

THE USE OF GEOGRAPHIC INFORMATION SYSTEMS (GIS): MAPPING FAST
FOOD RESTAURANTS (FFR), BMI, AND MENTAL HEALTH

A Thesis

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Abstract
of
THE USE OF GEOGRAPHIC INFORMATION SYSTEMS (GIS): MAPPING FAST
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The present study examined the relationships of fast food restaurant (FFR) density and proximity, Axis 1 psychiatric disorders, and gender to body mass index (BMI), using geographic information systems (GIS). The sample ($N = 123$) included adult patients primarily diagnosed with mood disorders (73%), female (63%), Caucasian (51%) and Hispanic (41%), and obese (55%) with an average BMI of 31 ($SD = 7.06$). On average, participants had access to 22 FFRs within two miles of their home. Findings were non-significant: FFR density and BMI were not correlated; BMI did not differ for those with primary mood disorder diagnoses versus other primary diagnoses; and women's BMI values were not differentially related to proximity to FFR. Despite the lack of significant findings, the use of GIS to examine environmental factors influencing obesity and mental health status has great potential. Future studies should include a sample with more variability on relevant risk factors.

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Chapter 1

INTRODUCTION

The escalating prevalence of overweight and obesity among adults is a leading public health concern in the United States (Wyatt, Winters, & Dubbert, 2006).

Overweight is defined as a body mass index (BMI) of 25 to 29.9 kg/m², and obesity is defined as a BMI of ≥ 30 kg/m² (CDC, 2012a). The BMI calculation is used to more accurately account for weight differences attributable to overall body habitus. For example, a BMI of 30 is equivalent to 221 lb. in a 6'0" person or 186 lb. in a 5'6" person (Expert Panel, 1998). The most recent surveys have revealed that 35.7% of adults in the US are considered obese (CDC, 2012b). If obesity rates continue on their current trend in the United States, by 2030, rates of obesity for adults could exceed 44% in every state and 60% in 13 states (Trust for America's Health, 2012). This epidemic is associated with increased death rates through its effects on heart disease, cancer, and diabetes and costs the US an estimated \$150 billion a year (CDC, 2011a).

Health care providers and researchers have expressed concern that the increase in eating food prepared away from home has contributed to the growing epidemic of obesity in the United States (French, Story, & Jeffery, 2001). Several studies have demonstrated that regular consumption of fast food, in particular, can lead to higher BMI scores, obesity, and related illnesses (Jeffery & French, 1998; Thompson et al., 2004). Most Americans live a fast-paced lifestyle and often value convenience over nutrition. Eating patterns have changed over the last several decades in the US, with an estimated annual

spending of \$110 billion in 2010 on convenience food (i.e., fast food) compared to \$6 billion in 1970. In addition to increased spending on fast food, the number of fast food restaurants (FFR) has increased; for example, the number of FFRs in California has increased from 27,082 in 2000 to 34,817 in 2010 (Census Bureau, 2013b). These changes parallel the increase in rates of overweight and obesity (Schlosser, 2001).

Obesogenic Environment

This study is centered on the concept of the “obesogenic environment.” This includes the entirety of environmental influences that promote obesity in individuals or populations (Swinburn, Egger, & Raza, 1999). The elements of an obesogenic environment consist primarily of barriers to maintenance of a healthy weight (Swinburn et al., 1999). For example, the physical environment (climate, topography, land use, etc.), laws, policies, costs, social attitudes, and values can be considered barriers for maintenance of healthy weight (Swinburn et al., 1999). The *2012 County Health Rankings* report ranks counties based on their health outcomes and health factors measures. The county health outcomes and health factors rankings, in turn, are based on equal weighting of mortality, morbidity, health behaviors, clinical care, social and economic factors, and physical environment measures (i.e., access to recreational facilities, access to healthy foods, and percentage of fast food restaurants) (County Health Rankings, 2012). The sample of patients who participated in this study came from Tulare County, CA, a county likely to have an “obesogenic environment” when one considers its overall *County Health Ranking* of 47 out of 57 California counties (California has 58 counties, but Alpine County was not included in the county health rankings) (County

Health Rankings, 2012). In addition to the overall rankings, the 2012 County Health Rankings provides a separate ranking on the physical environment (i.e., drinking water safety, access to recreational facilities, access to healthy foods, FFR density); on this measure, Tulare County is ranked at 51 out of 57. With such a low *County Health Ranking*, Tulare County can be considered to have an obesogenic environment, since many of the measures used in the ranking methodology are linked to overweight and obesity.

