Mapping and Modeling British Columbia's Food Self-Sufficiency

By

Kathryn Morrison
B.Sc., University of Victoria, 2009

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Kathryn Morrison
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Supervisory Committee:

Dr. Trisalyn A. Nelson, Co-Supervisor
(Department of Geography, University of Victoria)

Dr. Aleck S. Ostry, Co-Supervisor
(Department of Geography, University of Victoria)

Supervisory Committee:

Dr. Trisalyn A. Nelson, Co-Supervisor
(Department of Geography, University of Victoria)

Dr. Aleck S. Ostry, Co-Supervisor
(Department of Geography, University of Victoria)

ABSTRACT

Interest in local food security has increased in the last decade, stemming from concerns surrounding environmental sustainability, agriculture, and community food security. Promotions for consumption of locally produced foods have come from activists, non-governmental organizations, as well as some academic and government research and policy. The goal of this thesis is to develop, map, and model an index of self-sufficiency in the province of British Columbia. To meet this goal, I develop estimates for food production at the local scale by integrating federally gathered agricultural land use and yield data from the Agricultural Census and various surveys. Second, I construct population-level food consumption estimates based on provincial nutrition survey and regional demographics. Third, I construct a self-sufficiency index for each Local Health Area in the province, and develop a predictive model in a Bayesian autoregressive framework. I find that local scale comparable estimates of food production and food consumption can be constructed through data integration, and both datasets exhibit considerable spatial variability throughout the province. The predictive model allows for estimation of regional scale self-sufficiency without reliance on land use or nutrition data and stabilizes mapping of our raw index through neighborhood-based spatial smoothing. The methods developed will be a useful tool for researchers and government officials interested in agriculture, nutrition, and food security, as well as a first step towards more advanced modeling of current local food self-sufficiency and future potential.

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1.0 INTRODUCTION

1.1 Research Context

Agriculture and health are two key components of food security that are often studied independently. However, there is a growing body of literature that studies implicit and explicit linkages between food production and human health (Feenstra 1997; Pimentel, Houser et al. 1997; Duxbury and Welch 1999; Cowell 2003; Rideout, Seed et al. 2006; Peters 2008). One of the fundamental dimensions of food security research studies is promotion of local food self-sufficiency (Feenstra 1997; Anderson and Cook 2000; Bellows and Hamm 2001; Hinrichs 2003; Lapping 2004; Peters 2009). By definition, local diets are made up of foods produced close to consumers. The specific definition of proximity is subjective and a variety of definitions have been proposed. Euclidian distance is a common proximity measure, such as the popular 100-mile diet (Smith and MacKinnon 2007). Conversely, political boundaries delineating communities, states, provinces, or even countries have been used.

Local diets are promoted most often to address concerns surrounding environmental sustainability, disaster preparedness, and public health. Decreasing the distance between producers and consumers decreases the fossil fuels required to transport food; an important issue with rapidly increasing concerns surrounding climate change and greenhouse gas emissions (Olesen, Carter et al. 2007). Any region, such as a state or country, producing sufficient food to feed their population is considered agriculturally self-sufficient. In the case of a global disaster which stifles international trade, a self-sufficient region would benefit from having a self-sufficient agriculture production system while regions lacking this would be susceptible to food shortages (Allen 1999; Anderson and Cook 2000). Increasing community self-reliance with a local supply of fresh, nutritious food is positive for public health (Hamm and Bellows 2003;

Rideout, Seed et al. 2006). To decrease food transport distance, absolute proximity is the most important factor. However, in the realm of disaster management and public health policy, jurisdictional and political boundaries may be more relevant as these frame policy initiatives and responses. It is for these reasons that definitions of local scale food systems vary widely and lack a precise definition (Feagan 2007).

Research continues to expand on the ecological, environmental, economic, and social implications of the globalized food system, consistently citing local diets as a potential solution. However, there has been an ongoing lack of empirical research on these relationships, or study of the feasibility of large-scale shifts to local food systems. Kremer and DeLiberty (2011, pg. 2) state “a fundamental principle for the promotion of sustainable food systems is the understanding of the pathways between production and consumption of food. Many of these studies suggest that the way data [are] gathered and analyzed today is inherently prohibitive to making these connections.” In this research, I develop methods to directly assess local agricultural potential relative to local food demand as a foundational step towards better understanding of local food systems.

1.2 Research Focus

The province of British Columbia in western Canada is home to some of the most innovative and progressive local food policies in North America, and the now famous 100-mile diet concept was published in Vancouver in 2007 (Smith and MacKinnon 2007). The Agricultural Land Reserve (ALR) is a set of provincial policies which protect some of the most valuable land in the province from development, requiring it to be used for agricultural purposes or left dormant (Androkovich, Desjardins et al. 2008). The six regional health authorities have developed and implemented policies in which they explicitly promote locally produced foods to people in their jurisdictions.

For example, the 2005 Core Public Health Goals report states "Food security requires the development of local, provincial and national food policies that support equitable access to safe affordable healthy foods set in the context of local food systems" (BC Ministry of Health Services 2005, pg. 31) The BC Ministry of Agriculture and Lands states:

> *All British Columbians should have access to safe, locally produced food: One hundred years ago British Columbians grew much of their own food. While the trend towards a global economy has over the years changed our food production and distribution patterns, we are now refocusing on local food as a result of climate, environmental and social realities. Increasing importance is being placed on producing local, healthy food and reducing our environmental and carbon footprint.*
>
> BC Ministry of Agriculture and Lands 2010, pg. 1

Local food availability and security have clearly been established as determinants of community health (CCHS 2.2 2004; Dieticians of Canada 2004; Provincial Health Services Authority 2010). However, a lack of available data and methods for local food assessments are consistently cited as a significant limitation in advancing relevant policies in agriculture and public health. For example, the 2010 publication by the Provincial Services Health Authority, authored by some of the leading Canadian food security researchers, stated that local food production would have been a key determinant of community food security, but could not be included due to a lack of available data (Provincial Health Services Authority 2010). BC is an excellent case study for this research.

1.3 Research Goals and Objectives

The goal of this thesis is to develop, map, and model an index to assess theoretical self-sufficiency of local scale agriculture in BC. The self-sufficiency index (SSI) is calculates the proportion of a regional population that the local agricultural system could feed. It is theoretical because it assumes all food produced in a region would remain there. Therefore, it is a measure of *maximum local food capacity*. To meet this goal, I address three primary objectives and develop approaches to overcome methodological issues associated with constructing the SSI. In all forthcoming chapters, I use the spatial unit Local Health Area (LHA) of which there was 89 in the province in 2006. Further explanation and justification for choice of spatial unit is given in chapters 2, 3 and 4.

The first objective (Chapter 2) is to empirically estimate local food production in the province. While agricultural data on farmland use are available (i.e., hectares of food by type and size of livestock herds) production data are only released at the provincial level so that production data cannot be directly used to estimate local food production. By assessing for spatial autocorrelation on land use data, I show that farmland is highly regionalized for individual fruits, vegetables, and grains produced in the province. By quantifying the spatial extent of agricultural land use per product, I am able to demonstrate that provincial production is highly regionalized in BC and so I can avoid adjusting for spatial variation in agricultural yield. A brief analysis of temporal stability in agricultural yield shows that production of most foods varies over time some more significantly than others. Using an annual yield provides a snapshot of food produced that year, while using a time series average could provide reasonable prediction of longer-term potential. The data from this model provides an empirical assessment of local food production capacity in the province at a sub-provincial scale, which is the first of its kind. A flowchart showing the steps required to develop the SSI model is shown in Figure 1.1.

The second objective (Chapter 3) is to quantify local food demand in each region by estimating how much food is consumed annually. To achieve this, average individual food consumption data for men and women in different age groups are taken from the 1999 BC Nutrition Survey (BCNS) and temporally adjusted, using national average food consumption data, to better represent provincial consumption rates in 2006. Integrating the individual-level BCNS data with regional demographics provides an empirical picture of local food consumption that accounts for variation in the spatial distribution of age and gender groups throughout the province.

The third objective (Chapter 4) is to contrast the previously developed food production and consumption data, and I refer to this ratio as the self-sufficiency index (SSI). I then develop spatial models for the SSI, implemented in a Bayesian framework, exploring the potential for both model-based spatial smoothing and predictive modeling. I contrast two Bayesian autoregressive approaches: the spatial linear model (SLM) and a spatially varying coefficient model (SVCM). Use of models is motivated by severe correlation in the spatial structure of my exploratory and response variables, as well as residuals from traditional regression methods. I demonstrate in this thesis that manual construction of the SSI is a labor-intensive process, requiring the integration of many databases at different spatial scales. Therefore, a predictive model may allow others to estimate self-sufficiency with more readily covariates. The spatial units used to define local are political boundaries not necessarily delineating closed agricultural systems; any communities local food supply is heavily influenced by the neighboring regions. The use of model-based smoothing allows predicted estimates for the SSI to be a function not only of the covariates in that region, but also of the SSI and covariates in the neighboring regions.

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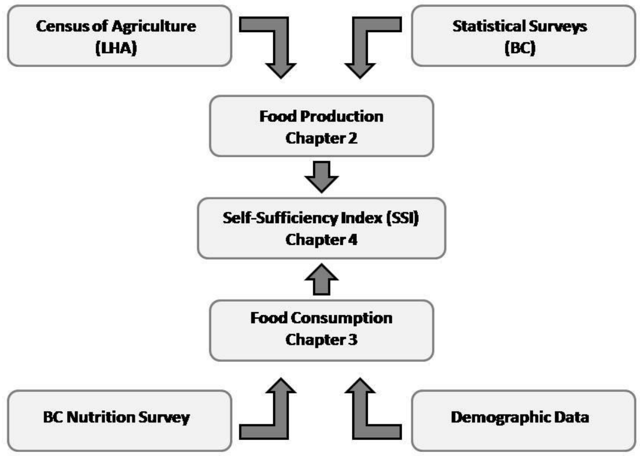

Figure 1.1: Flowchart for the development of the SSI.

2.0 METHODS FOR MAPPING LOCAL FOOD PRODUCTION CAPACITY FROM AGRICULTURAL STATISTICS

2.1 Abstract

Interest in local food security has increased in the last decade, stemming from concerns surrounding environmental sustainability, agriculture, and community food security. Endorsements for the consumption of locally produced foods have come from activists, non-governmental organizations, as well as some academic and government research and policy makers. Methods to empirically assess the types and quantities of crops and animals produced locally (i.e., local food production capacity) are under-developed, hindering the ability of policy makers to affect innovative local food security policy. In this paper, we demonstrate methods to estimate local food production capacity using regularly gathered federal agricultural census and survey data for a Canadian province. The methods are generalizable to other provinces and nations. Operating at the sub-provincial scale of Local Health Area (LHA), our goal is to integrate census farmland and survey yield data to construct local food production estimates in each LHA. We also assess the stability of these surveyed agricultural yields over time to determine the temporal extent of data required for reasonable representation of product yields. We find that provincial yield data may be used to construct reasonable estimates of local scale food production, due to the high level of regionalization in productive farmland of each product in the province. However, many products exhibit significant yield variability over time, suggesting that, for some foods, local production capacity is a dynamic and variable concept. The methods developed will be useful for researchers and government officials alike, as well as a first step towards more advanced modeling of current local food capacity and future potential.

2.1 Introduction

In many developed nations consumers are increasingly concerned about the ability of large industrial food systems to supply safe, nutritious food in a way that is environmentally sustainable. The emergence of periodic food safety crises have alarmed the public; for example, Avian influenza, Bovine spongiform encephalopathy ("mad cow" disease), the recent outbreak of melamine contamination of milk in China and, outbreaks of Listeriosis at a Maple Leaf Foods Canadian processing plant (Joffe and Lee 2004; Wilson 2008). Long food supply chains arising from the globalization of production and processing, with production often originating in politically unstable nations, may further undermine the reliability of timely, safe, and cost-effective food delivery.

Experts such as agricultural scientists and planners are increasingly required to consider and predict agricultural output based on local variation in fertilizer use, soil type, and weather conditions (Basso, Ritchie et al. 2001; Rounsevell, Annetts et al. 2003; Chakir 2009). Resource managers and disaster planners are also concerned with community agricultural self-reliance, should international trade in food products become stifled for environmental or political reasons (Feenstra 1997). Demand for information on food production at various local scales has increased as concerns grow about the impact of climate change on food security (Lobell and Christopher 2007; Olesen, Carter et al. 2007; Lobell, Burke et al. 2008). Agriculture is one of the most significant uses of land globally, and has considerable impact on economic systems, the natural environment, and human health (Rounsevell, Annetts et al. 2003). The availability of regional agricultural production estimates has not kept pace with information needs, particularly in methods to empirically estimate local food production capacity using the best available data.

There is demand for regional agricultural production estimates that allow for mapping of the spatial variation in agricultural productivity.

The definition of “local” is subjective, and is most commonly defined based on Euclidian distance or, as is used in this paper, administrative boundaries. In the latter case, foods may be considered locally sourced if they are produced in the same state, province, or even country as the consumers. Given that Canada is a large country and British Columbia is a large province, this may not be a meaningful definition; therefore, we operationalize smaller sub-provincial units as discussed further in the Study Area section.

The popular book “100-mile Diet”, which describes the attempt of a couple to eat a nutritious diet for an entire year using only foods accessible within 100 miles of their home, was a non-empirical attempt to determine if the food production system of south-western BC could supply their local needs; it could not (Smith and MacKinnon 2007). The popularity of the book attests to strong interest in local foods. Finally, the new public health act passed in the province in 2007 has made the five Regional Health Authorities (RHAs) in the province responsible for local food security, so that policy makers concerned with the nutritional health of the province’s population are beginning to focus on the health and sustainability of local agricultural and local food production systems (Provincial Health Services Authority 2010). In spite of interest and activism around local food security in BC, little research has been conducted to assess local agricultural capacity so that BC’s capacity to meet local food demands is unknown.

BC is an important case study for understanding regional food production, as it is home to unique agriculture and nutrition policies directly related to local food production. In particular, the Agricultural Land Reserve (ALR) is a province-wide land preservation policy of nearly five million hectares of protected farmland that cannot be developed for non-agricultural purposes

(Androkovich, Desjardins et al. 2008). Devoted to preservation of local food production capacity, the ALR should preserve capacity compared to other regions in Canada.

The goal of this paper is to estimate food production in each LHA. To do this, we develop map-based methods to estimate local food production capacity. We assess both the spatial and temporal variability in food production in British Columbia (BC), Canada. In considering the spatial variability in food production, we map regionally productive farmland. We also identify which agricultural yields remain relatively stable over time, and can be represented with a single year of data, versus those yields that vary temporally and may require multiple years of data for accurate representation. These methods can be expanded to other regions to determine the extent to which regional exploration of food production is possible with commonly available aggregate data.

2.2 Study Area and Data

2.2.1 Study Area

BC is Canada's westernmost province, with a diverse, industrialized agricultural sector worth about $2.2 billion dollars per year (BCMAL, 2006). The province is divided into five Regional Health Authorities (RHAs), each responsible for providing medical care, nutritional health, and food security to their residents (Figure 2.1). Each RHA disaggregates into a number of Local Health Areas (LHAs), with size (land area) inversely proportional to population. The 89 LHAs are a useful spatial unit for studying food systems as RHAs are responsible for promoting and ensuring the food security of their residents (Provincial Health Services Authority 2010).

2.2.2 Yield Data

All data used in this paper are provided by Statistics Canada. Data from the Agricultural Census are provided at a custom spatial unit of LHA. Agricultural Census data provide information on the number of food production units in each region (e.g., number of animals, area of currently productive farmland). Data from the agricultural surveys are disseminated at the provincial scale with no sub-provincial data available. Census and sample survey data are collected by Statistics Canada from direct questionnaires provided from farm operators in Canada. Sample survey data are used by Statistics Canada to extrapolate estimates of provincial totals for the sampled variables, such as total food production for a given food product over one year. A description of data products follows.

