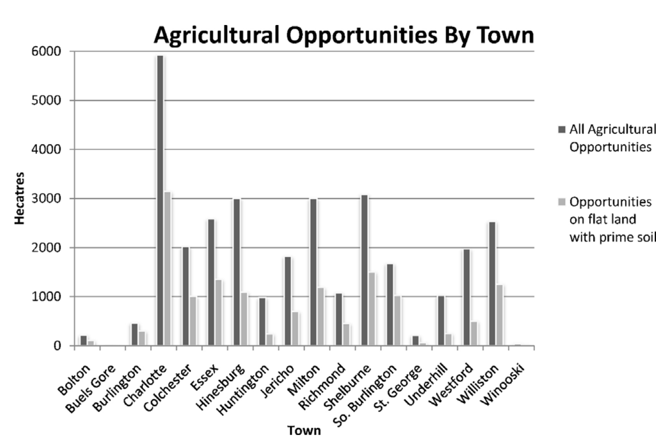

Fig. 5. Chittenden County agricultural opportunities by town.

Table 2
Area of agricultural opportunities (AO) on parcels with residential activity, function and structures.

N = 16,871 (AO polygons within residential parcels)	Hectares	Mean size of AO polygon	Std. dev. of AO polygon
Total area of residential parcels having AO	34,223	2.03	6.28
Total of AO within residential parcels	9212	0.55	1.74
Total of AO that are nearly level and have prime soil[a]	3346	0.20	0.86

[a] USDA prime as well as soils of statewide importance.

Residence parcels had 9756 ha AO and 3517 PAO. Overall, it is clear that parcels with residential structures, activity and function contain agricultural opportunities, which also include highly suitable agricultural land.

3.2. *Agricultural opportunities specifically within residential parcels*

Those parcels with *residential* structures, activity and function provide a total of 9212 ha of AO and 3346 ha PAO (Table 2). Five towns have greater than 875 ha of AO located within residential parcels, including Charlotte, Essex, Hinesburg, Jericho and Shelburne. Charlotte has the greatest areas with 1376 ha. Charlotte and Shelburne have the most area in PAO with 583 ha and 468 ha, respectively. Fig. 6 shows the spatial distribution of AO and PAO throughout the county within residential parcels.

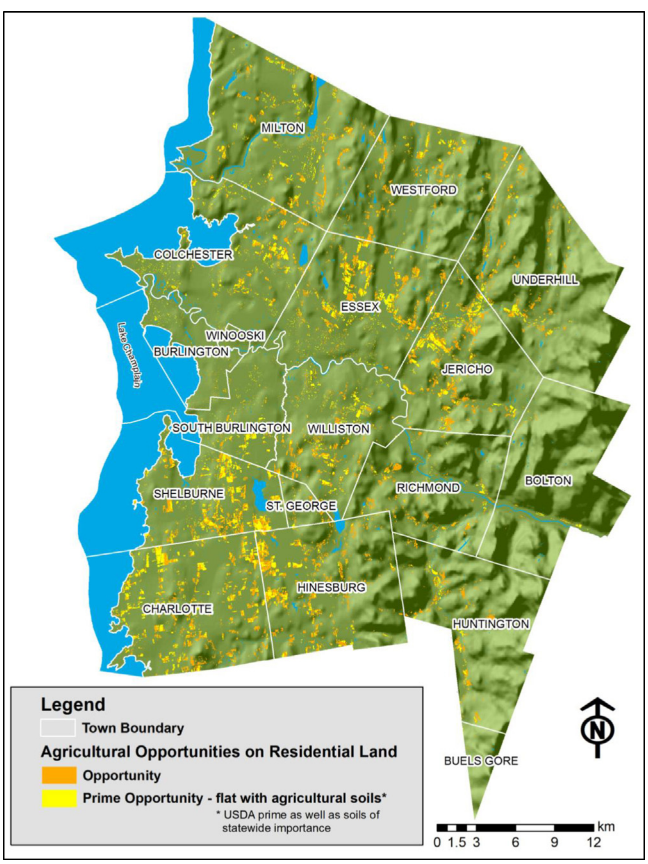

Fig. 6. Spatial distribution of all and prime agricultural opportunities throughout the county within residential parcels.