Key Elements of an Obesogenic Environment

The current study will explore one of the potentially obesogenic elements of Tulare County, the presence and availability of FFR. Tulare is a rural county in which 31% of the population is obese; this is slightly higher than the average obesity rate of 29% ($SD = 4.03$) found in its twenty-four peer counties (defined as counties that are similar in frontier status, population size, sociodemographic factors, and poverty level) (Community Health Status Indicators, 2009; County Health Rankings, 2012). Tulare County has a high percentage of FFRs, with 51% of all the restaurants in the area considered FFRs; nationally, 27% of all restaurants are considered FFR (County Health Rankings, 2012). The accessibility of FFRs in Tulare County may increase obesity risk for county residents. This study will test the relationship between FFR density and BMI, the relationship between depression status and BMI, and the impact of gender on the relationship between living in close proximity to a FFR (i.e., 0.25 miles or 0.50 miles) and BMI.

Income and education. Many urban low-income racial and ethnic minority group members live in obesogenic environments (Hill & Peters, 1998), which have an abundance of small food stores but few supermarkets (Franco et al., 2009; Larson, Story, & Nelson, 2009; Morland, Wing, Diez, & Roux, 2002). Income and education have been identified as socioeconomic factors related to obesity (Cohen, Rehkorf, Deardorff, & Abrams, 2013). Higher fruit and vegetable consumption and better health outcomes are generally associated with higher education and higher income levels (Lutz, Blaylock, & Smallwood, 1993; Michaud et al., 1998). Turrell, Hewitt, Patterson, Oldenburg, and Gould (2002) found that the least educated, those employed in blue-collar occupations, and members of low-income households purchased fewer types of fruits and vegetables than their more educated counterparts. Individuals from socioeconomically disadvantaged backgrounds were less likely to purchase grocery store foods that were high in fiber and low in fat, salt, and sugar (Nestle & Nesheim, 2012; Turrell et al., 2002). Diets high in fats and sweets represent a low-cost option to the consumer, whereas the recommended "prudent" diets based on vegetables, fruit, whole grains, poultry, and fish cost more (Drewnowski, Darmon, & Briend, 2004). Eating fast food is an unhealthy alternative for low-income individuals who cannot afford to eat healthy foods, and this behavior may be a key factor influencing obesity rates in the US.

Food costs represent a significant barrier to dietary change, especially for low-income families (Michaud et al., 1998; Papadaki & Scott, 2002). Epstein (2010) reported that the cost of healthy foods such as fruits and vegetables has increased almost 200 percent since 1983. The cost of unhealthy foods, however, has increased to a lesser

extent. For example, carbonated drinks cost only 30 percent more than they did in 1983, and sweets have increased in cost by just 65 percent (Epstein, 2010). Many Americans are considered “food insecure” because their access to food may be unreliable due to lack of financial resources; access to healthy foods may be particularly compromised, as well as their ability to live an active and healthy life (Pringle, 2013). When an individual has limited resources for purchasing food, having a cheap meal with large portions and more calories, such as those available in FFR, may take priority over the nutritional value of the meal (Logdberg et al., 2004; Young & Nestle, 2002).

Access to FFRs. Overall, poorer communities are at an elevated risk for obesity, and access to and availability of FFRs is higher in these communities compared to wealthy communities (Lewis et al., 2005). Health risks linked to obesity and diabetes prevalence were found to be correlated with increased access to FFRs (Ahern, Brown, & Dukas, 2011; Fleischhacker, Evenson, Rodriguez, Ammerman, 2010). *Food deserts* are areas characterized by relatively poor access to healthy and affordable food; these may contribute to social disparities in diet and diet-related health outcomes, such as cardiovascular disease and obesity (Cummins, 2007; Cummins & Macintyre, 2002; Wrigley, 2002; Zenk et al., 2005). There is strong evidence that both access to FFR and residing in a food desert correlate with a higher prevalence of overweight, obesity, and premature death (Ahern et al., 2011; Taggart, 2005; Schafft, Jensen, & Hinrichs, 2009).