Fruit, Field Vegetable, and Potato Surveys

The Statistics Canada Fruit and Vegetable Survey is conducted in Spring and Fall annually through stratified random sample survey of fruit and vegetable farms in Canada, with all large (> 10 acres) farms surveyed (StatCan 2010a). Farms growing only potatoes are generated through a specialized potato survey, that is similarly stratified, randomly sampling potato farms reporting a minimum of $1000 in sales. Annual totals of production and planted area for all fruits, vegetables, and potatoes are released by Statistics Canada each year as provincial means. (StatCan 2010a, 2010b).

Greenhouse Vegetable Survey

In BC, three main greenhouse vegetables (tomatoes, cucumbers, and peppers) are grown, and planted area and yield of each product are reported by Statistics Canada at the provincial scale (StatCan 2010c). Data are collected by Statistics Canada in the Annual Greenhouse, Sod, and Nursery Survey which includes all greenhouse vegetable producing farms in the province. Greenhouse fruits are grown in negligible quantities in BC and are not considered in this paper (Adams 2010, personal communication). Since greenhouse area is reported as a single value in the Agricultural Census at the LHA scale, we calculate a weighted mean for "provincial average greenhouse vegetable yield" based on the proportion of total greenhouse area each product occupies in the total in BC, and each respective yield.

Grains and Oilseed Surveys

Grain data are available through Statistics Canada Field Crop Reporting Series, in which farms producing grains in all non-Atlantic provinces are stratified by farm size and randomly sampled, reporting area planted, harvested, and production weight (StatCan 2010d). Crops grown in Peace River are reported separately from the remainder of BC and account for 90% of total grain production excluding forage corn.

A significant proportion of some grain crops (e.g., oats) are fed to livestock. The approximate proportion of livestock grain is removed from the production data, since it will not be available for human consumption. Livestock proportions are based on data from Statistics Canada Cereal and Oilseeds Review, where grain crops used for seed or livestock feed are separated from grains available for human consumption (StatCan 2010e).

Livestock, Dairy, and Egg data

Data on number of livestock animals producing meat, dairy, and eggs is reported for each LHA in the Census of Agriculture. Average yields for the amount of meat produced per animal, the amount of dairy produced per dairy cow, and the number of eggs produced per laying hen annually are reported in statistical surveys from Statistics Canada. Because the agricultural yield of meat, dairy, and eggs does not vary significantly with geography (for example, is not as susceptible to changes in soil types and temperatures), it is straightforward to estimate the production of meat and animal products per LHA. In in-depth analysis in the temporal and spatial variability in these yields is therefore excluded from this chapter.

2.3 Methods

To enable mapping of data several adjustments were made. Here we outline adjustments and then demonstrate how adjusted data can be integrated and used to map productivity.

2.3.1 Data Integration and Disaggregation

Data Suppression

When Census data are sparse, data are suppressed to protect the privacy of respondents. The Agricultural Census suppresses data where there are fewer than 16 farms within a region LHA. Suppression is problematic for mapping as it masks spatial distributions. In BC in 2006, 49% of greenhouse vegetable area was located in regions with suppressed data. This is problematic as our calculations show that greenhouse vegetables makes up approximately 40% of the total vegetables grown in BC. Most suppression occurred in the Delta LHA, where 14 large operations reported greenhouse production, accounting for about 40% of BC's total greenhouse area (Shiell 2010). Accounting for suppression in the Delta LHA reduces greenhouse vegetable data suppression from 49% to 7%.

Adjustments and Waste Factors

The amount of food available for consumption is typically less than actual amounts of production. In this paper we are interested in estimating the amount of food available for human consumption at the local scale, therefore it is desirable to estimate the food loss and waste that occurs in food production systems. We do this by accounting for waste that occurs on-farm, and waste that occurs between farm and consumer. On-farm waste is accounted for in Fruit and Vegetable Survey by reporting total and marketed production separately. The difference between total production and marketed production is the farm waste. In this paper, we calculate yield as marketed production per planted area to better estimate amounts of food available for consumption.

We then account for waste that inevitably occurs between “farm gate” and “human plate.” The United States Department of Agriculture (USDA) estimates food waste in households, restaurants, and institutions, such as from food preparation, storage, spoilage, and plate loss (Kantor, Lipton et al. 1997). Statistics Canada has adopted these waste factors, and applied them to their Food Statistics datasets to better estimate food consumed at the individual level (StatCan 2007).

2.3.2 Mapping Productive Farmland

We mapped productive farmland in the province to allow us to visually assess clustering or dispersion of the farmland for each product. Units were normalized using standard food production units to enable data integration and reporting of results. The Agricultural Census reports *planted* area of all fruits, vegetables, and grains. This was converted to food production using yield (kilograms per planted hectare) as described below.

To determine provincial food production at a sub-provincial scale, we need an average agricultural yield. Yields are reported by Statistics Canada as a provincial average, calculated from the area of planted farmland in BC, and marketed provincial food production:

$$Yield = \frac{Food\ Produced}{Planted\ Area}$$

Yield and f*ood produced* are available only as provincial averages. However, *planted area* is reported within each LHA as described above. We can calculate production for the i^{th} region, assuming that yield is uniform across the province (equation 2):

$$Food\ produced_{\ i} = Yield * Planted\ Area_{\ i}$$

When mapping, special consideration must be paid to classification of the data into different categories (colors or shading). The farmland dataset (productive area for each product) is positively skewed, with most regions comprised of relatively little farmland and a small number of regions containing the vast majority of the farmland. While often used for data which are normally distributed, using standard deviation is useful for highlighting the extreme skewness is datasets when the goal of mapping is to highlight atypical values (Hutchinson 2004). For each agricultural product, we calculated the average (mean) area of regional farmland per LHA for each product, and then categorized regions as those which are 1.5-2.5 and 2.5+ standard deviations above the mean. Because of the extreme skewness of the data, the mean amount of farmland per region is very low. Data less than 1.5 standard deviations above the mean are classified together and represent areas which contain little or no farmland in that category; because of the nature of the skewed data, no regions are more than 1.5 standard deviations below the mean. We calculate and present the results of a global Morans I statistic, which is an inferential method used to determine the presence or absence of spatial clustering in a dataset, testing against the null hypothesis of random spatial patterns (O'Sullivan 2003). Neighborhoods are constructed using first order polygon contiguity (adjacency).

2.3.3. Assessing Temporal Trends in Agricultural Yields

We assess the spatial distribution of productive farmland to determine if provincially averaged yields can be applied to local regions. Assessing the temporal variability of agricultural yields is also of interest. Weather patterns vary annually and impact food production.

To assess yields over time, we calculated annual yield and summary statistics for each product. A simple linear regression equation was constructed for this time span of each agricultural product, with yield (kilograms of food produced per hectare) regressed against time (years, 1986-2006). The derivative of the regression equation (the slope) represents a metric for assessing the strength and direction of change in yield over time, in kilograms per year. The magnitude of the slope is proportional to the magnitude of the yield, and the coefficient of variation (CV) is a useful normalized statistic to compare change over time between products. The slope indicates the net change during the entire time series, while the CV is a measure of the total variation in the time series. A t-test was used to determine if the slope differs significantly from zero (in other words, testing the significance of the regression model), indicating whether the slope has changed significantly over time. We also report the coefficient of determination (R^2) value which likewise represents whether there has been a significant change in slope over time, and how well a linear model explains the relationship yield and time. A lower (but significant) R^2 may indicate that yield has changed significantly while exhibiting considerable variability over time. We use simple linear regression model as an exploratory tool, therefore we are not concerned with the predictive ability of these models and do not perform model diagnostics. Allowing for exponential and logarithmic relationships between yield and time did not improve model fit for these data and would have complicated the interpretation of the slope parameter, therefore were not included in this paper. Assessing the temporal variation in agricultural yield will guide the decision in whether to use a single year (e.g., 2006) or time series average yield to construct the most meaningful estimates and maps of food productions.

2.4. Results

2.4.1 Mapping Productive Farmland

We present figures showing the proportion of each food group that individual products comprise (Figure 2.2). We also present maps of the three most abundant products for fruit, vegetables, and grains, based on the proportion of total farmland they make up in their food group (Figure 2.4-2.6).

Figures 2.3-2.6 show the distribution of farmland on a food group basis and for the most important three products within each food group. Farmland is present in all regions of the province, but when broken down, each food group clearly shows a high level of regionalization. For fruits, vegetables, and grains, the spatial distribution of farmland is highly significantly clustered with $p < 0.01$ in each case (vegetables: Moran's I = 0.1856, Z = 3.94; fruits: Moran's I = 0.2378, Z = 4.72; grains: Moran's I = 0.221, Z = 4.90).

Of 9,060 hectares of vegetable farmland in BC, potatoes, sweet corn, and green beans comprise 63% of all vegetable farmland. The production of blueberries, apples, and grapes comprises 64% of fruit farmland. Oats, Canola and barley production comprise 76% of grain farmland (Figure 2.2). The spatial distributions are shown in Figures 2.3-2.6. More than three quarters of all vegetable farmland is located in the lower mainland, where the primary vegetables are produced almost exclusively. Fruit farmland is evenly distributed between the lower mainland and the Interior RHA Okanagan region (Figure 2.3). However, each fruit or berry is largely isolated to one RHA; blueberries are the primary fruit produced in BC, grown in the lower mainland, while apple orchards and grape vineyards are located in the Okanagan (Figure 2.5). Significant grain production is essentially isolated to the Northern RHA Peace River region (Figure 2.6). Clearly, while productive farmland is distributed throughout the province, food production is highly regionalized by food group and food type.

2.4.2 Temporal Variability Agricultural Yields

Some agricultural products show a relatively negligible change in yield over time, with a small coefficient of variation and slope close to zero (e.g., cauliflower). Other products experience substantial changes over time (Table 2.1). For example, radishes, lettuce, and sweet corn have large, significant negative slopes and relatively large CVs, suggesting that their yields have decreased significantly since 1986. Products with an insignificant slope but relatively large CV show more variation over time, but the net change during the entire time series is relatively small. Conversely, products with a significant slope but smaller CV show a more substantial but steady net change over time.

While several key vegetables have significantly changing yields (e.g., sweet corn), most fruits have experienced insignificant increases in average yield. Only peaches have increased significantly since 1986, with considerably inter-annual variability. Consistency in CV suggests that most fruits tend to exhibit less variability in yield between growing seasons while vegetable yields are more variable over time. Oats, field peas, and rye have significantly decreasing yields, while other grain yields have gone relatively unchanged (Table 2.1).

Since 1986, peaks and troughs in agricultural yields have often occurred across all products simultaneously. For example, the four primary vegetables grown in BC exhibit a highly similar pattern, where the change in yield over time varies similarly (Figure 2.7), and the same is true for oat and barley yields (Figure 2.8).

2.5. Discussion

Productive farmland is distributed throughout the province, but production is highly regionalized. On a food group basis (e.g., fruit or vegetables) farmland is isolated to small regions. On an individual product basis (e.g., blueberries) the geographic extent of farmland is even smaller. Though yields are presented as provincial averages, based on provincial production data, the provincial average yield represents a regional yield when production is geographically isolated. Extreme regionalization of farmland has implications for production analysis and food security. Regionalization impacts local scale food security by limiting nutritional variety and the feasibility of a local diet (Guptill and Wilkins 2002).

Viewed comprehensively, maps show patterns that may not have been obvious from aspatial analysis. Total farmland in BC is distributed throughout the province; because oilseeds and grains are produced in greater amounts than fruits and vegetables, analyzing and mapping total farmland would have given unfair weight to grains. If researchers and regional health officials are interested in knowing what foods are available in their areas, it is important disaggregate data into nutrient-based food groups so nutritional variety can be assessed. Mapping regionalization in BC agricultural products demonstrates that no regions have sufficient agricultural variety to meet nutritional needs with a local diet at the scale of LHA.

Temporal analysis indicates that some agricultural yields have substantial annual variation likely related to year-to-year weather patterns that impact amounts of rainfall and sunlight hours (Rounsevell, Annetts et al. 2003). Products grown within a relatively small geographic region tend to exhibit similar patterns over time. For example, oats, canola and barley are grown primarily in the Peace River region and have common temporal trends in yield that are likely attributed to weather. Poor weather from 1997 to 2000 reduced yield and gross production of many vegetable products. Warmer weather in 2001 increased production and yield of most crops (BCMAFF 2003). Temperature increases with higher than average precipitation in the Fraser Valley in 2005 could explain the increase in yield of many products that year.

Temporal trends in berry and tree fruit yields, most grown in the Fraser Valley and Okanagan, may reflect unusually cool growing seasons in the years prior to 1997, followed by the warmer temperatures in the following years, with a particularly good growing season in 2003. Yields in most berries and tree fruits were lower in the late 1990’s and higher than average after 2000 (StatCan 2004). As well, in BC older fruit trees have been slowly replaced with new high-yield dwarf stock. Apples are susceptible to changes in heat and humidity; hot and dry growing seasons will cause a spike in yield whereas a cooler or more humid growing season will decreased productivity substantially (StatCan 2000).

Grain yields have varied over time more than field vegetables and fruits, exhibiting similar temporal yield fluctuations as they are grown in the same region and are subject to the same weather conditions (Figure 2.8). Agricultural yields of fruits, vegetables, and grains in BC exhibit considerable variability over time. Using a single year's yield is reasonable if the research goal is to construct a snapshot of local food capacity.

If a general view of local food capacity or future prediction is required then using a time series average yield will make the final estimate less reflective of weather-driven annual variability. This is particularly important if products are abundant or produced over a broad geographic area. For example, green beans and peas together make up 34% of vegetable farmland in BC, and both yields have increased considerably over time. Apples, grapes, and peaches account for 41% of fruit farmland, and peach yields have increased significantly over time (Table 1). Temporal variation in these products could significantly impact the final food production estimate in an LHA.

2.6. Conclusion

This paper presented a method for estimating regional food production in BC with census and survey data and assesses spatial and temporal variability in food production. The absolute quantity of food produced in each region can be estimated as the product of farmland devoted to growing that product from the Agricultural Census, multiplied by the average provincial yield for the product from the appropriate federal survey product. Given the high level of regionalization in BC agriculture, this is methodologically sound. Constructing these estimates of regional food production has not previously been possible using available datasets. As well, assessment of yield stability over time has not been incorporated into any local food security research in the province (Vancouver Food Policy Council 2009).

Health officials and policy makers are increasingly recognizing that healthy eating at a population level does not only depend on public nutrition education; the underlying structure of food production systems, and how foods are processed, distributed, and sold will ultimately determine what foods people consume. Health officials require access to research and data which describe the food production systems and food availability in their regions, which currently is lacking at any local scale. The lack of supportive data and research indicate a need for methods development in this area (BC Ministry of Agriculture and Lands 2006; Peters 2009).

The methods applied here are transferable to other provinces in Canada, as Agricultural Census and survey data are available. If farmland is highly regionalized, isolated to relatively small regions on a per-product basis, then provincial average yields can be applied to local farmland area data. The importance of this step will depend on the size of the region. Reported values for area of productive farmland are available from the Agricultural Census in a variety of sub-provincial spatial units. The methods in this paper would also be adaptable to other countries, contingent on data availability and the farmland distribution as described above. In some countries, if soils and climates are fairly homogeneous, then nationally aggregated yields may suitable. National average yields are often available for common crops from the United Nations Food and Agriculture Organization (UNFAO 2010).