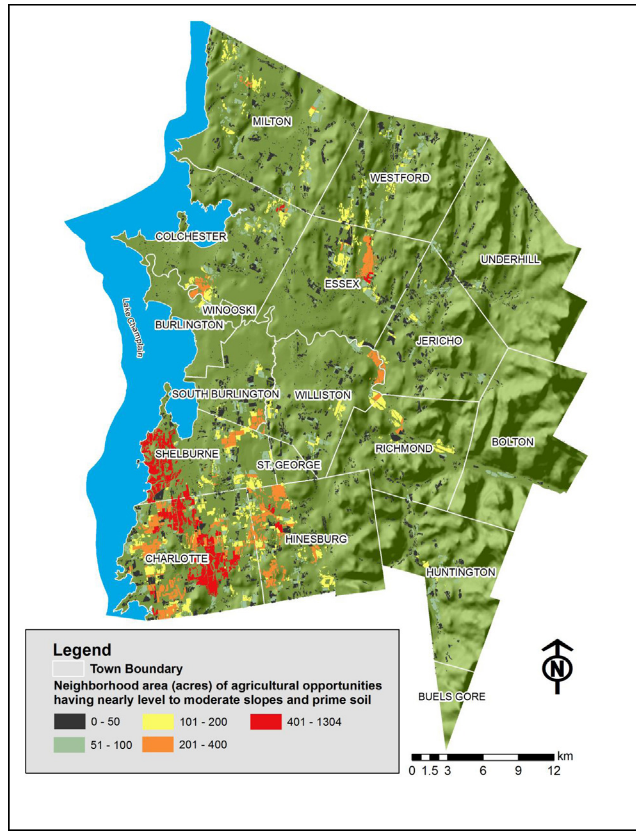

Fig. 7. Neighborhood area of agricultural opportunities having nearly level to moderate slopes and prime soil.

3.3. *Agricultural opportunity neighborhood analysis*

The neighborhood analysis results are summarized in Table 3. It comes as no surprise that larger, existing agricultural parcels had the most neighbors. The maximum number of neighbors for the agricultural parcels was 74, three times that of the residential parcels. Further, the mean area of the neighborhood of agricultural opportunities around the agricultural parcels (42.8 ha) was more than twice that of the mean of the residential neighborhood (18.29 ha). The maximum neighborhood areas for both parcel types are quite large (over 500 ha) and presumably have a mix of existing farms and residential parcels. The largest 'neighborhoods' are located in the towns of Shelburne and Charlotte (Fig. 7).

3.4. *Clusters*

The first two-step cluster algorithm, run on residential parcels, only determined four clusters. Clusters were assigned names based on their dominant characteristics (Table 4). Cluster 1 – prime, consisted of parcels with a high mean percent prime agricultural opportunity (36%) and mean percent total agricultural opportunity (60%). Cluster 2 – rural, consists of parcels with the lowest mean neighborhood index, longest distance to town and Burlington, as well as the lowest population. On average 31% of these parcels had agricultural opportunities with an average of 6% being prime. The most suburban of the clusters with a mean distance to town of 3.38 km and a mean population density of 709 pers./mi^2 was cluster 3. Lastly, cluster 4 was the most urban with a neighborhood index of 0.96 and a mean population density of 4326 pers./mi^2. While the parcel sizes in this cluster are small, 25% of the lot has agricultural opportunities, with 11% of the lot consisting of prime

Table 3
Agricultural opportunity neighborhood analysis.

Parcel type	# of parcels	Number of neighbors				Neighborhood area (ha (acres))			
		Min	Max	Mean	Std. dev.	Min	Max	Mean	Std. dev.
Agricultural	1177	0	74	7.11	4.43	0	527.78 (1304.18)	42.80 (105.77)	61.92 (153.03)
Residential	6359	0	25	5.54	2.87	0	517.07 (1277.73)	18.29 (45.2)	44.80 (110.72)