Researchers have developed a number of methods for studying the influence of fast food access on obesity. Fast food access is generally measured in one of four ways: coverage, proximity, density, or ratios—all of which can be assessed using geographic

information system (GIS). *Coverage* refers to the number of different fast food opportunities within a specific distance. *Proximity* refers to the distance between an individual's residence, work place, or school, and a fast food location. Fast food *density* is a measure of the number of fast food restaurants per square mile within in a designated area, such as a county. *Ratios* of fast food outlets compare the number of fast food sources to the total number of restaurants in a specific area (Fleischhacker et al., 2010; Sharkey, Johnson, Dean, & Horel, 2011). This study used coverage, proximity, and density to study the influence of FFRs on BMI. *Coverage* was used to identify the number of FFRs at each of four distance buffers (i.e., 0.25 miles, 0.50 miles, 1 mile, and 2 miles). *Proximity* was used to identify whether participants had access to at least one FFR within the four distance buffers designated above. FFR *density* was calculated by dividing the number of FFRs per square mile (within each distance) by the area of the distance buffer.

Mehta and Chang (2008) analyzed the relationship between the restaurant environment and weight status across counties in the US using data from the 2002-2006 Behavioral Risk Factor Surveillance System ($N=714,054$), which was linked with restaurant data from the 2002 U.S. Economic Census. FFR density and higher ratios of fast food to full-service restaurants were both associated with obesity. In a similar study, GIS was used to observe fast food density and proximity to residential addresses. Spence, Cutumisu, Edwards, Raine, and Smoyer-Tomic (2009) calculated a Retail Food Environment Index (RFEI) based upon a ratio of the number of FFR and convenience stores to supermarkets and specialty stores within 800 meter (approx. 0.50 mile) and

1600 meter (approx. 1.0 mile) buffers around people's homes (Spence et al., 2009). The median RFEI for adults was 4 within an 800-meter buffer around their residence and 6.46 within a 1600-meter buffer around their residence. Approximately 14% of these participants were considered obese. The odds of being obese were significantly lower if they lived in an area with a low RFEI (below 3.0) compared to an area with a high RFEI (5.0 and above) (Spence et al., 2009). The lower the ratio of FFR to grocery stores near people's homes, the lower the odds of being obese (Spence et al., 2009).

Obesity and mental illness. Past research has linked physical illness to obesity, and researchers are now examining the relationship of obesity to mental illness (Allison et al., 2009; Dickerson et al., 2006). For example, Daumit and colleagues (2003) reported that 29% of men and 60% of women with persistent mental illness were obese, compared to 17.7% of men and 28.5% of women in the general population. Studies have shown that individuals with mental illness (especially depression and anxiety disorders) are at greater risk for obesity and *vice versa* (Calkin et al., 2009; Kessler, Chiu, Demler, Merikangas, & Walters, 2005; Kessler et al., 1996; Luppino et al., 2010; Simon et al., 2006). Using a cross-sectional epidemiologic survey design to study the US population, Simon and colleagues (2006) found a relationship between obesity and a range of mood, anxiety, and substance use disorders. Obesity was associated with an approximately 25% increase in the odds of a mood disorder diagnosis (e.g., major depression and bipolar disorder) and anxiety disorders (e.g., panic disorder and agoraphobia) and an approximately 25% decrease in the odds of a substance use disorder diagnosis (Simon et al., 2006). Subgroup analyses found no difference in these associations between men and women, but the

association between obesity and mood disorder was strongest in non-Hispanic whites and in college graduates (Simon et al., 2006). This variation across demographic groups suggests that sociocultural factors may moderate the association between obesity and mood disorder (Simon et al., 2006).

Obesity, mental illness, and gender. Links between obesity and mental illness may differ across race and gender, although results are not consistent. Dong, Sanchez, and Price (2004) showed that obesity increased the risk for depression across races and genders, even after controlling for chronic physical disease, familial depression, and demographic risk factors. In contrast, Stunkard and colleagues (2003) found that higher SES increased the strength of the relationship between obesity and major depression, but only among women; among men, there was no relationship with SES.

Geographic Information Systems

Considering the information on the relationships among access to fast food, mental health status, and BMI, the current study will use GIS to map the relationships among these three variables.