Through local food production estimates, presented here, we can construct baseline estimates of local scale food self-sufficiency, assuming that regional food consumption can be estimated. Contrasting food production and food consumption at a local scale would provide an empirical assessment of local food self-sufficiency, which is not currently available in BC, or described extensively in the food security or agricultural literature. More sophisticated modeling could be incorporated, such as forecasting of future agricultural self-sufficiency, based on demographic changes (aging, population growth, or urbanization) or agricultural changes (due to climate or land use change). This research is a first step towards a more sophisticated analysis of local diets and regional decision making. The methods presented in this paper do not allow for a theoretical estimate of productivity in regions where crops are not currently grown, since these yield data would only reflect yields in the localized production regions. More sophisticated modeling of predicted yield and further research into the spatial stability in agricultural yields based on regional characteristics (such a soil and climate) would help quantify the level of regionalization required to justify the use of aggregate yield data. Local foods recommendations will only be effective when local agricultural systems can meet current or increased demand for agricultural products. Understanding the current state of local scale agriculture is a first step towards aligning agricultural and nutritional goals.

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Table 2.1: Summary statistics for agricultural yield in BC, 1986-2006. Products with a statistically significant slope, ($p < 0.05$), indicating significant change over time, are shown. All R^2 values are significant ($p < 0.05$). Min, max, and mean in units of kilograms.

	Min	**Max**	**Mean**	**Cv**	**Slope (kg/year)**	**R^2**
Radishes	5,910	38,507	17,078	0.53	-838.88	0.32
Lettuce	15,735	30,220	24,079	0.18	-550.10	0.60
Corn	7,787	14,745	10,842	0.19	-245.75	0.56
Asparagus	806	2,057	1,361	0.29	31.88	0.25
Peppers	5,780	13,699	8,971	0.25	203.22	0.32
Beets	10,216	23,640	16,450	0.24	281.17	0.18
Peaches	7,072	10,817	8,864	0.12	204.18	0.43
Oats	841	2,723	1,589	0.3	-34.35	0.21
Mixed grains	750	3,167	1,740	0.46	-67.85	0.27
All rye	425	2,375	1,476	0.45	-77.36	0.33

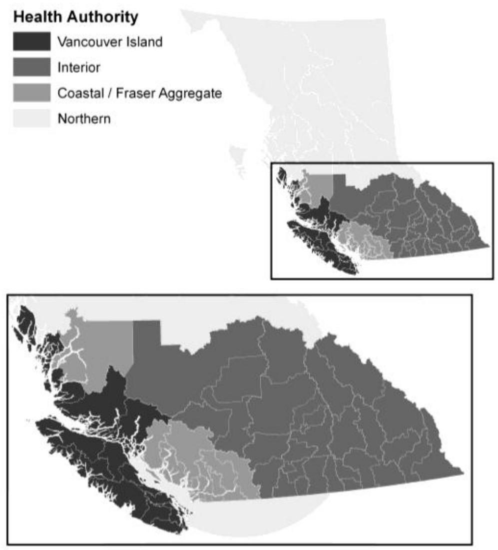

Figure 2.1: Aggregated BC Regional Health Authorities. Local Health Areas are outlined in white. BC is shown in four regions based on the five RHAs; the Vancouver Coastal Health Authority and Fraser Health Authority have been aggregated in this figure because they make up a relatively homogeneous agricultural area in the province, which we also refer to as the "lower mainland."

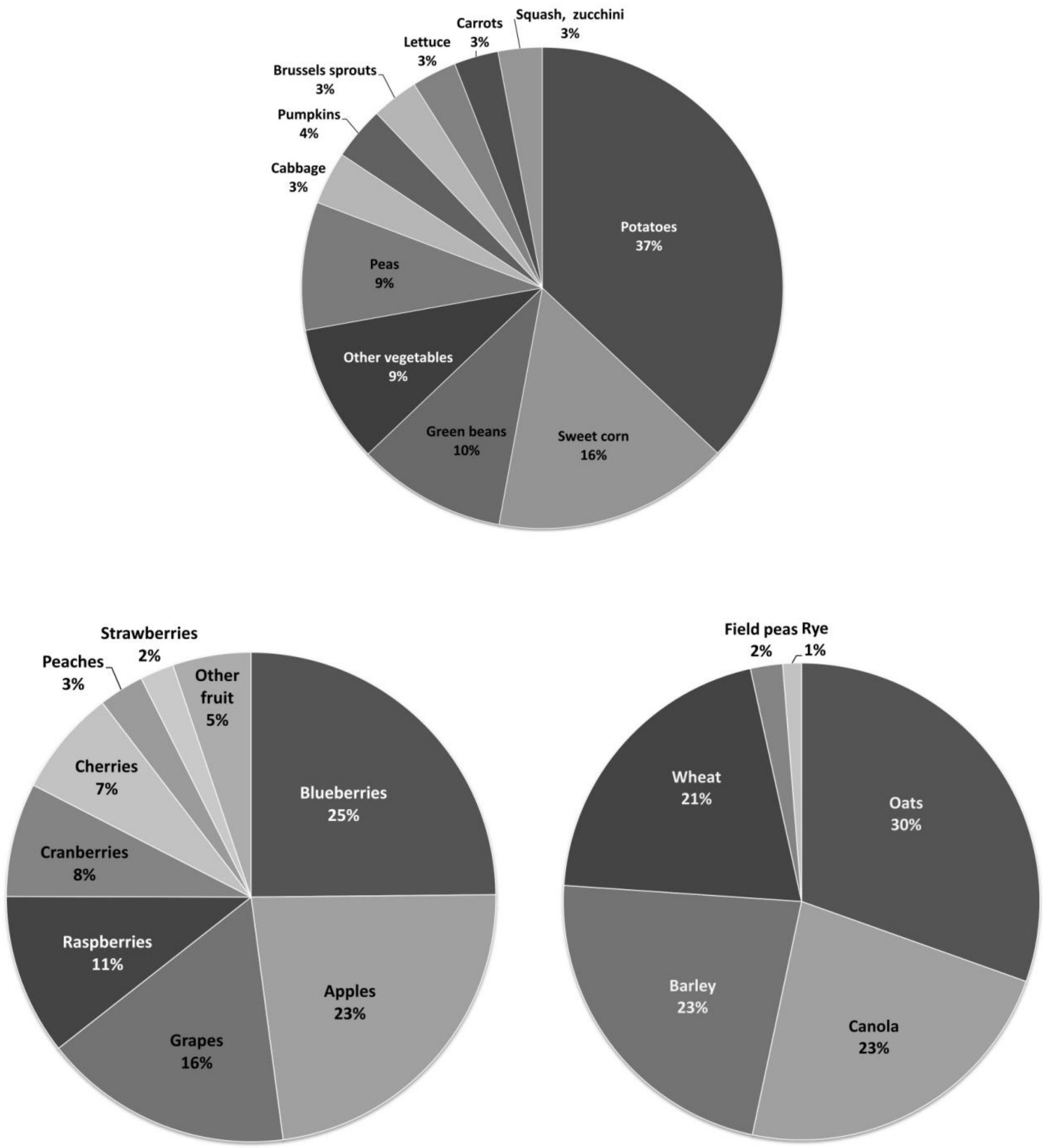

Figure 2.2: Farmland Allocated to Produce Fruits, Field-grown Vegetables, and Grains in British Columbia, 2006.

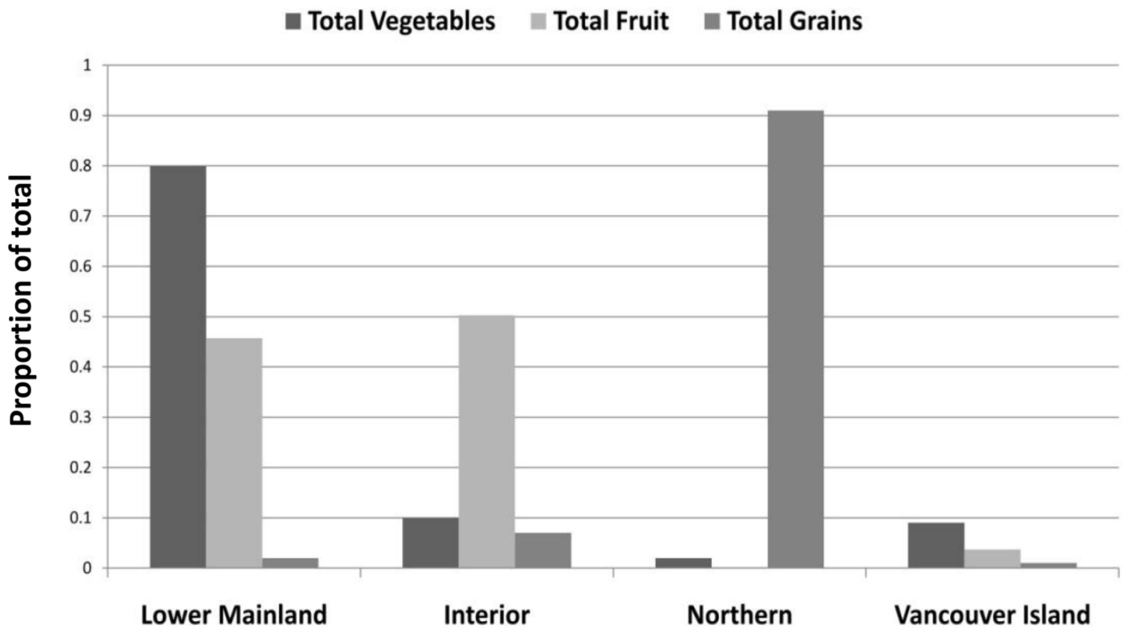

Figure 2.3: Regional Distribution of Farmland in BC. Lower mainland includes Fraser and Vancouver Coastal Health

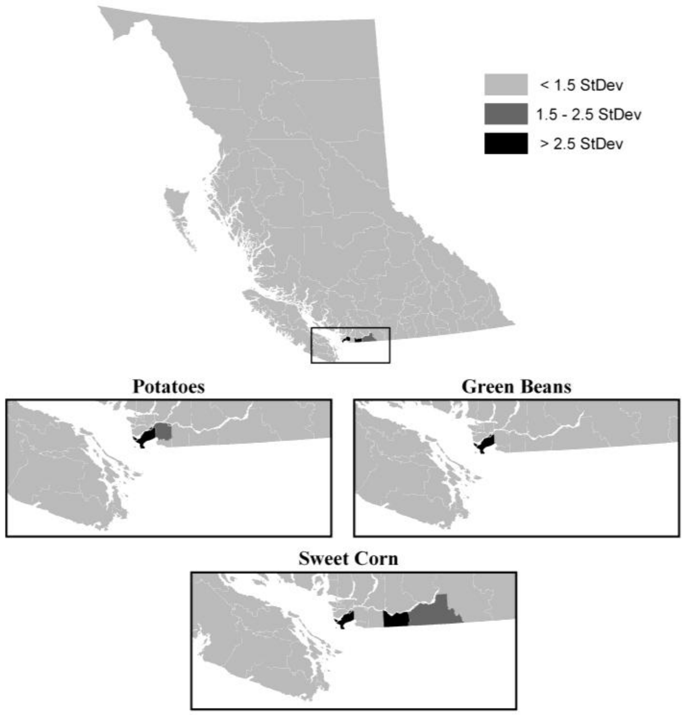

Figure 2.4: Vegetable Farmland in BC, 2006. Does not include greenhouse grown vegetables.

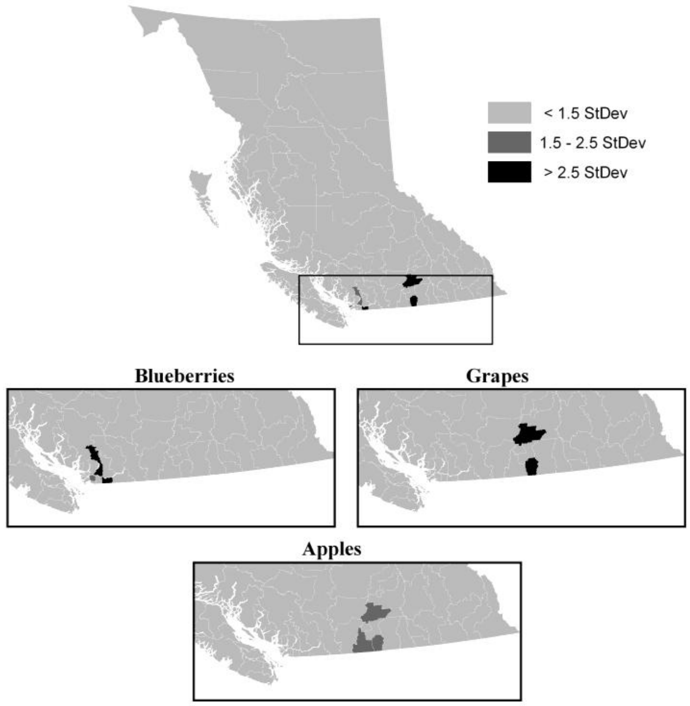

Figure 2.5: Fruit Farmland in BC, 2006.

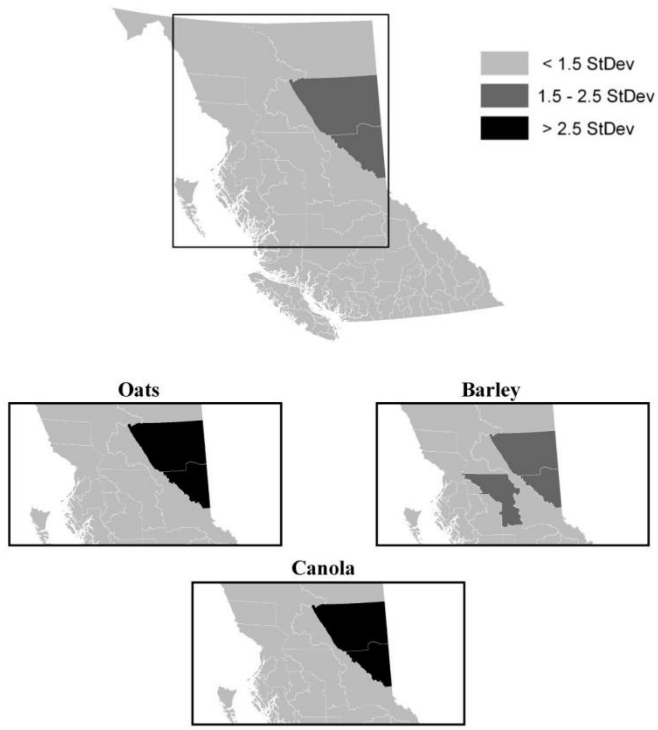

Figure 2.6: Grain and Oilseed Farmland in BC, 2006.

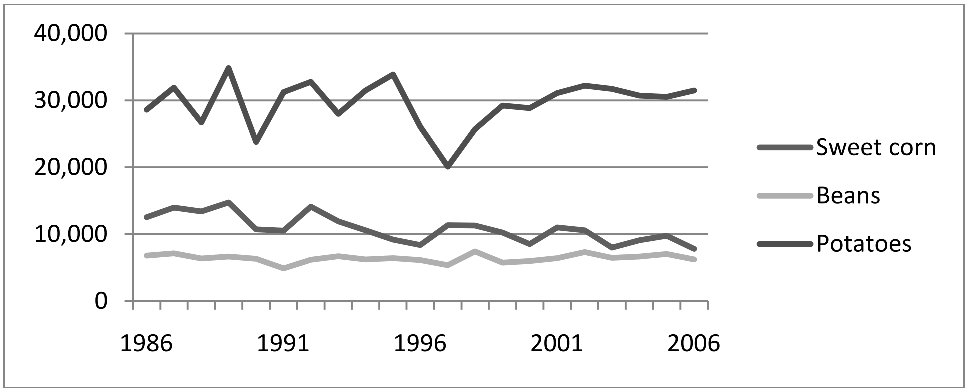

Figure 2.7: Field Vegetable Yields in BC, 1986-2006, kilograms per planted hectare.