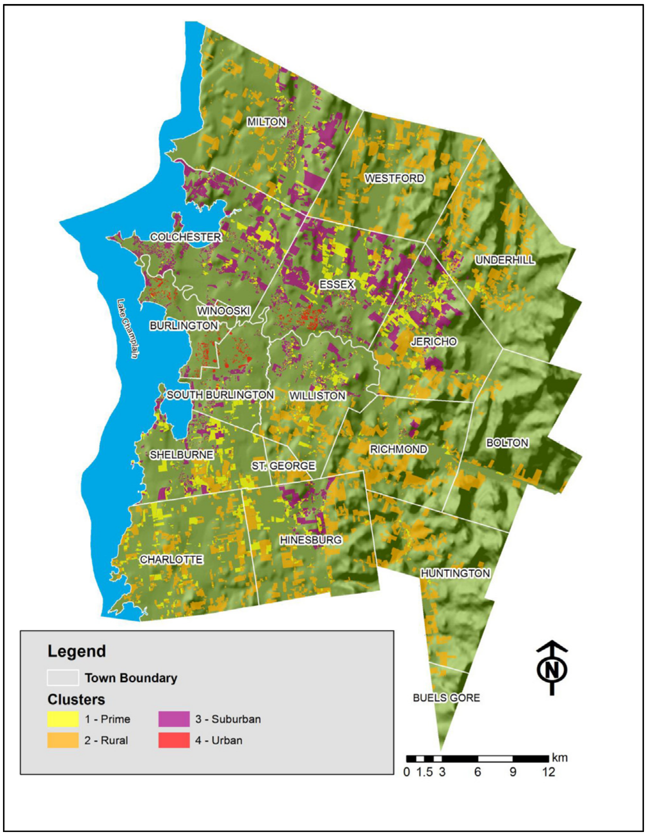

Fig. 8. Spatial distribution of four clusters of *residential* parcels assigned by the first cluster analysis.

opportunities. The spatial distribution of these clusters is visible in Fig. 8.

The second two-step cluster algorithm run on residential and agricultural parcels determined five clusters. These clusters were assigned automatically using Akaike's Information Criterion (AIC). Clusters were given names based on their dominant characteristics (Table 5). Cluster 1 – urban consisted of parcels with the highest mean neighborhood index (0.94), mean population density (1720.24/mi^2) and the smallest mean sum of neighborhood acreage (10.70 acres). Cluster 2 – suburban-rural farms is the only cluster containing *only* agricultural parcels. This cluster group has the second highest mean sum of neighborhood acreage with 86.05 acres. Cluster 3 was the most suburban of the clusters with a mean neighborhood index of 0.88, and a mean population density 278.68/mi^2. Cluster 4, with the lowest neighborhood index of 0.72, was the most rural. The only cluster that was comprised of *both* residential and agricultural parcels was cluster 5 – big ones. This cluster is aptly named since it had over nine times the neighborhood area of the next largest cluster. The mix of parcel types is an indication that farms are bordered by large residential lots. This cluster also had the third highest neighborhood index at 0.80.

The designation of clusters could be useful for determining the types of agriculture that would be appropriate based on contiguous area and location. The production of biofuel crops, for example, would most likely occur on large rural parcels easy to cultivate mechanically. Diversified vegetable production, on the other hand, could occur on smaller parcels located near the population centers to reduce the distance of supply chains. The spatial distribution of these clusters is visible in Fig. 9.

4. Discussion

As per our primary study objective, we have developed a process to identify, quantify and organize agricultural opportunities (AO). While we did not engage community members as part of this study, we believe the process as we have outlined is flexible enough to support input from citizens and civic leaders at various stages. Thus, if feasible, providing opportunities for community discourse during the process itself, and subsequently to evaluate the results, can only enhance this approach.

In Chittenden County, VT, of the 31,637 ha of AO identified, 24,254 ha contain prime soils (i.e. USDA prime and those of statewide importance) and 14,187 ha are nearly level with prime soil. Based on consumption and food production land requirement estimates made by MacRae et al. (2010) and McKellips (2009) (as noted above in Section 1.3), this is enough land to meet the demand for fresh organic vegetables, hard wheat and fodder crops for increased beef and pork production. However, we recognize that the size of individual or pooled AO, as well as their underlying soil quality, will have an impact on what crops can be grown and their associated yields. Thus, we believe a 'second pass' analysis is warranted to provide decision makers with more detailed information. This additional analysis would provide residents, planners, agroecologists and agronomists an opportunity to work together in an interdisciplinary fashion toward common goals such as planning crop rotations and nutrient management. While growing biofuel is also a possibility, it was beyond the scope of this study to quantify how much and what types can be grown.

Table 4
Profiles of residential agricultural opportunity clusters generated using a two-step cluster algorithm.