What is a GIS? “GIS integrates hardware, software, and data for capturing, managing, analyzing, and displaying all forms of geographically referenced information” (Esri, 2008, p. 1). GIS is a software application that utilizes data containing a spatial attribute to conduct robust geographic analyses (Bloch, 2011). For example, socioeconomic and mental health data can be geocoded (placed on a map) and layered to illuminate relationships that would otherwise go unseen (Bloch, 2011). GIS uses cartography (the art and science of making maps) in which every location is symbolized

using latitudes and longitudes to assign geographical locations such as addresses, neighborhoods, counties, or countries (Bloch, 2011). GIS allows us to view, understand, question, interpret, and visualize data in many ways that reveal relationships, patterns, and trends in the form of maps, globes, reports, and charts (Esri, 2008). GIS is used for: mapping where things are, facilitating pattern detection, and mapping quantities to assist in strategic interventions (Esri, 2008). For example, because healthy food is more expensive than fast food, city officials might choose to map the number of low-income families per 1,000 square miles in order to determine if the area is large enough to support a low-cost warehouse-style supermarket that sells food in bulk. Also, GIS is useful for mapping densities and clearly seeing the distribution of several features (Esri, 2008). For example, when mapping FFRs, a small rural county with a low-median income may show more fast food per square mile (e.g., high density) than a large affluent area with fewer FFRs per square mile (e.g., low density). GIS can also be helpful for comparing characteristics of a target area to surrounding areas in order to identify differences in a visual way that can't be seen through traditional data analysis.

Using GIS to Map Key Elements of Obesogenic Environment

Using GIS to map characteristics of a target area is a modern approach to identifying relationships between pre-defined variables. This study will use GIS to map key elements of the rural area in which the participants resided. Key elements include access to FFR, mental health status, and BMI.

Obesity. GIS software products have been useful in research studies examining the relationship between childhood obesity and built environments (Miranda et al., 2012).

Built environments are comprised of important factors that may contribute to inactivity, either directly through physical barriers to activity (e.g., lack of gyms or recreational parks) or indirectly through the impact of the social context of the neighborhood (e.g., high crime rates), which may cause individuals to avoid outdoor physical activity because of safety concerns (Miranda et al., 2012). For the purposes of identifying barriers to physical activity and maintaining a healthy weight, the built environment measures identified violent crime, total crime, and housing damage rates as important factors associated with weight status (Miranda et al., 2012). After adjustment for the patient-level characteristics of race, age, sex, and insurance status, results indicated that higher levels of violent crime, total crime, and nuisances in a child's residential area were associated with higher risk of being overweight (Miranda et al., 2012). These findings are useful for parents who want to identify safe neighborhoods where their children can play outside and be physically active in order to maintain a healthy weight.

Mental illness. GIS has been used in epidemiological research on schizophrenia (Logdberg, Nilsson, Levander, & Levander, 2004), physical activity, BMI, and obesity (Berke, Koepsell, Moudon, Hoskins, & Larson, 2007; Kligerman, Sallis, Ryan, Frank, & Nader, 2007). In a case-finding study of schizophrenia combined with a victimization survey, Logdberg and colleagues (2004) used GIS and factor-analyzed data to investigate the relationship between the prevalence of schizophrenia and measures of social deprivation in varying areas in the city of Malmo (Sweden's third largest metropolis). The prevalence of schizophrenia among the 87 communities of Malmo varied from 0 to 1.42%. The results indicated that people with schizophrenia lived predominantly in

socially disorganized areas characterized by high levels of mental illness and fear of crime and victimization (Logdberg et al., 2004). These results illustrated that people with schizophrenia still aggregate in socially deprived areas and suggest that this segregation may result in worsening of the illness as well as increasing the social disorganization in the local residence (Logdberg et al., 2004). Findings such as these may be helpful for use in planning the types and locations of social service programs for people with schizophrenia.