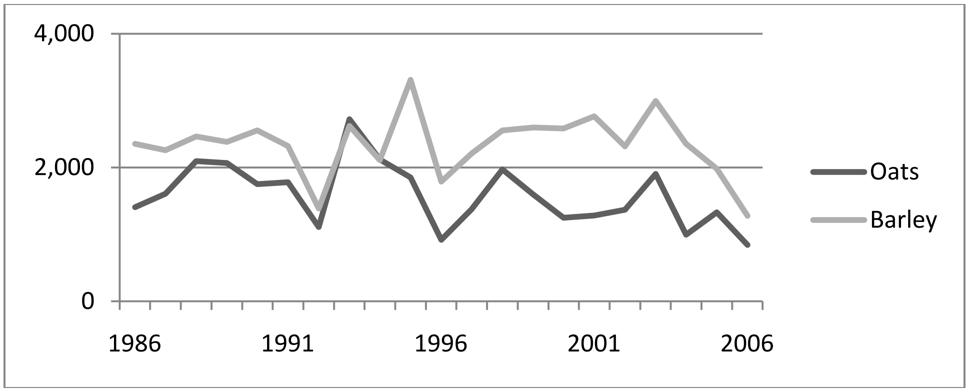

Figure 2.8: Oat and Barley Yields in BC, 1986-2006, kilograms per planted hectare.

3.0 MAPPING SPATIAL VARIATION IN FOOD CONSUMPTION

3.1 Abstract

Data on food consumption trends are often provided nationally and spatial variation in eating habits is difficult to estimate in Canada. Here, we present methods for mapping provincial aspatial food consumption data by accounting for spatial variability in population structure (age and gender). This type of data and analysis is useful for researchers and policy makers interested in promoting the consumption of locally produced food, as assessing nutritional demand will be a critical first step. We present a method for constructing food consumption estimates for Local Health Areas in British Columbia; however, methods outlined could be applied to other jurisdictions and other units when demographic characteristics are known. Because age and gender impact food consumption, the demographic profile of a given local area will drive food consumption patterns. For instance, among 18-44 year olds, men consume 50% more food than women, but eat 30% fewer fruits and vegetables. Given regional differences in demographic composition, consumption patterns for men and women at different ages have notable spatial variability. Linking aspatial consumption data with demographic data enables mapping spatial variation in food consumption.

3.2 Introduction

There is a growing body of research on the benefits and limitations of local food systems. The consumption of locally produced foods has been actively promoted by non-governmental organizations as well as health officials and policy makers in some levels of government (Cowell 2003; Public Health Agency of Canada 2005; Dietitians of Canada 2007; Smith and MacKinnon 2007; United States Congress 2008). Promotions for the consumption of local food arises due to concerns about agricultural sustainability, the need to decrease food miles travelled, supporting local economies, and strengthening community food access (Feenstra 1997; Anderson and Cook 2000; Hinrichs 2003).

In order to understand the level of demand on local food systems, researchers must first determine how much food is currently consumed in a region, regardless of where it was produced. Food consumption varies spatially and is driven not only by population size but also by various demographic characteristics (Gittelsohn, Wolever et al. 1998; Deshmukh-Taskar 2007). Estimating food consumption at a local scale will allow policy makers and planners to assess the capacity for local food systems to meet their own populations food needs, assessed with either current agricultural productivity or agricultural potential (based on characteristics such as spatial variability in soils and climates).

The standard data used for studying population-level food consumption are aspatial and mask variation in consumption habits that may be related to demographic characteristics, discounting spatial variability in eating trends. Various methods have been employed for estimating the quantity of food consumed at a population level. Commonly used are national-level statistics that estimate what an average individual within a country would consume in a year, without adjustments for age, sex, or other characteristics. For example, Cowell and

Parkinson based food consumption on National Food Disappearance (NFD) data in the U.K., where domestic food production (plus imports, minus exports and waste) is divided by the annual population (Cowell 2003). In their U.S. study, Christian Peters et al. used a novel method of Human Nutrition Equivalents (HNE) to determine how an average American meets their nutritional needs, and performed an optimization model to calculate the amount of agricultural land required to produce that food. Although their analysis did account for spatial variation in food consumption based on population density, variability in the composition of populations was not considered (Kantor and Young 1999; Peters 2009). In Canada, regional estimates of the quantities of food consumed have used NFD data to measure per-capita consumption (Markham 1982; Riemann 1987; BC Ministry of Agriculture and Lands 2006; Vancouver Food Policy Council 2009). National data are typically applied to the populations in the region of interest to generate regional food consumption values for major food categories such as fruit, meat, dairy, and vegetables. In some research, idealized consumption has been used to determine the impact of widespread adoption of recommended policies, such as the Canada Food Guide or U.S. Food Pyramid (Kantor 1996; Kantor 1998; Peters, Fick et al. 2003).

In this paper, we propose a unique methodology for mapping regional variation in food consumption. Our approach is based on linking aspatial consumption aggregates to mapable demographic data. To meet our objectives, we:

1. Link aspatial individual-level consumption data for men and women in different age groups to demographic data in each LHA
2. Correct for missing data (youth consumption) and temporally adjust datasets from 1999 to better reflect consumption in 2006

3. Compare demographic-based consumption estimates with aggregate consumption estimates to assess spatial deviation from average

Mapping spatial variation in food consumption has not been incorporated into previous agriculture and food security research; the methods presented in this paper will be useful for future research on regional food consumption as well as understanding the consumption of locally produced foods.

3.3 Data and Study Area

The province of British Columbia is a suitable study area for this research, given that it is home to strong community, activist, and political interest in food security and nutrition. The spatial unit used in this paper is the Local Health Area, of which there are approximately 90 in BC in 2006. The LHA is a spatial unit at which health and nutrition policy is implemented in the province, and much nutrition research is performed, so it is a useful unit for this research. The methods presented in this paper can be applied to any spatial unit for which demographic data are available.

The most widely available data for studying food consumption patterns in Canada is the National Food Disappearance data (NFD) which is gathered annually and disseminated by Statistics Canada through their annual publication "Canada Food Stats" (Statistics Canada 2009). The NFD estimates the quantity of food available for Canadian consumption each year by summing gross Canadian food production, imports, and estimates of the quantity of food in storage on January 1st. Canadian food exports, the quantity of food in storage on December 31st of the same year, and estimated waste incurred during distribution and processing are subtracted from this total. This value can then be divided by the average annual population of that year to estimate the per-capita quantity of food available for consumption. Statistics Canada also applies adjustment factors to estimate the waste lost during retail sale and food preparation, including cooking losses and the removal of inedible portions (Statistics Canada 2009). The final data provides an estimate of the the quantity of food actually consumed by an average Canadian each year.

An alternative method to estimate population-level consumption habits is through the use of dietary surveys. Dietary survey methods were first developed in the early 1930s as policy makers in many jurisdictions became increasingly concerned about the impacts of poverty and malnutrition on health (Ostry 2006). The world's first major national nutrition survey, involving tens of thousands of respondents, was conducted in Canada in 1972 (Sabry 1974). Since then, nutrition surveys have been conducted only occasionally in Canada, largely because they are time consuming and costly. Instruments vary between surveys, and therefore the data collected are often not comparable as survey products measure different variables (Forster-Coull, Milne et al. 1999; Forster-Coull, Milne et al. 1999; CCHS 2.2 2004). The usual methods used are face-to-face interviews using detailed interview questions on the exact composition of meals consumed within the 24 hours prior to interview. A strength of nutrition surveys is that they provide a direct measure of individual dietary intake. As well, they measure demographic characteristics of the participants so that comparison of consumption habits between different ethnic groups, genders, and age groups, or differences in consumption patterns of geographic regions can be undertaken. However, because they are costly they are conducted sporadically, limiting the ability to measure change in dietary intake over time.

The last detailed dietary survey conducted by the province of BC was in 1999. The Chief Nutritionist of the Province of BC provided us with a custom analysis of this BC Nutrition

Survey (BCNS) data set, reporting the annual quantities of food (by major food category) consumed by men and women aged 18 to 44, 45 to 64, and over 65. The 1999 study included only adults aged 18 and over.

To determine consumption for the youth in each region, we use data from the Canadian Community Health Survey Cycle 2.2 (conducted in 2004) (CCHS 2.2 2004). The CCHS 2004 data are not available in units of mass, and therefore cannot be used to construct actual consumption estimates. However, they do report daily consumption habits of both youth and adults in BC, in units of food servings.

3.4 Methods

We calculate population level food-consumption separately with two datasets (NFD and BCNS) for the sake of comparative analysis. The NFD method requires only the individual-level food consumption estimate, multiplied by the population of each LHA. Methods for using the BCNS survey data to construct population-level food consumption estimates are outlined below.

3.4.1 Linking Aspatial Individual Consumption Data to Mapped Demographics

Data from the BC Nutrition Survey provides us with food consumption averages for men and women in different age categories. In order to calculate and map variation in population-level food consumption, we combine the individual level consumption estimates for each age and sex group with demographic population data in each LHA in BC:

$$C_i = \sum_{j=1} C_j P_{ij}$$

where the total consumption *(C)* of a food group in the i^{th} region is equal to the consumption of the j^{th} age/sex category multiplied by the population of the j^{th} age/sex category in the i^{th} region, and summed for j age/sex categories. This allows for calculation of the total food consumption for each food, and can be summed into convenient food groups (e.g., fruits, vegetables, dairy, meat).

3.4.2 Estimating Youth Consumption and Temporal Adjustment Factor

Since youth were not surveyed in the BCNS, we needed to develop a method to estimate their food consumption for each category. There is no standardized way to do this reported in the literature, so we rely on data from the CCHS 2.2, which reports food consumption (in number of servings) for each food group in different ages, including children and youth. Because the publically available data are reported in number of servings rather than units of mass, they cannot be directly used in lieu of BCNS data. However, we developed an adjustment factor between the amounts of food consumed, on average, by a person under the age of 18 in BC, versus an adult in the province, based on these CCHS data:

$$Youth\ Adjustment\ Factor = \frac{Youth\ Servings}{Adult\ Servings}$$

This adjustment factor is calculated for each food group and applied to our BCNS data to create consumption estimates in the under 18 age group. Young children tend to eat less food than adults, with the exception of dairy, while adolescents often consume more food than adults.

The major benefit of the NFD data normally used in estimating population-level food consumption is the temporal availability of data; in Canada, NFD are available from 1960 to 2009 inclusive. These data show that there have been some changes in the Canadian diet between 1999 and 2006, with some foods consumed in slightly larger quantities (e.g., vegetables) and some foods consumed less. To account for this temporal mismatch between our 2006 demographic data, and our 1999 BC Nutrition Survey consumption data, we use NFD data to create a temporal adjustment factor, equal to the ratio between the 2006 and 1999 reported consumption values in the NFD data. This is applied to all consumption estimates in all gender and age groups in our BCNS dataset.

$$Temporal\ Adjustment\ Factor = \frac{NFD\ 2006}{NFD\ 1999}$$

Both the Canadian Community Health Survey Cycle 2.2 data and the Food Statistics data from Statistics Canada are widely used in the food security and population nutrition literature (Riediger 2007; Witkos, Uttaburanont et al. 2008).

3.4.3 Mapping Variation Between BCNS and NFD Consumption Estimates

We perform exploratory mapping on the spatial patterns in the two consumption estimates. We will refer to the NFD method as aspatial and the BCNF method as spatial. We calculate the percent difference ("error") between spatial and aspatial methods, and consider the spatial distribution of the errors. The two datasets are compared with a non-parametric two-sample paired test to determine if the difference between the distributions differs significantly from zero (Wilcoxon Rank Sum, $\alpha = 0.10$) (Pal 1998). Global and local Moran's I statistics are used to assess and map spatial clustering (consumption overestimate or underestimate) of errors ($\alpha = 0.10$), with neighborhoods defined with first order polygon contiguity, as is commonly used in spatial cluster detection (Pal 1998). Finally, we explore the demographic explanations for the spatial distribution of errors between these methods.

3.5 Results

3.5.1 Constructing Adult Consumption Estimates

The BCNS individual level consumption estimates are similar the NFD data, confirming that the BCNS dietary recall data has been used here to construct reasonable consumption estimates for these categories. Consumption estimates from the BCNS show substantial differences in consumption between age and gender groups. For example, adult men age 18-44 eat 50% more food than women, but only 30% more fruits and vegetables (Figure 3.1). Nearly half of total food consumed in youth is in dairy products (47%) but only approximately one third for adults. Adult women tend to consume more fruits and vegetables and less meat and grains than men in the same age group. Women consume similar amounts of food throughout each age group, while men’s food consumption drops considerably as they age.

3.5.2 Analyzing Geographic Variation in Food Consumption

There are minor differences between the average consumption estimates of the BCNS and NFD datasets, which is to be expected given the different methods used to derive them. For example, the meat consumption estimates differ by approximately 2%, but range from -9% to +7% depending on location. It is this spatial variability in the difference that is of interest. In this section we will present the differences in spatial patterns of total food consumption for illustration, but the patterns are similar within each food group.

The primary driving force of food consumption in each LHA is the regional population, which is expected. However, there are variations between the two consumption estimates. Figure 3.2 shows a map of the percent difference between the two total food consumption datasets, classified by standard deviations from the mean percent difference. Therefore, areas which deviate significantly from the mean are depicted.

The Wilcoxon Sum Rank Test compared the distributions of the two datasets, and reveals a statistically significant difference ($W = 3387$, $p = 0.095$, $\alpha = 0.10$) against the null hypothesis that the distributions do not differ significantly. The global Moran's I analysis reveals highly significant clustering of error ($Z = 5.911$, $p < 0.01$). The local Moran's I cluster analysis reveals the regions which have significant clustering of relatively high or low error, indicating difference between the two methods ($p < 0.10$). Clusters of high error indicate regions in which the NFD method underestimated the total food consumption; clusters of low error indicate regions in which the NFD overestimated the total food consumption.

These overestimated and underestimated regions have demographic makeup which are markedly different from the remainder of the province; for example, the demographic breakdown of age groups as a provincial average is shown in Figure 3.3, along with four of the cluster LHAs in the province. The total food consumption estimates in each of these regions deviates significantly depending on the method used to estimate it (NFD vs. BCNS). Regions with higher error have a younger than average population, and therefore consume more food in total, which the NFD method underestimates. Conversely, the regions with lower error have older populations than average, consume less total food, and their total regional food consumption is overestimated by the NFD data (Figure 3.4).

3.6 Discussion

Regional estimates of food consumption are often based on aggregate national food disappearance estimates and applied to population data at a finer spatial scale (Riemann 1987;

BC Ministry of Agriculture and Lands 2006; Vancouver Food Policy Council 2009). The major limitation in using NFD to develop estimates of food consumption at the LHA level is that they represent Canadian averages, and do not necessarily reflect the consumption habits of British Columbians. Food consumption differs greatly between individuals, especially between gender and age groups, with men consuming much more of most food types than women, and teens and young adults tending to consume more than the very young and seniors. If NFD data are used to construct regional consumption estimates, regional consumption will simply be a function of population size, without accounting for any other regional variation. When the objective is to compare regional differences in food consumption at a local scale, these data are largely unsuitable.