Clusters	*N*	Mean residential development index	Mean distance to town center (km)	Mean distance to Burlington (km)	Mean population density (persons/mi^2)	Mean % prime AO (open, nearly level with prime soil[a])	Mean % total AO
1 – Prime	4158	0.87	2.57	14.07	452.91	36	60
2 – Rural	4614	0.75	4.17	19.99	98.77	6	31
3 – Suburban	6122	0.91	3.38	11.45	709.21	7	18
4 – Urban	1977	0.96	1.99	4.61	4326.02	11	25
Combined averages	4217.75	0.86	3.23	13.63	902.92	14	33

[a] USDA prime as well as soils of statewide importance.

Table 5
Profiles of agricultural opportunity clusters located within residential and agricultural parcels, generated using a two-step cluster algorithm.

Clusters	*N*	Mean residential development index	Mean population density (persons/mi^2)	Parcel type – residential vs. agricultural as noted by the LBCS[a]	Mean sum of neighborhood acreage
1 – Urban	587	0.94	1720.24	99.8% R	10.70
2 – Suburban-rural farms	1140	0.77	184.51	100% A	86.05
3 – Suburban	3042	0.88	278.68	100% R	24.69
4 – Rural	2629	0.72	90.05	100% R	47.89
5 – Big ones	134	0.80	116.31	76.1% R 24.9%A	793.01
Combined Averages	1506.4	0.81	308.04		54.65

[a] LBCS is the American Planning Association's land based classification system used by the regional planning commission.

Based on our results, we feel that in order to realize a higher degree of food self-sufficiency here, farming practices on some of the existing farm land would need to change. For example, some fodder crops now used for dairy herds could be used for pork and beef production. In addition, some of the land suitable for agriculture found within residential parcels that is not currently being utilized for food production would also need to be brought back into use. We identified 9212 ha of AO located within residential parcels. Of this amount, 3346 are nearly level with prime soils. Again, based on the land estimates noted by MacRae et al. (2010), this amount of land is more than adequate to produce the annual fresh vegetable needs for 250,000 people. This outcome, however, would most likely require at least two things: (1) the pooling of AO on neighboring parcels to create bigger land areas suitable for larger scale production and (2) the willingness of residential landowners to pool land with their neighbors and to allow production agriculture on their land. Regardless of what we as researchers think, ultimately, the community at large will need to determine the level of commitment to significantly increasing local food production. Further, the community will need to decide where and how this additional food is produced through a suitable, location based, public engagement process. The neighborhood analysis we conducted during this study shows, on average, that the AO on residential parcels had an AO 'neighborhood' of 18.29 ha. This indicates the potential of these agricultural opportunity 'neighborhoods' to be used for larger scale commercial agricultural enterprises. We demonstrated in a related study (Erickson et al., 2011 masked for blind review) that residential, non-farming landowners within the study area appear to be willing to embed production agriculture within their land, and that this could be accomplished via voluntary participation in a cooperative land management scheme with their neighbors.

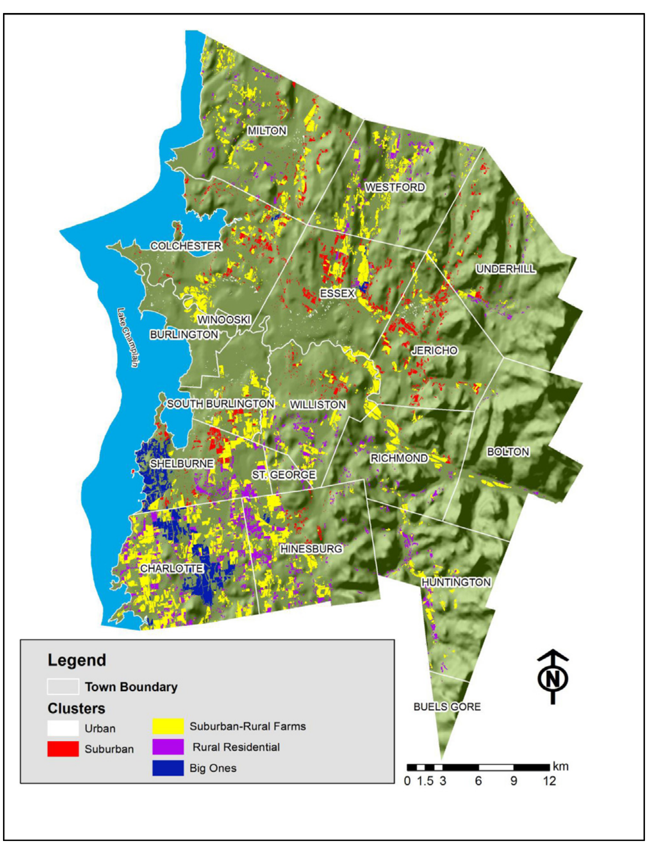

Fig. 9. Spatial distribution of residential and agricultural parcel clusters generated by the second cluster analysis.