Current Study

The present study focused on the relationships among proximity to and density of FFRs, mental health status, gender, and BMI, and among a sample of primary care patients from Tulare County, a rural county in Northern California. Based on the obesogenic environment model and previous research, the current study tested whether increased access to FFRs, with their characteristic energy-dense foods that are high in saturated fat, is linked to BMI (Calkin, et al., 2009; Diaz, Mainous, & Pope, 2007; Simon, et al., 2006). Density of FFRs and the proximity to FFR from the subject's home were calculated in order to compare differences in BMI across mental health status. GIS will be used to map BMI, mental health status of the patients, and FFRs near the patient's home. Past research has used several distances to investigate the relationship between FFRs and obesity. The 400-meter (e.g. $\frac{1}{4}$ mile) buffer is commonly used since it approximates the distance an average adult can walk in 5 minutes (Austin et al., 2005; Pikora et al., 2002). For the purposes of this study, four distances were used for

descriptive data: 0.25 miles (approx. 400 meters), 0.50 miles (approx. 800 meters), 1 mile (approx. 1600 meters), and 2 miles (approx. 3200 meters).

Based on past literature, the following hypotheses will be tested:

H1) FFR density will have a positive relationship with BMI.

H2) Depressed patients will have higher BMI scores than patients with other primary mental health diagnoses.

H3) The relationship of close proximity to FFR to BMI will be stronger for women than for men.

The null hypothesis, H0, is that there are no detectable differences in BMI associated with FFR density or mental health diagnosis, and gender will not affect the relationship between FFR proximity and BMI.

Chapter 2

METHODS

Participants

The participants in this study were derived from a previous study that aimed to test the use of asynchronous telepsychiatry and psychiatric consultations in primary care (Yellowlees, Odor, & Burke Parish, 2012). The data were collected from 2008-2009 and included 127 English- and Spanish-speaking patients referred to the study by their primary care physician (PCP) (Yellowlees et al., 2012). For the purpose of this study, 4 of the 127 study participants were excluded because they did not report a residential address. The sample for the current study ($N = 123$; see Table 1) consisted of non-Hispanic Caucasian (51.20%) and Hispanic (40.70%) women (68.30%); the average age of participants was 48 years ($SD = 11.63$ years). The average BMI of participants was 31 ($SD = 7.06$), which was considered obese. A majority of participants received a mood disorder diagnosis as their primary mental health diagnosis. Within each diagnostic group, a majority of the patients diagnosed with a primary mental health illness were also diagnosed with a comorbid mental health illness (see Table 2). Specifically, 30.3% ($n = 10$) of the participants in the “other primary diagnosis” group had a secondary diagnosis of depression

Table 1. *Demographic Characteristics of Participants*

	<i>n</i>	%
Gender		
Male	39	31.7
Female	84	68.3
Race/Ethnicity		
Non-Hispanic Caucasian	63	51.2
Hispanic and/or Latino	50	40.7
African American	5	4.1
Asian	3	2.4
Native American	2	1.6
Primary Mental Health Diagnosis		
Mood Disorder	90	73.2
Anxiety Disorder	21	17.1
Substance Abuse Disorder	3	2.4
Psychotic Disorder	5	4.1
None	4	3.3
BMI		
Underweight	3	2.4
Normal	16	13
Overweight	37	30.1
Obese	67	54.5

Note. *N* = 123.

Table 2. *Mental Health Diagnosis and Comorbidity*

Primary Mental Health Diagnosis	Primary Diagnosis N (%)	Within primary diagnosis, comorbidity with any other mental health diagnosis N (%)
Mood Disorder	90 (73.2%)	59 (65.6%)
Anxiety disorder	21 (17.1%)	15 (71.4%)
Substance Abuse Disorder	3 (2.4%)	3 (100%)
Psychotic Disorder	5 (4.1%)	3 (60%)
None	4 (3.3%)	0 (0%)