Variation exists in the distribution of age and gender groups throughout the province of BC and regional food consumption estimates should reflect these patterns. This finding is somewhat intuitive, but is of particular importance to food security research. Many of the demographically atypical regions are located in the north of the province. These regions have very young populations with high fertility rates and large numbers of First Nations people, who are affected disproportionately by nutrition-related disease (Power 2008; Kirkpatrick and McIntyre 2009). They are also extremely rural, remote locations, far from the agricultural and urban hubs of the lower mainland; food price are often significantly higher in remote areas (Minister of Indian Affairs and Northern Development 2007). For these reasons, individuals in northern Canadian provinces and territories experience much higher rates of food insecurity, evidenced from both from self-reported surveys and indirect measures such as rates of food bank usage (CCHS 2.2 2004; Lawn and Harvey 2004; Act Now BC 2006; Power 2008). Northern areas are also more susceptible to the effects of climate change, including agricultural impacts

(Wesche and Chan 2010). It is therefore extremely important to estimate their food consumption accurately, not underestimating it as the NFD data would do, as these populations are of key interest and consequence in food security and population nutrition research.

The BC Nutrition Survey data are ten years old, which is the major drawback of using this data. It is difficult to know, in the absence of a more recent survey in BC, whether or not consumption has changed significantly over the past decade in the province. However, we can estimate crudely at the national level using NFD to show changes in consumption by major food category over this time, and this adjustment addresses some of this temporal change issue.

Researchers are often interested in more detailed consumption comparisons than age and gender, such as between minority groups or vulnerable subpopulations (Gittelsohn, Wolever et al. 1998; Deshmukh-Taskar 2007). Further research could utilize our methodology by expanding the age and gender sub-groups to include, for instance, ethnic groups, urban versus rural area typology, and socio-economic measures.

The methods presented here set the stage for other research which might utilize aspatial consumption estimates to perform spatially explicit analysis, particularly in nutrition and food security research. BC is a unique province with high citizen involvement in local food systems, and a motivated health ministry concerned with local scale provincial food security. Understanding consumption demand, particularly at the regional level, is a key component of studying the impact of nutrition policies made at the provincial level.

3.7 Conclusion

In this paper, we present a unique method of using the aspatial nutrition survey data to assess differences consumption between age groups and genders. We found considerable variation in consumption of each food group based on these demographic differences. In addition, we studied the demographic makeup of different regions, finding significant differences in the age and gender distribution over space. We can conclude that applying a purely population-based consumption estimate would not accurately represent regional food consumption in the province. Our method accounts for these regional demographic differences so as to better estimate the consumption habits of local residents.

Two patterns largely drive spatial variation in food consumption. Firstly, consumption habits differ between men and women, and eating habits change as people age. Secondly, our analysis shows significant demographic differences between regions. If the demographic variation is not taken into account through gender and age based consumption estimates, and instead is based exclusively on population size, then regions with atypical demographic characteristics will be poorly estimated. This is particularly problematic when these areas are already vulnerable to food insecurity, and thus are of special research interest.

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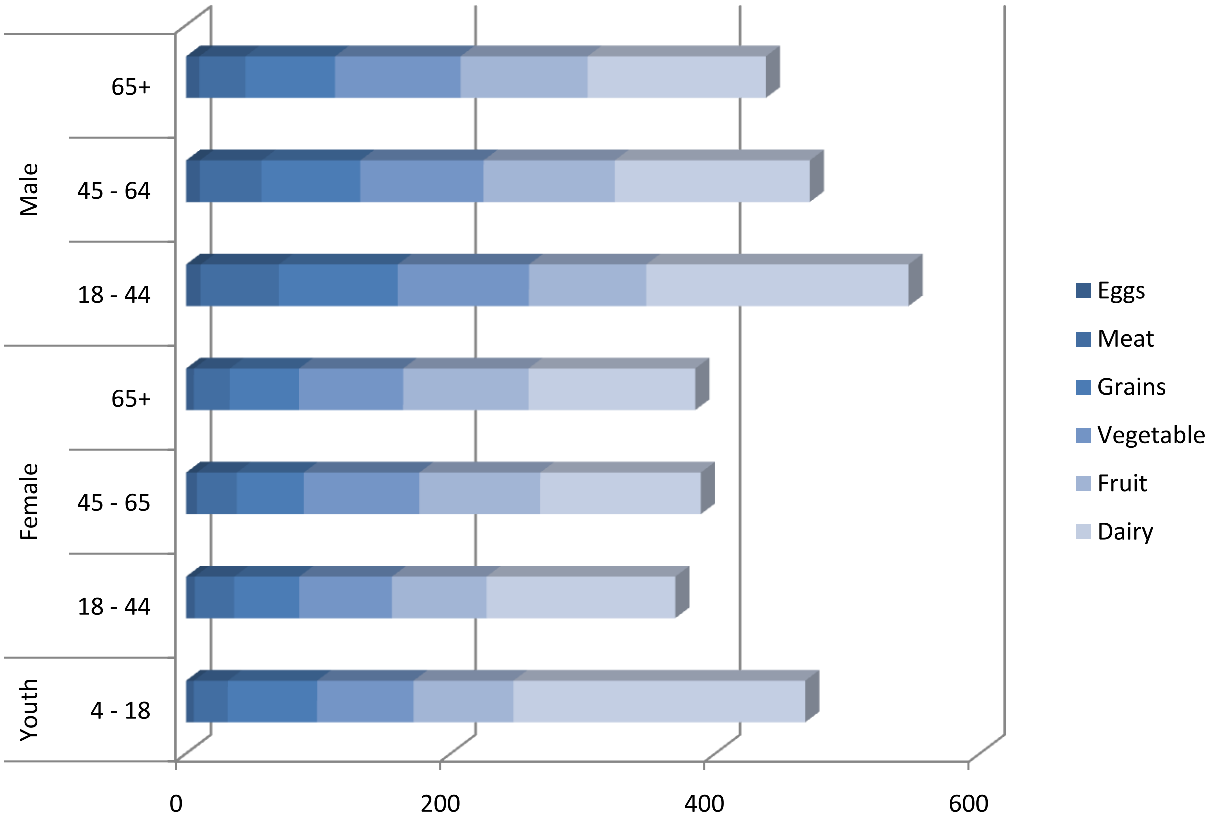

Figure 3.1: Temporally adjusted food consumption estimates based on the BC Nutrition Survey, in kilograms of food, by gender and age categories.

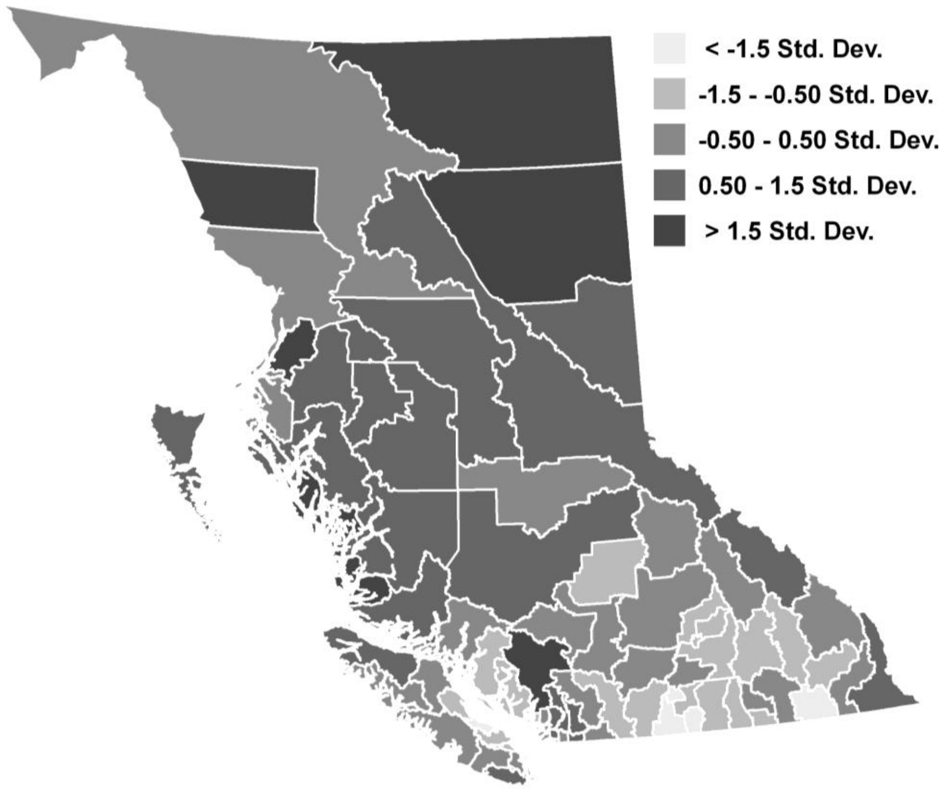

Figure 3.2: Clusters of significant difference between consumption estimate methods. Map is classified by standard deviation of the difference between BCNS and NFD consumption data, revealing areas of significant deviation from the mean error between consumption estimate methods.

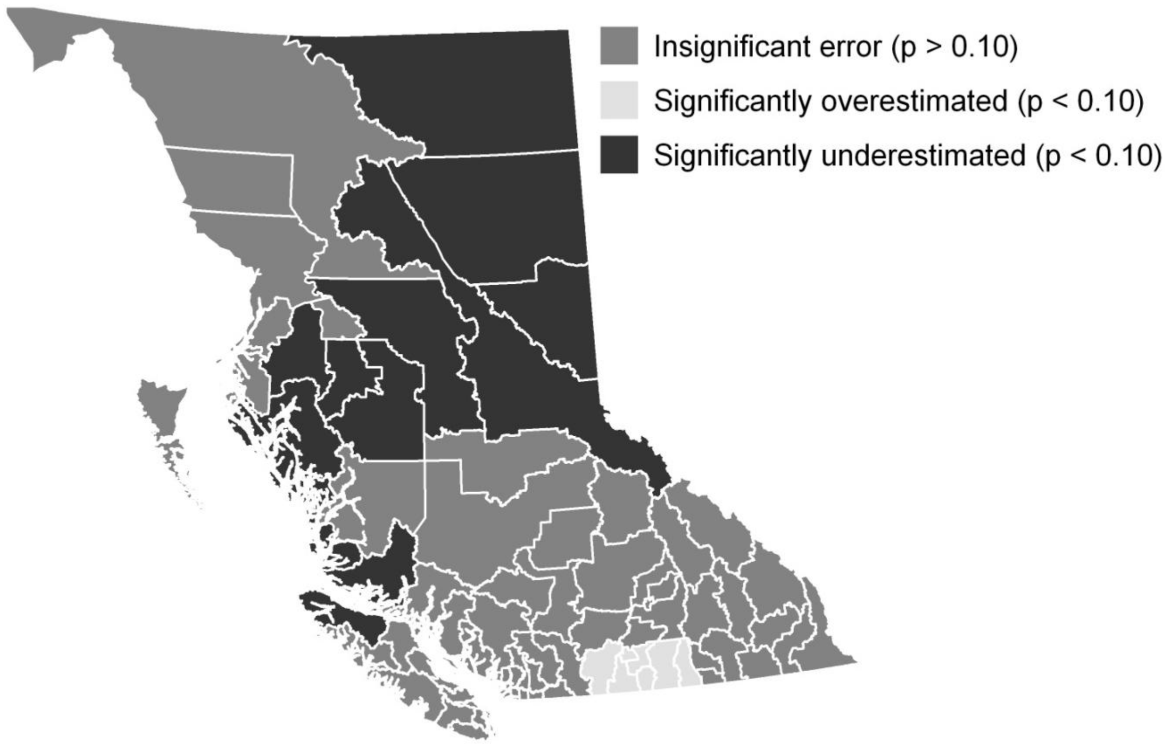

Figure 3.3: Moran's I local cluster detection. Significant clusters (p < 0.10) of high or low mean error are shown.

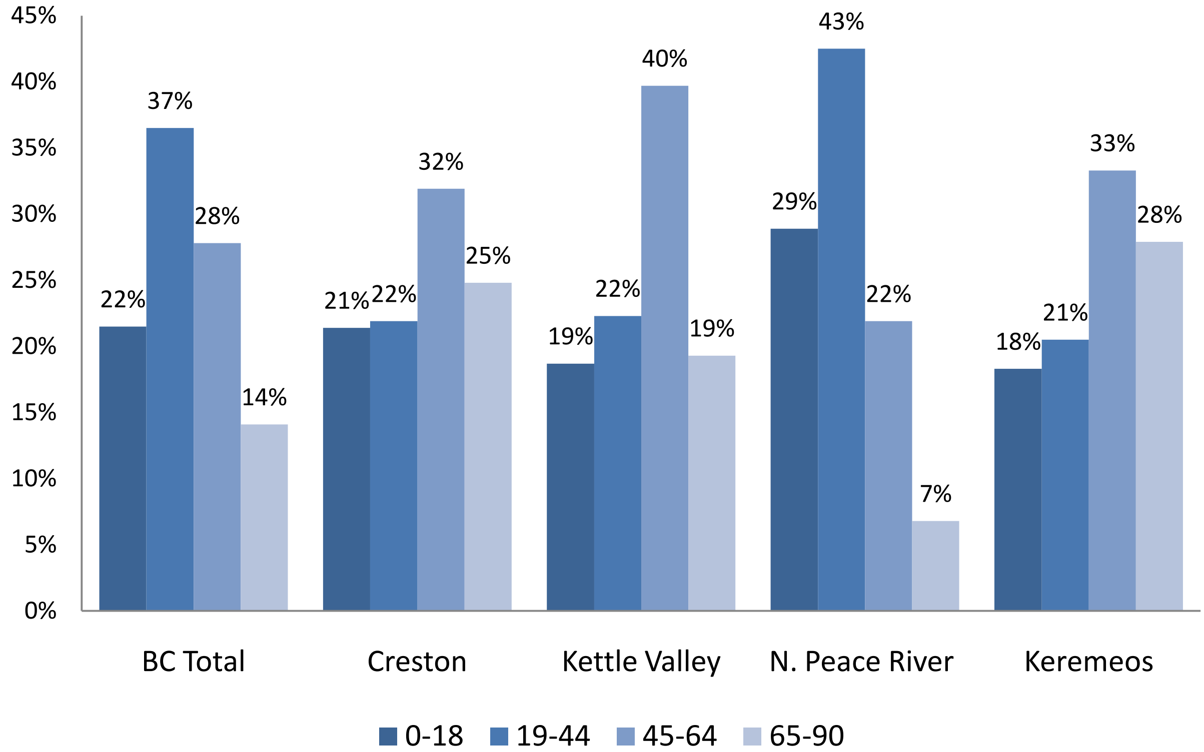

Figure 3.4: Demographic breakdown of British Columbia and four selected Local Health Areas, as a percentage of the total regional population.

4.0 APPLICATION OF BAYESIAN SPATIAL SMOOTHING MODELS TO ASSESS AGRCULTURAL SELF-SUFFICIENCY

4.1 Abstract

With the rising oil prices, climate change, and the ever increasing burden of nutrition-related disease, food security is of growing research interest in academic disciplines spanning agronomy to epidemiology to urban planning. Some governments have developed progressive policies encouraging individuals to consume locally produced foods in order to support local economies, improve agricultural sustainability and community access to food, and to plan and prepare for adverse environmental impacts on food security. However, fundamental methods are lacking for conducting research on food security across these various disciplines. In this paper we first present a method to measure agricultural self-sufficiency, which we refer to as our self-sufficiency index (SSI) for the province of British Columbia, Canada. We then present a Bayesian autoregressive framework utilizing readily available agricultural data to develop predictive smoothing models for the SSI. We find that regional capital investment in agriculture and cropland acreage are the strong predictors of SSI. To accommodate spatial variability, we compare linear regression models with spatially correlated errors to less traditional spatially-varying coefficient models, and find that the former class results in better model fit. The smoothed maps suggest that relatively strong self-sufficiency exists only in subset clusters in the Okanagan, Peace River, and lower mainland regions. In spite of policy to promote local food, the existing local agricultural system is insufficient to support a large-scale shift to local diets. Our approach to estimating neighborhood-based self-sufficiency with a predictive model can be extended for use in other regions where limited data are available to directly assess local agriculture and benefit from explicit consideration of spatial structure in the local food system.