The two sets of clusters, when viewed spatially (Figs. 8 and 9), begin to show groupings of related parcels. The cluster analyses provide a means by which to begin to organize the agricultural opportunities and related 'neighborhoods' of opportunities. The fact that the cluster groupings are data-driven and automatically grouped based on shared attributes, removes the potential for human bias that might occur if the grouping process was performed manually. However, human bias still exists with respect to which variables were used to perform the cluster analysis. Even so, our approach provides a relatively neutral way to organize the thousands of AO and their associated parcels. We do acknowledge, however, that a technical filter such as the cluster approach presented here may insert bias of its own. Regardless, presenting a map of clustered AO to a group of local stakeholders can serve as a starting point for a participatory community discussion to aid future planning efforts.

Knowing where similar AO are located is valuable to help towns develop better ordinances for agriculturally zoned areas and to figure out which agricultural uses would be appropriate within non-agriculturally zoned lands, particularly residential. For example, it makes sense for perishable produce to be grown within close proximity to consumers. Thus, organic vegetable operations could be set up in the urban and suburban clusters (Figs. 8 and 9). In contrast, it may be more appropriate for biofuel production to be located within the rural residential cluster, in addition to the existing suburban-rural farms and the big ones clusters. Livestock might be integrated within multiple types of agricultural systems at different scales, although the complexities of locating farm animals near humans (e.g. odors from manure) should be recognized (Fig. 9).

The groupings and associated visuals can provide valuable aids to decision makers. Visualizing how some clusters are distributed throughout the county while others are concentrated in certain areas has the potential to foster coordination amongst neighboring towns when establishing trans-town agricultural zones. For example, the results from the first cluster analysis, which typed residential parcels only, could be used by efforts concerned with bringing additional agricultural land back into production. As a starting point, policies and/or incentive programs could target parcels assigned to the 'prime' cluster group (Fig. 8) to insure agricultural soils are being used to their full potential. Further, based on the second cluster analysis, one could imagine a "rural-residential" agricultural zone/district in the towns of Shelburne, Charlotte and Hinesburg (Fig. 9). To the casual observer this may seem obvious; however, when coupled with a quantification of how much land is available, along with specific location based information (e.g. landowners) the overall approach can facilitate concrete planning efforts.

4.1. Limitations of the research

One limitation of our study was the resolution ($30\,m^2$) and accuracy (≈85%) of the source imagery. There is inherent error or misclassification when using lower resolution imagery such as NLCD and C-CAP. However, these datasets are widely available and are suitable for a 'first pass' land inventorying effort like the one described here. Another limitation to our findings is that we did not conduct any post analysis ground-truthing. Thus, we would recommend visiting sites before any policies are implemented based on our findings. It is, however, worth noting that in many areas (primarily urban and suburban); it is now possible to 'ground truth' land inventorying data with the aid of Google Maps – Street View (www.maps.google.com/streetview). In order for this to be effective, the imagery available in Street View would need to be newer than what was used to conduct the original land inventory. The Street View ground truthing, while a low cost addition to the process, should not replace actual on-the-ground checking when possible. This is similar to the approach developed by Taylor and Lovell (2012) to identify backyard agriculture in Chicago with the aid of Google Earth.