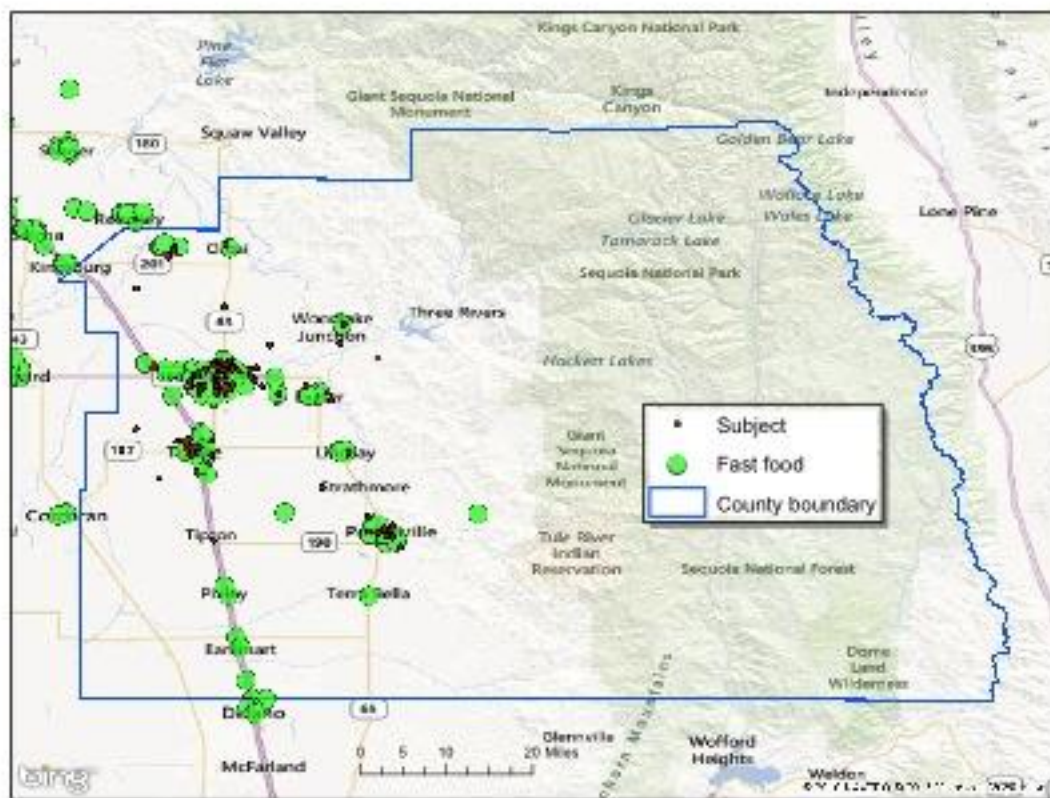
Note. N = 123.

Study Area

Tulare County (Figure 1) is geographically one of the largest counties (4,863 square miles) in the San Joaquin Valley, with an estimated population of 451,977 (Census Bureau, 2013a). It is centrally located in California, about midway between San Francisco and Los Angeles (Tulare County, 2013). The western half of this county boasts a fertile valley that has allowed Tulare County to become the second leading producer of agricultural products in the United States (Tulare County, 2013). The population is predominantly White (88.4%) with Hispanic/Latino ethnicity comprising 61.8% of the population (Census Bureau, 2013a). In Tulare County, 67.8% of persons age 25 or older are high school graduates or higher and 12.9% have a bachelor's degree or higher

(Census Bureau, 2013). The current study used 2010 Census Bureau data rather than 2000 Census Bureau data to describe Tulare County because the original dataset was collected in 2008-2009.

Figure 1: Study area boundaries in Tulare County, CA



Measures

Measures of Participant Characteristics

BMI. Participants self-reported height and weight. BMI was calculated by using the standard formula [(weight in lbs.) / (height in inches)² x 703] (CDC, 2011b). BMI standard weight categories, underweight (BMI < 18.5), normal (BMI 18.5-24.9), overweight (BMI 25-29.9), and obese (BMI ≥ 30) were used to group the participants (CDC, 2012a). The BMI value represented the degree of obesity and was used as a continuous dependent variable in the statistical analyses.

FFR. This study defined fast food establishments as those that have a limited menu and no table service and that serve items that are prepared in advance or heated quickly, in disposable wrappings or containers; these included dine-in, drive-in, or carry-out establishments (Abdollah, 2007). The Standard Industrial Classification (SIC) is a system used for classifying industries by a four-digit code that identifies a company's type of business (Academy of Corporate Governance, 2001). The SIC code (#5812) for FFRs defines FFRs as restaurants that provide food service to customers who order and pay at a counter (Hoovers, 2013). The supplemental data for FFR density were collected in 2011 (two to three years after the participant data were collected). In order to compile a list of FFRs, an online yellow page search of FFRs using the 22 ZIP codes corresponding to participants' areas of residence was completed. Next, a web content extractor was used to capture the yellow page search results in a usable format. We used the SIC code for FFRs to further identify and supplement our dataset, ensuring that all FFRs in the study area of interest were captured. The download caused some duplicates

which were identified and eliminated.