4.2 Introduction

Local food is a topic of growing interest among academics, planners, and health officials, who are concerned with community food security, disaster management, and public health. Our research is motivated by the promotion of "local diets," popular in the general public and promoted increasingly by various ministries in the province of British Columbia (BC Ministry of Health Services 2005; Act Now BC 2006). In spite of recommendations to eat locally produced "healthy" foods, local agricultural capacity in British Columbia is unknown. Yet local food policies, designed to address nutritional health disparities and improve community food security, will only be effective if local foods are available. Agricultural self-sufficiency is often calculated as the ratio between agricultural food production and population-level food consumption at a defined scale and used to assess how well a geographic area can potentially meet its own population's food needs. Alternatively, it is sometimes estimated with economic, trade, or national accounts data; for example, self-sufficiency is often estimated at a national scale, with international imports and exports compared to determine the quantity of domestic food production (Riemann 1987; BC Ministry of Agriculture and Lands 2006). Assessments of food self-sufficiency at more local scales are uncommon and usually focus on only one small region, yet there is demand to systematically model the theoretical self-sufficiency of local food systems (Vancouver Food Policy Council 2009).

Bayesian autoregressive smoothing models are often used in spatial epidemiology, where the relative risk of a disease in a region is estimated from data on observed and expected disease counts and relevant covariates. One crucial component of Bayesian spatial models is their ability to smooth raw indices. In order to explore spatial patterns in relative risk, raw maps of standardized morality ratios (SMRs) are often subjected to spatial smoothing since SMRs from areas with low expected counts will exhibit a relatively large degree of variability, creating artificially elevated risks. Additionally, when used in conjunction with a regression modeling framework, Bayesian autoregressive models allow for the assessment of covariate influence and control for confounding variables, with the resulting inference adjusted for spatial autocorrelation.

Bayesian spatial models based on Markov random fields have found use in a variety of applications ranging from image processing (Besag, York et al. 1991) to econometrics (Anselin 1988) to disease mapping (Lawson 2008), but have not previously been applied to model indices of local food self-sufficiency. There are several key reasons for use of a Bayesian conditional autoregressive (CAR) approach in this context. We define self-sufficiency using an index that compares the ratio of food production to food consumption, analogous to observed versus expected disease counts. Like disease ratios, the self-sufficiency index is susceptible to artificially extreme values in regions with very large or small populations. It is thus desirable to smooth anomalous regions with neighborhood-based spatial models (Lawson 2008), as this enables the borrowing of information across contiguous regions, which then stabilizes the rate estimates, and accommodates spatial correlation when assessing the influence of covariates.

Direct assessment of local food self-sufficiency through construction of a self-sufficiency index is a costly and labor-intensive process, requiring the integration of multiple datasets across different spatial scales (Morrison, Nelson, Ostry 2011a; 2011b). Given the importance of food self-sufficiency data for policy, planning, and health it is useful to estimate a local SSI with available data. Bayesian spatial smoothing models allow us to explore the influence of covariates and develop a predictive model for the SSI using data that are more readily available to government and academic researchers. While the CAR model is not always considered a good choice of predictive model because of the conditional nature of the fitted values (Banerjee, Carlin et al. 2004) in this application it may actually be preferable to estimate local scale food capacity as a function of neighborhood capacity. Choice of spatial units used is the result of data reporting, and a community's food system is heavily influenced by the food systems in neighboring regions. However, the precise definition of neighborhood, and therefore appropriate spatial weights matrix, is not necessarily intuitive.

It is possible to fit an autoregressive model in a frequentist framework (Anselin 1988); however, Bayesian analysis benefits from a fully random (rather than fixed) effects specification for the model parameters, including the spatial correlation and regression coefficients, as well as more straightforward interpretation of model inference and credible intervals (Banerjee, Carlin et al. 2004). Implementing a Bayesian model also allows for inclusion of prior information. While this model is developed with weakly-informative priors, future research could, for example, use posterior distributions from this research to begin their analyses, and propagating information in this way is a major strength of the Bayesian paradigm (Gelman, Carlin et al. 2004). Population-level food consumption and particularly agricultural production are dynamic processes, continually changing over time and space. It would be useful to iteratively update the current state of local food self-sufficiency as new data become available, which could be achieved with the model and data presented in this paper.

The goal of this paper is to demonstrate a Bayesian framework for spatially explicit modeling of agricultural self-sufficiency with available census data. To meet this goal, we address the following objectives:

1. Demonstrate calculation of a raw data driven SSI, which is our response variable.

2. Develop a Bayesian spatial linear model for SSI, with spatial dependence accounted for in the error term, and spatial smoothing of errors defined by four different neighborhood definitions.
3. Develop a Bayesian spatially varying coefficient model for SSI, based on assigning a multivariate CAR prior to model the geographic variability in the coefficients of a regression model (Waller, Zhu et al. 2007; Wheeler and Waller 2008).
4. Compare raw SSI data to model-based predictions to select the an optimal model and highlight advantages of the Bayesian spatial smoothing framework.

4.3 Study Area

The study area for this research is the province of British Columbia in western Canada. All analyses are performed at the Local Health Area level, of which there are 89 in the province. Agricultural data are only disseminated by Statistics Canada in aggregated spatial units in order to protect the confidentiality of the farm operators. Population-level food demand can only be assessed at an aggregated scale. Therefore, we select LHA as a spatial unit as they are small and numerous enough to perform spatial modeling, and yet large enough to minimize mandatory data suppression for confidentiality purposes. In addition, much of the health and food security research in the province is done at the LHA scale, and the Regional Health Authorities (which the LHAs aggregate into) are charged with ensuring the nutritional health and food security of their populations.

4.4 Data

4.4.1 Food production and consumption data

Two specific datasets are required to construct the SSI. First, an assessment of the quantity and types of food produced within the local agricultural system in a meaningful unit, such as tons of edible mass per year. Second, an assessment of local food demand, such as the amount of food the community consumes each year, in comparable units to production. Development and analysis of these databases are described in previous research papers and are outlined briefly here (Morrison, Nelson, Ostry 2011a; 2011b).

To estimate local scale food production, we integrated data from the 2006 Census of Agriculture with survey yield data from several Statistics Canada agricultural survey products:

$$P_i = \sum_{j=1}^{m} A_{ij} Y_j W_j$$

where total food production in the i^{th} region *(P_i)* is equal to the product of the farmland area (or number of animals) in the i^{th} region (A_{ij}) and of the j^{th} food type, multiplied by the associated yield (kilograms per hectare or per animal) for the j_{th} food (Y_j), and multiplied by the proportion of estimated waste associated with the j^{th} food type (W_j), summed for *m* foods.

To estimate local scale food consumption, we combined individual-level estimates for annual dietary intake along by LHA demographic data. Typically, consumption data are provided aspatially. The general approach to spatializing the consumption data was to consider population size in combination with age- and gender-based consumption data from the BC Nutrition Survey in order to allocate expected spatial variation in provincial values across regions of BC. By integrating individual-level food consumption data with demographic population data from each LHA, we were able to estimate population level food consumption that was not purely a function of population size, but also takes into account some regional variation in the consumption patterns:

$$C_i = \sum_{j=1}^{m} \sum_{k=1}^{p} C_{jk} N_{ik}$$

where total food consumption in the i^{th} region (C_i) is equal to the product of food consumption of the j^{th} food category for that age/sex category (C_{jk}) multiplied by the number of people in that age/sex category within the region (N_{ik}).

Our past research on mapping estimates of local scale food production and consumption have lead to new models which can be overlaid to construct a map of the SSI (see Methods). In this paper, these estimates are used to calculate the response variable (SSI) and the maps of the raw SSI are compared to the model-based predicted values.

4.4.2 Census data

Census data were used to develop a model of SSI that used commonly available data. The Statistics Canada Census of Agriculture and Census of Population are performed every 5 years. Some data are released to the public at no charge while others are available to researchers under special academic licensing. To select appropriate covariates, we performed a data-driven correlation analysis with a large number of variables available at the LHA spatial unit from various census data products. To achieve the strongest, most linear relationship possible, we try a variety of log and square root transformations, and report the strongest associations possible.

The two covariate datasets used in this paper are available free of charge at sub-provincial spatial units. *Value of farm capital* is the estimated market value of land, buildings, machinery, and livestock and represents the invested capital per region (Statistics Canada 2010).

Land in crops is the estimated total amount of cropland per region that is producing fruits, vegetables, grains, nursery products or sod (Statistics Canada 2009).

4.5 Methods

4.5.1 Self-Sufficiency Index (SSI)

The SSI is a ratio of local scale food production to consumption (Figure 4.1). The SSI can be interpreted in several ways. The SSI can be considered the theoretical ability for a local agricultural system to produce sufficient quantities of food for their population. The SSI can also be used as a proxy to assess reliance on food imports; assuming that the majority of the regional population is consuming a sufficient diet, then any local region must be importing a minimum of *(1- SSI)%* of their food.

The SSI can be calculated for individual foods, aggregated (summed) into food groups (e.g., fruit, vegetable, meat), or calculated for total food. In this paper we use total food self-sufficiency. We apply a food group-based capped weighting scheme to calculate total self-sufficiency in each region:

$$\overline{SSI}_{total} = \sum_{i=1}^{n} \min\left(SSI_i \times P_i, P_i\right)$$

where P_i is the proportion each food makes up in an average BC diet. For example, since fruits comprise 20% of the average British Columbian diet, fruit self-sufficiency is weighted at $P_i = 0.2$ and cannot contribute more than 20% to the total SSI. Therefore, no region will be over 100% self-sufficiency even if one or more products are overproduced.

4.5.2 Conditional autoregressive models

The conditional autoregressive approach allows for simultaneous spatial smoothing and predictive modeling with covariate data. Regions with more cropland are expected to be more self-sufficient, so it is useful to assess the relationship between capital investment and self-sufficiency while controlling for the effect of cropland. Developing a predictive model with two covariates is a straightforward process as the distribution underlying our dependent variable is well approximated by a log-normal distribution. However, there are two key motivations for considering more complex spatial models for the analysis of SSI. First, using our data, the residuals from an ordinary least-squares (OLS) regression exhibit significant spatial structure, indicating a violation of the independence assumption underlying inference with a standard linear model. Second, we are interested in neighborhood-based smoothing for our raw SSI. Given the arbitrary boundaries of Local Health Areas, the local food capacity of an entire neighborhood of spatial units is of interest. Model-based smoothing will allow us to explore regional variations in neighborhood-based averages, while at the same time studying the relationship between the SSI and our covariates. Here, we outline two spatial models which utilize the conditional autoregressive approach: a spatial linear model which adjusts for residual correlation in the error term, and a spatially-varying coefficient model which allows slope parameters to fluctuate over space. The spatial linear model and the space-varying regression model represent two different approaches for modeling spatial correlation, and thus comparison of the two approaches is of general interest as well.

4.5.3 Spatial linear model (SLM)

We account for the spatial correlation by specifying a multivariate normal distribution for the regression errors, with this distribution having a spatially structured covariance matrix. The spatial structure is based on a proper conditional autoregressive model, and we refer to this approach as a spatial linear model (SLM). In a standard OLS regression, the covariance between response variables Y_i and Y_j is assumed to be zero, an assumption that is inappropriate in the present context. The SLM model relaxes this assumption, and specifies the conditional distribution of the response variable as a function of both the covariates *and* the response values at all other locations within a defined neighborhood:

$$Y_i|Y_{j\neq i} \sim N(\, E[Y_i|Y_{j\neq i}], VAR\left[Y_i\middle|Y_{j\neq i}\right])$$

$$E[Y_i|Y_{j\neq i}] = \mu_i + \rho \sum_{j\neq i} \boldsymbol{W}_{ij}(y_j - \mu_j)$$

$$\mu_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i}$$

$VAR\left[Y_i\middle|Y_{j\neq i}\right] = \sigma^2 / \sum_{j\neq i} \boldsymbol{W}_{ij}$ where Y_i is the SSI at the i^{th} location; ρ is an unknown spatial dependence parameter; σ^2 is an unknown variance component; $\boldsymbol{W}$ is the known weights (neighborhood) matrix; X_1 is the capital regional investment in agriculture; and X_2 is the regional cropland area. The model specification, which is based on conditional distributions, yields a multivariate normal model for $\mathbf{Y} = (Y_1, \ldots, Y_n)'$ (see e.g., Banerjee et al. 2004), with marginal means given by $E[Y_i] = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i}$, so that the regression coefficients retain their usual interpretations. We assign the following weakly-informative prior distributions:

$$\beta_0 \sim N(0, 10000000)$$

$$\beta_1 \sim N(0, 10000000)$$

$$\beta_2 \sim N(0, 10000000)$$

$$\tau = \sigma^{-2} \sim \text{Gamma}(0.001,0.001)$$

$$\rho \sim \text{uniform}(\rho_{\min}, \rho_{\max})$$

where ρ is a scalar value representing the spatial dependence in the model, with hyperparameters $\rho_{\max}$ and $\rho_{\min}$ calculated deterministically as the inverse minimum and maximum eigenvalues of the matrix $\mathbf{M}^{-1/2}\mathbf{C}\mathbf{M}^{1/2}$ (see Lawson 2008; Thomas, Best et al. 2004).

The most popular alternative to the CAR model is the simultaneous autoregressive model (SAR). The CAR model is preferred for more efficient estimation through Gibbs sampling and related procedures, although results from the two models are often similar (Cressie 1993; J. W. Lichstein, Simons et al. 2002). .

The main deviation of spatial autoregressive models from alternatives such as OLS regression is the required specification of a neighborhood structure though the weights matrix $\boldsymbol{W}_{ij}$. The choice of weights matrix impacts model parameter estimation, degree of smoothing, and model fit (Earnest, Morgan et al. 2007). Exploring this impact in-depth is beyond the scope of this paper; however, rather than arbitrarily selecting a conventional neighborhood definition, a selection of reasonable weight matrices (1st order contiguity, 2nd order contiguity, 4 nearest neighbors, and 8 nearest neighbors) will be compared, providing a brief sensitivity analysis. Nearest neighbors are measured from polygon centroids.

4.5.4 Spatially varying coefficient model (SVCM)

As an alternative approach to accommodating spatial variability, we consider a spatially varying coefficient model (SVCM). Here, the regression coefficients of a linear model will vary across geographical regions, and these coefficients are modeled as spatially correlated random effects, so that the regression model is:

$$Y_i = \beta_0 + (\beta_1 + \beta_{1i})X_{1i} + (\beta_2 + \beta_{2i})X_{2i} + e_i$$

$$e_i \mid \tau \sim N\left(0, \frac{1}{\tau}\right)$$

where τ is the precision (inverse variance) of the errors; β_1 and β_2 are baseline parameters representing the overall mean of the regression coefficients; and $\boldsymbol{\beta_i} = (\beta_{1i}, \beta_{2i})'$ are region specific random effects accommodating geographic variability in the regression model. To model this variability, we adopt an intrinsic multivariate CAR (MCAR) prior based on the conditional specifications:

$$\boldsymbol{\beta_i} | \boldsymbol{\beta}_{(-i),} \sim MVN\left(\overline{\boldsymbol{\beta_i}}, \frac{\boldsymbol{\Omega}}{m_i}\right), i = 1, \dots, n$$

where Ω is a 2-by-2conditional covariance matrix, m_i is the number of neighbors for area i, and $\overline{\boldsymbol{\beta_i}}$ is:

$$\overline{\boldsymbol{\beta_i}} = \sum_{\boldsymbol{j} \in \boldsymbol{k_i}} \frac{\boldsymbol{\beta_j}}{m_i}$$

where k_i is the set of neighboring areas for region i and the spatial neighborhood structure is determined from the results from the SLR. We assign the following weakly-informative prior distributions:

$$\beta_0 \sim \text{uniform}(,)$$

$$\beta_1 \sim N(0, 100{,}00{,}000)$$

$$\beta_2 \sim N(0, 100{,}00{,}000)$$

$$\tau = \sigma^{-2} \sim \text{Gamma}(0.001{,}0.001)$$

$$\boldsymbol{\Omega} \sim \text{Wishart} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

Our Bayesian models were fit to the data by sampling the associated posterior distributions using Markov chain Monte Carlo (MCMC), with implementation in WinBUGS

(Lunn et al 2000). In all analyses, two parallel MCMC chains were run for a 10,000 iteration burn-in period followed by a production run of 40,000 iterations. Convergence of the samplers to the corresponding stationary distributions was assessed using both visual inspection of the posterior sampling history, and the Gelman-Rubin statistic (Gelman et al., 2004). Model selection was based on the deviation information criterion (DIC), which combines the deviance with a penalty for model complexity (Spiegelhalter, Best et al. 2002).