Another possible limitation of our study and one that could be eliminated with ground truthing is the question of agricultural versus residential land types, in terms of identifying if the land is really one type or the other. We know that some of the land in our study area that is technically classified as residential does have some commercial agricultural activity on it. In our experience, this often consists of the haying of grasses and legumes (e.g. alfalfa) for winter livestock feed. Thus, to get more accurate tabulations of AO, it would help to know which residential parcels already have some type of agricultural activity beyond a vegetable garden for use by the homeowners. One possible way to do this in the US is to look at active/current common land units or CLUs (FSA, 2011). These are polygon datasets of land units (e.g. fields) enrolled in a USDA farm program. Unfortunately, these data are currently unavailable to the public. Further, even if the data were publically available, they only contain land that is enrolled in a USDA program. Thus, it is possible to 'miss' land used for agriculture within a residential lot that is not formally enrolled in such a program. Regardless, we recognize that there is some error in our tabulations based on the fact that some non-farming landowners are currently allowing various types of farming on their land.

4.2. Contributions to the literature

As more cities and regions throughout the world begin to investigate the potential of their land resources to produce more food and biofuel, they will benefit from automated tools and/or processes. Thus, the automated neighborhood analysis we introduced here, if employed by other land inventories, will provide additional information to aid decision making efforts. While the neighborhood area totals are useful here, we believe that this information will be particularly useful to land inventories concerned with urban agricultural opportunities (such as those noted in the introduction). Knowing where large agricultural opportunity 'neighborhoods' are located within urban areas can facilitate, amongst other things, the allocation of limited resources. Furthermore, a concentration of agricultural opportunities on a grouping of vacant lots, for example, might warrant a change in zoning or an overlay district. In our study area, the identification of large 'neighborhoods' could allow a farmer seeking new or additional land to form a group of neighboring landowners. In addition, the cluster analysis approach presented here provides an automated process by which to facilitate the organization of large numbers of agricultural opportunity sites.

Our findings have also illustrated the utility of looking at land classified as residential with the purpose of 'finding' additional land to farm. When one considers that development in the US has led to the conversion of 3,527,486 ha of prime agricultural land to other uses (AFT, 2010; USDA, 2009), it makes sense to see if some of this already developed land is still 'available' for agriculture. Lastly, the results of the two cluster analyses show promise as a means to organize the agricultural opportunities identified during the other analyses. Agricultural opportunities grouped together, based on shared demographic and bio-physical characteristics, can facilitate targeted land management efforts.

4.3. Implications of findings

The most exciting implication of our findings is the realization that the Chittenden County has the land area to produce most of its local food needs. Along these lines, aspiring farmers have noted that access to affordable farmland in the study area is an issue. The existence of programs such as the Vermont Land Trust's Farmland Access Program provides tangible evidence for this situation. Thus, land that is suitable for agriculture but not being farmed could total over 9200 ha within residential parcels alone. Further, the 2007 Census of Agriculture has seen an increase in the number of small farms within the county (USDA, 2011). We see this increased farming activity as an indicator of an attempt to meet increasing local food demand within the study area.

We do, however, acknowledge that there is a potential for conflicts to arise if agriculture is embedded within residential areas on a larger scale. Possible conflicts may include complaints about odors, machinery noise, slow moving vehicles and dust. However, depending on the agricultural practices employed (e.g. use of draft power) some of these concerns may not exist. Regardless, the potential for NIMBY (not in my backyard) attitudes exist.

4.4. Future research

Increasing local food production to a higher level of self-sufficiency will require changes in how land is utilized within the study area. For example, some of the open land with productive agricultural soils that is currently residential lawns will need to be brought back into production. We have explored that possibility in a previous study considering the potential for embedding agriculture on large lots (Erickson et al., 2011, masked for blind review), and a resident attitude survey would further add to our understanding. This survey could also explore the potential conflicts that might arise, as noted above.

5. Conclusion

An increasing number of communities around the globe are recognizing that the potential to produce food and biofuel locally could contribute to the development of larger sustainability plans. As such, local and regional planners would benefit from additional tools that can provide actionable information to decision makers with regard to potential agricultural opportunities. Agricultural opportunities exist in a variety of interstitial spaces located along an urban to rural transect, from vacant lots to large suburban yards and working farms. The geospatial analyses outlined here provide planners with a methodology by which to conduct a 'first pass' analysis concerned with identifying and quantifying these diverse agricultural opportunities. The cluster analyses provide an automated, data driven means by which to begin to organize these opportunities. This approach has the advantage of being conducted more rapidly and on a larger scale than 'on the ground' land mapping which has its own inherent limitations. The visuals associated with these analyses can provide a starting point for community planning. These tools have the potential to facilitate participatory planning by bringing residents and farmers to the table with planners, in an effort to better plan for an unpredictable future.

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