SCID-I. The Structured Clinical Interview for DSM-IV disorders (SCID-I) was used to collect data on mental health status of the participants. The SCID-I is a semi-structured interview for DSM-IV-TR Axis I diagnoses and has an administration time of approximately 1 hour (First, Gibbon, Spitzer, Williams, Benjamin, 1997). This interview is widely considered to produce reliable and valid psychiatric diagnoses for clinical, research, and training purposes, and has been used in over 1000 research studies (Hersen, Turner, & Beidel, 2007).

MINI. The Mini-International Neuropsychiatric Interview (M.I.N.I.) is a short, structured diagnostic interview that was developed in 1990 by psychiatrists and clinicians in the United States and Europe for DSM-IV and ICD-10 psychiatric disorders (Sheehan et al., 1998). With an administration time of approximately 15 minutes, the M.I.N.I. is the most widely used structured psychiatric interview for psychiatric evaluation and outcome tracking in clinical psychopharmacology trials and epidemiological studies (Sheehan et al., 1998). This interview instrument was also used with each participant.

The primary diagnosis was established by combining data from the SCID and the MINI. The clinical interview lasted between 20-30 minutes, was video-recorded and included a diagnostic assessment with the MINI (Yellowlees, 2010).

Measures of Community Characteristics

ArcMap. ArcMap v10.1 (Esri, Redlands, CA) was the GIS software used to analyze and display the patient and fast food data in this study. This study used ArcMap

to create selection sets, geocode addresses, calculate fast food proximity and fast food density, and view analysis results.

Procedures

Mental Health and BMI

Data for this study were extracted from a previous study led by Dr. Peter Yellowlees (Yellowlees et al., 2010). Briefly, the participants included in the Yellowlees et al. (2010) study were identified by the PCP as having mental health concerns that warranted a non-urgent psychiatric consultation. Interviews were conducted in the largest of the four community health clinics in Tulare County. Patients gave informed consent prior to admission to the study and were paid \$100 each to take part. All patients were informed that the video of their one- to two-hour interview would be viewed by two psychiatrists and that a consultation opinion would be written and provided to their PCP. The participating psychiatrists reviewed all electronic data (video and health record) available on the Web record, including the MINI and SCID-I results, and then completed a structured consultation, which incorporated their overall best-fit DSM-IV diagnoses, a rating on the Global Assessment of Functioning (GAF), and a comprehensive treatment plan (Yellowlees, 2010). The two psychiatrists who conducted the consultations gave 11 active diagnoses to the participants ($N = 123$) including, major depressive disorder (62%), dysthymic disorder (9%), panic disorder without agoraphobia (7%), primary psychotic symptom (4%), panic disorder with agoraphobia (3%), bipolar disorder not otherwise specified (NOS) (3%), substance abuse (2%), generalized anxiety (2%), adjustment disorder (2%), anxiety (2%), and post traumatic stress disorder (PTSD) (1%). For the

purposes of this study, diagnoses were grouped into five categories: mood (major depressive disorder, dysthymic disorder, bipolar disorder NOS), anxiety (panic disorder without agoraphobia, panic disorder with agoraphobia, generalized anxiety, adjustment disorder, anxiety, and PTSD), substance (substance abuse), psychotic (primary psychotic symptom), and none (no primary diagnosis given) (see Table 1).