4.6 Results

4.6.1 Mapped Self-Sufficiency Index (SSI)

The raw SSI shows considerable spatial variability in local food capacity throughout the province of BC (Figure 4.2). Some regions (e.g., lower mainland in the southwest corner) appear to have groups of regions with high SSI while most of the remaining LHAs appear to have low SSI. The SSI data quantify how well each individual LHA can meet the populations' food demands with the existing agricultural system.

4.6.2 Spatial Linear Model

An analysis for suitable covariates finds that the vast majority of data from the Agricultural Census and Population Census (such as population size and population density) are insignificantly correlated with the SSI. A selection of significant variables ($p < 0.05$) are displayed in Table 1, the majority of which have a weak or non-linear relationship with the SSI. The exception is two variables very strongly correlated, linearized by log-transformations: regional capital investment in agriculture, and regional cropland area.

The parameter estimates from the SLM suggest that the regional capital investment in agriculture and regional cropland area are strongly associated with regional self-sufficiency; in a non-spatial ordinary regression model, the coefficient of determination is 0.754, suggesting that 75.4% of the variation in self-sufficiency can be explained by capital investment and regional cropland area. To assess model fit in the SLM, we calculate the root mean square error (RMSE) to be used as an approximation to the number of deviations from cross-area predictions. The posterior mean and 95% credible interval for the RMSE is 0.781 (0.760, 0.832). Given our data units, this is a low RMSE, suggesting an overall good level of model fit (MacNab 2003). The DIC from a non-spatial regression model is higher (DIC = 454) than from the spatial models, suggesting that the spatial models provide a more optimal combination of fit and parsimony. Achieving a good level of model fit increases the predictive potential for these models.

Since both the explanatory and response variables have been log-transformed, we can interpret the parameters in the SLM as “elastic” (Greenberg 2008). Therefore, a 10% increase in capital investment could potentially yield a 0.5% increase in self-sufficiency, holding constant the effect of cropland. Likewise, a 10% increase in cropland area could potentially increase self-sufficiency by 5%, holding constant the amount of invested capital (Table 4.2).

The maps of predicted SSI show smoothing as a result of the neighborhood-based conditional autoregressive model. Level of smoothing can be impacted by neighborhood structure; these data appear robust to neighborhood definition as each smoothed map is similar in overall spatial pattern.

The mean of the posterior distribution for each parameter along with its 95% credible interval is given in Table 2. The posterior distributions of the regression coefficients are impacted by neighborhood definition to a mild degree but do not change significantly in magnitude and do not change sign. The 95% credible interval for the intercept spans zero, which seems reasonable since regions without cropland and capital investment would have no self-sufficiency. All other parameters, while relatively small in magnitude, have 95% credible intervals that exclude zero, and therefore the associated covariates be considered significant for these data. The models with neighborhood structure based on first order contiguity and four nearest neighbors are selected as most appropriate based on DIC, while second order contiguity and eight nearest neighbors are not as well supported by the DIC.

The smoothed SSI maps suggest that the north-central (Peace River) section of the province, the Okanagan, the far south-east, and the lower mainland (Fraser Valley) do relatively well in total food self-sufficiency compared to other regions of the province, such as Vancouver Island, the western coast, and the remainder of the interior (Figure 4.3). However, while some regions do have SSI over 75% in the raw dataset, the CAR model averages most of this data out over space, suggesting that regions with very high SSI tend to be surrounded by regions with relatively low SSI. Clusters of strong local food production systems (relative to local food demand) are rare in BC.

4.6.3 Spatially Varying Coefficient Model

The SVCM based on first order polygon adjacency allows the relationships between the covariates and the SSI to vary over space. Figure 4.4 shows maps of the posterior mean parameter estimates expressed as standard deviations from the mean (non-spatially varying) parameter estimate, as we are interested in how significantly these parameters deviate from this mean over space.

The capital investment parameter is substantially larger than the mean parameter estimate in the central interior region of the province. The relationship between capital investment and SSI is strong in these regions, with smaller increases in invested capital potentially leading to larger increases in SSI, relative to other regions of the province. The north-western and north-oastal regions have essentially no farming systems and approximately zero self-sufficiency, explaining why these regions have anomalous relationships relative to the mean provincial parameter estimate (Figure 4.2). The Peace River, lower mainland and north-central regions of the province have capital investment slope estimates very similar to the provincial average (Figure 4.4).

The relationship between regional cropland area and SSI does not vary greatly over space with a few exceptions; notably, the lower mainland has coefficients which are close to or higher than the provincial average parameter estimate, while the majority of the province has a smaller magnitude relationship between cropland area and SSI. Compared with the SLM, the SVCM results in a higher value of the DIC for these data (DIC = 444.6), indicating that the increase in model complexity does not lead, in this case, to a sufficient improvement in the model goodness-of-fit. Thus, for our application it seems that accommodating spatial variability through regression errors, as opposed to through the regression coefficients, leads an improved representation of the data. The SVCM appears to over-predict the SSI in some regions, particularly the Okanagan and lower mainland, and under-predict the SSI in other regions (Figure 4.2, 4.5).

4.7 Discussion

The raw SSI data mapped in this paper, based on previously developed GIS estimates of these parameters (Morrison, Nelson, Ostry 2011a; 2011b), show the spatial trends in LHA-level food production capacity relative to food demand. Understanding relative supply and demand of local foods in British Columbia is hindered by a lack of available data, and this is a common problem elsewhere in the country. Methods development for estimating self-reliance capacity (such as the SSI) are needed, but based on the data currently available, such methods will require considerable expense and time investments. While more local scale data would be ideal, it seems unlikely that these data will be readily available in the foreseeable future. In this paper, we have proposed a potential alternative by providing a predictive model for estimating regional SSI based on more readily available datasets. The correlation between the SSI and each of capital investment and regional cropland area are very high, and together the multivariate model results in a good potential predictive ability. More research is needed to determine if the relationships observed in this paper will hold at other spatial scales, or in other provinces of the country.

Given the nature of the geographic data necessary to assess local food capacity over space, traditional regression methods are inappropriate as our data and regression errors are not identically and independently distributed (Cressie 1993). The spatial regression models employed in this paper are two reasonable options for working with spatially correlated data and are widely used in the literature (Lawson, 2008; Waller et al. 2007; Wheeler and Waller, 2008; MacNab 2003). Spatial dependence is introduced either through explicit definition of spatial neighborhoods in the error term (the SLM) or through allowing the parameters to vary over space (the SVCM). The definition of spatial neighborhood in the SLM has a relatively small impact on parameter estimation and level of smoothing but does impact model fit based on DIC.

It is likely that the spatial structure in the four nearest neighbors and first order polygon contiguity definitions are similar, resulting in similar model fit. In the context of assessing local food capacity, regions sharing a common geographic border more likely to have integrated agricultural production systems, and therefore we select first order polygon contiguity as the neighborhood definition for this paper. Defining first order adjacency is likely the most common neighborhood definition used in research, particularly in Bayesian spatial models where it is the only default weight matrix provided by the popular freeware WinBUGS (Spiegelhalter et al., 2003). Based on our data, we find that the slope parameters do not seem to vary significantly over space, based on comparisons with the SLM. The SLM is selected as the best based on model fit and complexity, with considerable improvements over a non-spatial model and the SVCM.

Another considerable benefit to the SLM is the smoothing property (Lawson, 2008). The SSI is susceptible to exaggerated self-sufficiency rates in areas with small populations. As with epidemiologic data, agricultural production and food consumption data are only available in aggregated ecological units. The choice of spatial unit is usually driven by data availability, but may or may not be particularly meaningful for the context of the analysis, given the arbitrary nature of political boundaries. For example, the LHAs used in this paper are useful spatial units for studying local food capacity, since they are the unit at which food security policy is implemented. However, the land area of LHAs is inversely proportional to their population, therefore regions with larger populations to feed will have a small land base with which to produce food, and vice versa. The CAR model allows for neighborhood-based smoothing so that the predicted self-sufficiency is a function not only of the covariates, but also of the self-sufficiency in the neighboring regions. Clusters of LHAs with high SSI retain an overall high SSI while areas with mostly low values along with few anomalous highs are averaged out, and vice-versa. For example, the mapped raw SSI shows spatial variability but it is difficult to assess overall provincial spatial pattern disentangled from the LHA scale. The smoothed maps indicate that there are pockets of relatively strong local food capacity with areas of poor or no capacity. There are no regions which are 100% self-sufficient and most regions do not have enough nutritional variety to sustain a local diet for more than a relatively small subset of the population. Both the raw SSI and smoothed predicted data suggest that local food capacity in the province is low.

Our regression model uses only two covariates. Adding additional variables could potentially improve model fit; however, one goal of this research is to build a predictive model for estimating self-sufficiency in different provinces or at different spatial scales. Achieving the most parsimonious model is desirable to minimize input data requirements. The CAR approach is a good choice of predictive model for this application, spatial units used will likely be arbitrary, and a community's food system is heavily influenced by the food systems in neighboring regions.

The raw and modeled SSI maps presented are based on total food using a capped weighted average. In some applications, researchers or government officials may prefer to map or model individual food groups such as fruits and vegetables versus meat and dairy, which would be straightforward to implement and would allow for overproduction to be included in the model.

The food production data estimate the amount of edible mass produced by the existing agricultural system in the province. The SSI represents the current ability for the amount of food production to feed local populations. The concept of local food capacity could also encompass the potential for unused agricultural land to become productive, or existing land to be reassigned to produce different products. For example, if a small portion of the land used as livestock pasture were reassigned to fruit and vegetable production, the provincial average self-sufficiency rates may increase dramatically. However, this would depend on the agricultural potential of soils and climates at a local scale. Using remotely sensed datasets could aid this type of analysis (Hatfield, Hitelson et al. 2008).

The food consumption data estimate the amount of food actually consumed by the local population. Food consumption data could instead be based on recommended diets coming from nutritional authorities such as the Canada Food Guide or American Food Pyramid (Kantor and Young 1999). Further research using additional data sources could provide a more complete picture of the true potential for local systems to support local communities while improving public health.

4.8 Conclusion

Interest in small scale agriculture and local diets has become a global phenomenon, but British Columbia is an original area of activist, academic, and political interest in local food. If provincial health authorities are implementing policies encouraging the consumption of local foods, then BC should also lead the way in local food security research, from assessing the current and future production potential, the limitations of promotional policies, and the social, ecological, and economic implications of a large-scale shift to agricultural self-reliance. In order to tackle these important questions, we must begin with basic understanding of supply and demand; not only as a province, but also at the local scale.

The methods developed in this and the two supporting papers (Morrison, Nelson, Ostry 2011a; 2011b) provide a framework for 1) assessing local scale food capacity directly, using the best available data and 2) modeling the SSI to assist in understanding spatial patterns through model-based smoothing, understanding the relationship between our SSI and relevant covariates, and presenting a potential predictive model. We utilize spatial regression techniques given our spatially explicit data. It is our hope that these data and model based approaches are useful for researchers interested in local scale food capacity, and that methods continue to be developed for this extremely important under-researched area.

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Table 4.1: Correlation analysis for suitable covariates. Correlations are significant at α = 0.05. Descriptions based on a visual assessment of scatterplot.

Variable	Pearson Correlation	Description
Wheat (hectares)	0.4	Non-linear
Corn (hectares)	0.2	Weak, non-linear
Hay (hectares)	0.15	Non-linear
Fruit (hectares)	0.37	Non-linear
Cropland (fruit, vegetable, and grain)	**0.86**	**Very linear, strong**
Pastureland (hectares)	0.14	Very weak
Irrigated field crops (hectares)	0.51	Non-linear
Irrigated vegetables (hectares)	0.4	Weak
Greenhouse (sq meters)	0.41	Weak
Poultry production (kilograms)	0.42	Weak
Number of cattle (number)	0.36	Non-linear
Capital investment (dollars)	**0.78**	**Very linear, strong**

Table 4.2: Comparison of posterior means of model parameters and model fit measures between neighborhood definitions in the SLM CAR model. 95% credible intervals in parentheses.

Neighborhood Definition	**Contiguity 1st order**	**Contiguity 2nd order**	**4 Nearest neighbors**	**8 Nearest neighbors**
DIC	332.981	427.957	332.117	393.9
β_0	-0.018 (-0.51,0.49)	0.053 (-0.46,0.59)	0.008 (-0.43,0.44)	0.0086 (-0.44,0.45)
$\beta_{1\ (capital\ investment)}$	0.071 (0.029,0.11)	0.064 (0.021,0.10)	0.055(0.017,0.094)	0.055 (0.019,0.093)
$\beta_{2\ (cropland\ area)}$	0.44 (0.28,0.59)	0.44 (0.31,0.58)	0.52 (0.37,0.68)	0.53 (0.37,0.68)

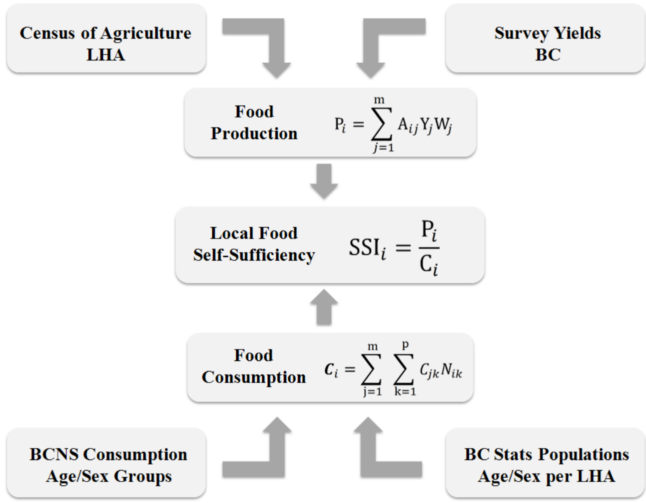

Figure 4.1: Flowchart of data integration and overlay to construct the SSI.

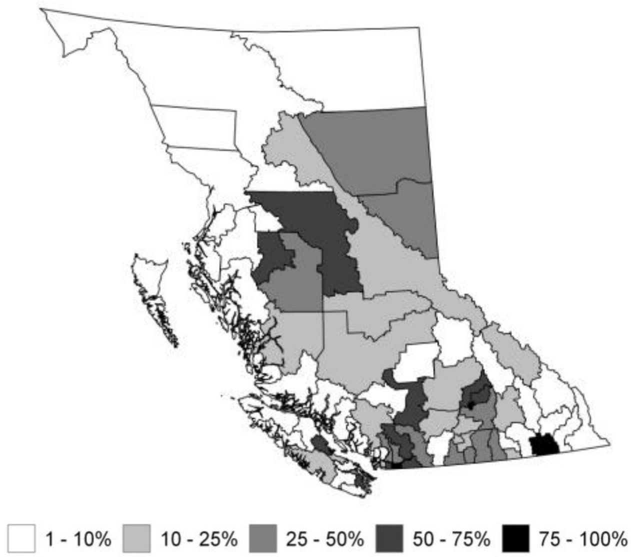

Figure 4.2: Map of raw SSI data.

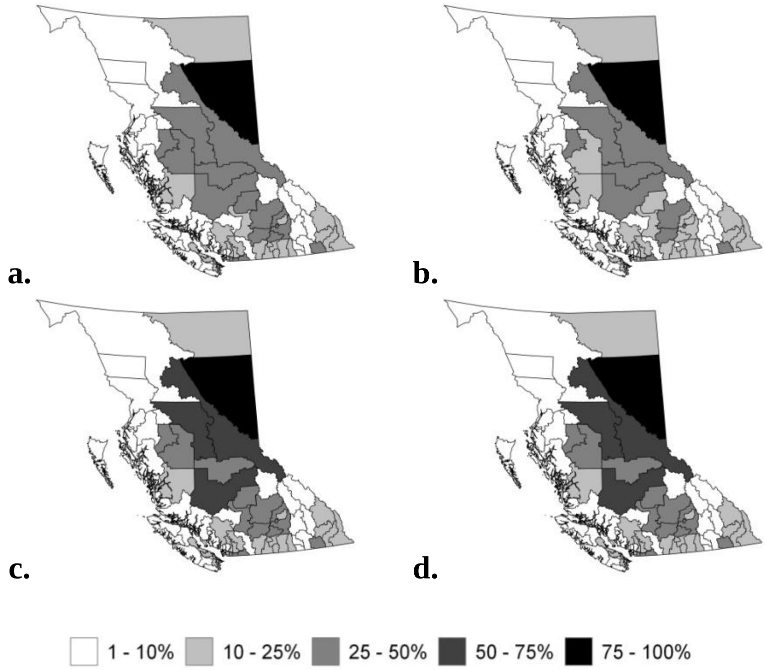

Figure 4.3: Maps of predicted SSI from SLM with selected neighborhoods. a = 1st order Queens contiguity, b = 2nd order Queens contiguity, c = 4 nearest neighbors, d = 8 nearest neighbors.

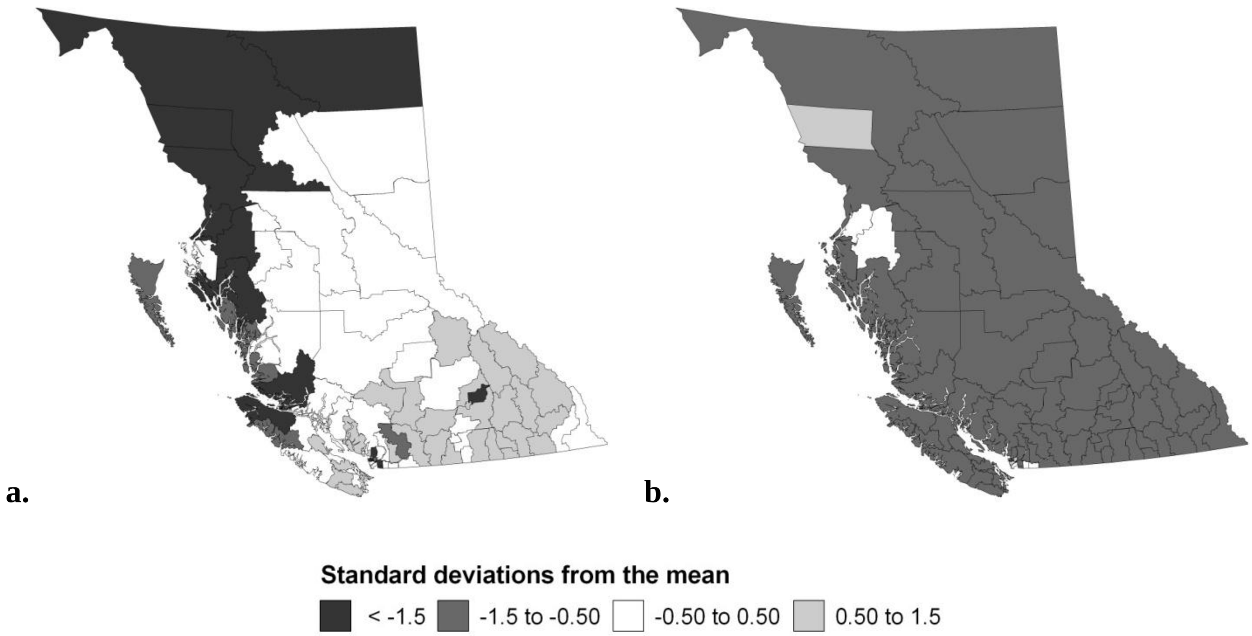

Figure 4.4: Maps of spatially-varying coefficient β1 (investment, a) and β2 (cropland, b).

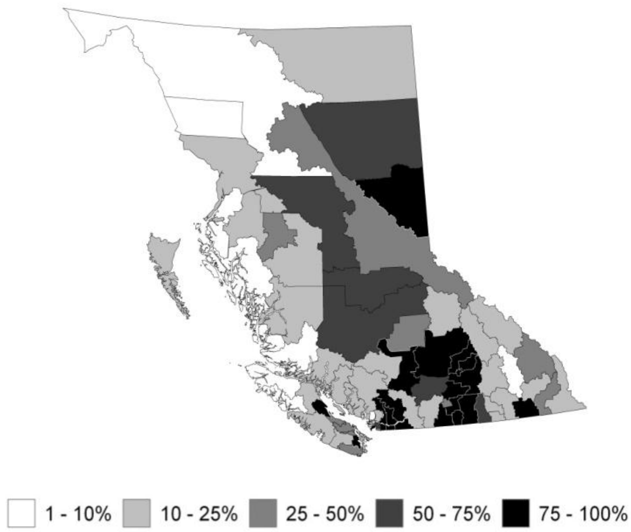

Figure 4.5: Maps of predicted SSI from SVCM.

5.0 CONCLUSIONS

5.1 Discussion and Conclusions

Assessing local scale agricultural capacity is a challenging but important endeavor, given the widespread popularity of the "local foods" movement now promoted by community groups, activists, and government officials. The development of novel methods is needed for empirically assessing the viability of meeting nutritional needs at a local scale, particularly over a large area. Previous research has performed case studies on small areas (Vancouver Food Policy Council 2009), or large areas at an aggregate (provincial or national) scale (Riemann 1987; BC Ministry of Agriculture and Lands 2006). Small-area studies are generally not consistent in data collection methods and therefore cannot be extrapolated to other regions, while aggregate-scale studies are not relevant for local scale analysis. The goal of this research was to develop, map, and model an index of self-sufficiency for local scale food assessment across BC. I addressed this by: 1) estimating food production at the local scale, in units of edible mass, 2) assessing food demand or consumption, in the same units of edible mass, and 3) calculating local food self-sufficiency as the ratio of production to consumption.

In Chapter 2, I find that agricultural farmland is highly regionalized on a product basis. Regionalization is a negative finding for local food security, as many regions in the province produce significant quantities of only one or two food groups. Most regions do not contain enough nutritional variety to form a complete diet. Even if the "local" definition is expanded to include the entire province there is a food distribution issue, with rural and remote regions far less self-sufficiency than areas close to the urban center of Vancouver. Since rural and remote regions are already at an increased risk for food insecurity, the spatial distribution of food production is noteworthy to researchers interested in food insecurity and food access issues.

In Chapter 3, I integrated data from the BC Nutrition Survey with demographic data to assess local food demand through an annual assessment of population-level food consumption. I found that the spatial distribution of food consumption is highly dependent on demographic characteristics of the population (age and gender). Men and women consume different quantities of food throughout their lives, and the distribution of these groups is significantly different across LHAs in the province. Northern areas which are rural or remote have much younger populations than the provincial average; since food consumption is highest in the younger years, these populations consume more food than is expected. Given the increased risk for food insecurity in these regions, this is once again a noteworthy finding for researchers interested in the geographic and socio-economic drivers of food access issues and food insecurity.

In Chapter 4, I calculate the ratio of food production and consumption, using the datasets constructed in Chapters 2 and 3 to map and model the spatial distribution of local food self-sufficiency throughout the province. The mapped raw SSI and the neighborhood-smoothed predicted estimates both show that self-sufficiency is only strong in a small subset of areas, clustered in the lower mainland and Peace River regions. The majority of the province (76 out of 89 LHAs) are below 50% self-sufficient in total food, and nearly half are below 10% self-sufficient. If health and agricultural policies in the province are promoting the benefits of local food consumption, then an analysis of the existing agricultural system is essential. My research serves as a case study and analysis framework for a large-scale empirical analysis of local food systems, which can be expanded to other provinces in Canada and likely other regions of the world.

5.2 Research Contributions

The research in this thesis contributes to a relatively new body of literature on the analysis of local foods (Anderson and Cook 2000; Lapping 2004; Feagan 2007; Peters 2009; Kremer and DeLiberty 2011). An index of self-sufficiency is a new idea, providing a framework with which to map variation in local scale food production relative to food consumption or demand. Constructing this index required integration of multiple datasets and several different types of analysis, therefore each thesis chapter is distinct and utilizes different datasets; however, all chapters rely heavily on geographic theory and methods of spatial analysis, offering an opportunity for several key contributions to the field of local food system analysis, and some in the more general field of spatial analysis.

Spatial cluster analysis has not been previously used in the assessment of local food self-sufficiency. Using measures of spatial autocorrelation allowed for two key contributions. First, it quantified the level of spatial clustering present in farmland data at a sub-provincial scale, showing that agricultural production (disseminated only as provincial totals) is significantly clustered to small areas for individual agricultural products. Without spatial analysis, local scale estimates could not have been constructed from aggregated data. Since agricultural data are so often disseminated from statistical authorities aggregated beyond a meaningful local scale, developing a method to estimate local-scale production by integrating databases is a unique contribution to local food systems analysis. Second, spatial cluster analysis was used to highlight and quantify significant spatial patterns in food consumption in BC. Using a spatial framework to assess local scale food demand, I discovered that food consumed throughout the province depends heavily on the spatial distribution of demographic variation throughout the province; as well, I characterized significant clusters of previously under-estimated and over-estimated consumption rates. Previous research has relied on national averages applied to local scale populations (Vancouver Food Policy Council 2009), therefore this spatially-varying demographic-driven approach is a significant improvement.

Chapters 2 and 3 provide methodological details for the construction of the SSI, demonstrating the substantial time and expertise required. A predictive modeling framework offered a potential alternative for estimating food self-sufficiency with covariate data that are readily available to researchers, government officials, and even the public. A Bayesian framework benefits from a random-effects approach to parameter estimation as well as well as specification of prior information. As new agricultural and demographic data become available, models like the ones presented in this thesis can be iteratively updated to reflect the current state of self-sufficiency, while benefiting from knowledge gained in the previous model.

In addition to predictive modeling, the conditional autoregressive approach specifically benefits from neighborhood-based spatial smoothing. When rates are mapped across areas, it is advantageous to smooth areas with small populations, which may be artificially elevated. The spatial models borrow strength from neighbors through conditional specification of parameter estimates, stabilizing the spatial distribution of the predicted values. Applying models traditionally used to smooth disease and crime incidence rates to measures of local food self-sufficiency is a unique application, expanding the potential uses for these models.

Finally, the methodological implications of the findings in Chapter 4 are of general interest in the field of spatial analysis. A huge variety of spatial regression models are used for spatial data, such as spatial error models (e.g., the SLM), spatial lag models, geographically weighted regression, and spatially-varying coefficient models founded on multilevel modeling statistical theory (Waller, Zhu et al. 2007). The motivation for use of any spatial regression model is spatially explicit data with residual spatial correlation from ordinary regression techniques. While the statistical framework for these models is very different, they all require spatial neighborhood definitions through specification of a weights matrix (Waller, Zhu et al. 2007; Wheeler and Waller 2008). The geographic literature has shown that this specification can have a significant impact on model fit, level of smoothing, and even model inference (Earnest, Morgan et al. 2007). In spite of this, choice of neighborhood is almost exclusively left to defaults, particularly in Bayesian applications where first-order polygon contiguity is the only available option in the common freeware WinBUGS (Thomas, Best et al. 2004). Additionally, comparisons between various types of spatial regression models are rarely done, and justification for choice of model or neighborhood definition is rarely mentioned. Chapter 4 compared two commonly used spatial models in a Bayesian autoregressive framework: a spatial linear model with residual correlation specified in the conditional error term, and a spatially varying coefficient model with correlation introduced into the model parameters that are allowed to vary over space. The results suggested that the former model performed significantly better than the latter. Also, a brief sensitivity analysis was performed on the SLM to investigate the impact of changing neighborhood definition, finding that it significantly impacted model fit (assessed as a function of model deviance) but not level of smoothing or parameter estimation to any significant degree. Selection of a suitable model should not be arbitrary, but rather there needs to be more investigation to determine the correct type of spatial model for different types of data and applications.

5.3 Research Opportunities

The databases constructed and methods developed in this research are fundamental to more sophisticated analyses of local food systems. The potential directions that further research could take are numerous. To estimate the SSI, I took a snapshot in time of food production and food consumption for one year (2006) in one province. I also assumed that food production only occurred on already productive large-scale agricultural operations included in the Agricultural Census. Small-scale farming, underground operations, urban agriculture, and community gardens were not included in any of the analyses, nor was the productive potential of marine products (farmed or wild) for coastal communities. It would be useful to include these additional types of food production, if data could be collected consistently over a large area. As well, the productive potential of unused farmland could be explored with remotely sensed imagery. Estimating agricultural yields and productivity over large areas from satellite imagery is a rapidly developing field, directly relevant to local food assessments (Salazar 2007; Hatfield, Hitelson et al. 2008).

Food consumption was calculated to assess current local demand, but alternative methods could provide additional insights. For example, some research has conducted aggregated analysis on domestic production (at a federal level) compared to idealized consumption based on prescribed diets (Kantor 1998; Duxbury and Welch 1999). Constructing consumption data for different diets (such as the Canada Food Guide, or vegetarian versus meat-centric diets) could show whether local food promotions align with nutritional promotions for healthy eating. Assessing consumption in this way could directly lead to assist policy analysts in whether agricultural policy levers could or should be used to improve population nutrition (Kantor and Young 1999).

One key limitation of this research is the spatial unit definition of LHA, which are political boundaries that differ substantially in size and do not correspond to meaningful agricultural boundaries. Exploration of the spatial variation in the SSI at different scales is noteworthy, but it may be difficult to find a meaningful political unit since food is produced and consumed continuously over space. In 2009, Peters et al. developed a spatial optimization model to define the spatial extent of local *foodsheds*, which are boundaries delineating a closed self-sufficient area (Peters 2009). Allowing the spatial boundaries to vary based on a function which minimizes distance from production is an improvement over arbitrary political boundaries.

The two spatial models presented in chapter 4, the spatial linear model (SLM) and spatially varying coefficient model (SVCM), provide a Bayesian autoregressive framework to simultaneously smooth and predict local scale food self-sufficiency. As explored above, various methods could improve local food production and consumption calculations. Once this is performed, stabilizing the raw indices with smoothing models and exploring productive modeling will again be a useful step. Spatial models could then be improved upon or further validated. Exploring the impact of the modifiable areal unit problem on self-sufficiency by changing spatial scales is of interest, particularly to see if the correlation analysis performed in Chapter 4 is robust to scale change. Next, expanding the modeling to other time series (historic estimating or future forecasting) and other provinces (spatial extrapolation) will be of interest, to determine if the relationship between SSI and covariates still holds. Comparisons of SVCM to geographically weighted regression and spatial linear models with non-Gaussian errors could potentially improve the model fit. A lack of available local-scale agricultural data is often cited as a reason preventing the analysis of local scale agriculture; the methods and models presented in this thesis could potentially address this gap.

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