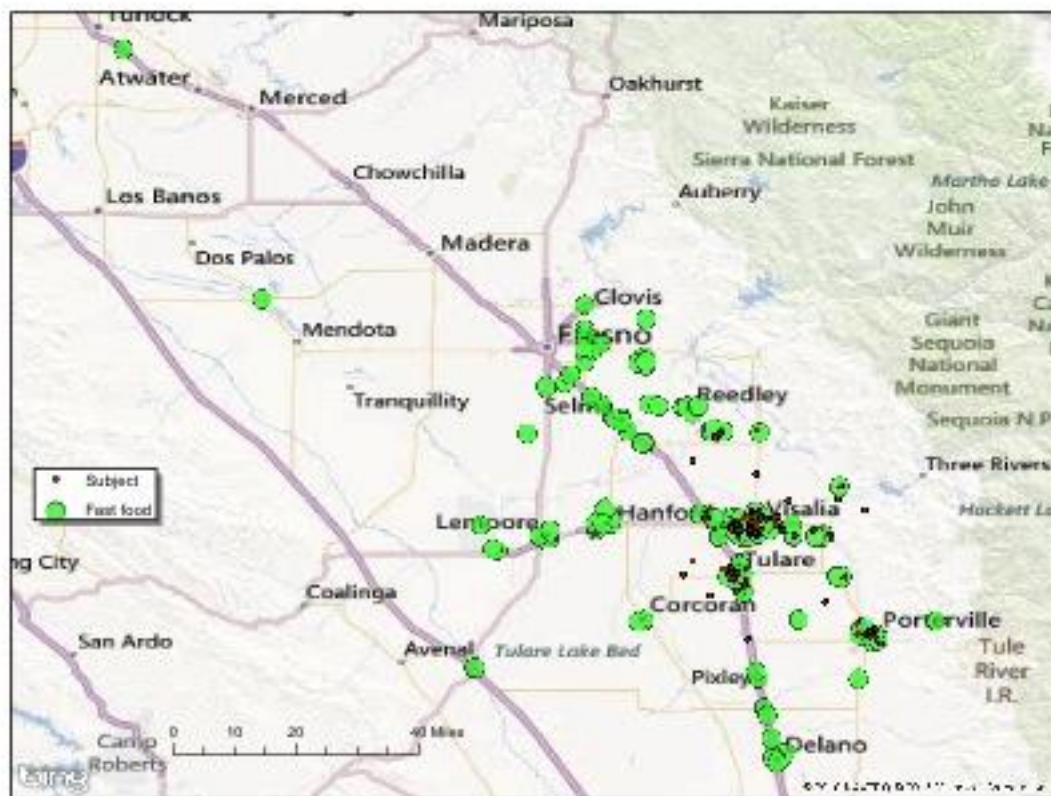
Mood data were entered into Microsoft Excel (Microsoft Office 2011, Richmond, WA) worksheet. The participants reported height and weight, allowing a calculation of their BMI using the standard formula. Finally, the raw data were entered into SPSS statistical software (IBM SPSS Statistics 19, Chicago, IL) and analyzed for descriptive data and comparative statistics.

Spatial Analysis

ArcMap v10.1 (Esri, 2008) was used to geocode 123 patient addresses. Most of the patients lived in the cities of Visalia, Tulare, or Porterville (Figure 1). Twenty-two ZIP codes were identified inclusive of all 123 participant addresses. Boundary problems are often prominent in studies of spatial point patterns. Edge effects occur when the location points (i.e., FFRs) that are outside of the study area influence descriptive measures of point patterns (i.e., FFR density or frequency) (Clark & Evans, 1954). In order to avoid edge effects, each participant address was reviewed for its nearness (e.g., within 2 miles) to a ZIP code border. There were no edge effects in this study because the participant addresses ($N = 123$) were at least 2 miles away from the 22 ZIP code boundaries. FFR data (collected as described previously) were entered into the mapping software and geocoded to produce points on a map (Figure 2). The number of FFRs

within multiple distance buffers (i.e., 0.25 miles, 0.50 miles, 1 mile, and 2 miles) around each participant's address was recorded. That frequency of FFRs was then divided by the square mile area for each distance buffer to create a FFR density variable and adjusted to reflect density per square mile.

Figure 2: Participant locations and FFRs



Chapter 3

RESULTS

A preliminary analysis computed descriptive data for mental health diagnostic category, average BMI, and number of FFRs at each proximity (i.e., 0.25 miles, 0.50 miles, 1 mile, and 2 miles) (see Table 3). Table 4 shows descriptive data for mental health diagnostic category, average BMI, and FFR density at 0.25 miles, 0.50 miles, 1 mile, and 2 miles distances. The geocoded data revealed 619 FFRs existed within the 22 ZIP codes comprising our subject addresses. GIS data revealed that on average, in this community, the participants ($N = 123$) lived within 2 miles of 22.07 ($SD = 15.31$) FFRs. A map derived from GIS software (see Figure 2) visually shows the characteristics of this sample: the patients' locations and FFR density. GIS was used to create a map to visually show that the majority of the sample was diagnosed with a mood disorder (73%) and considered obese (55%) (see Figure 3).

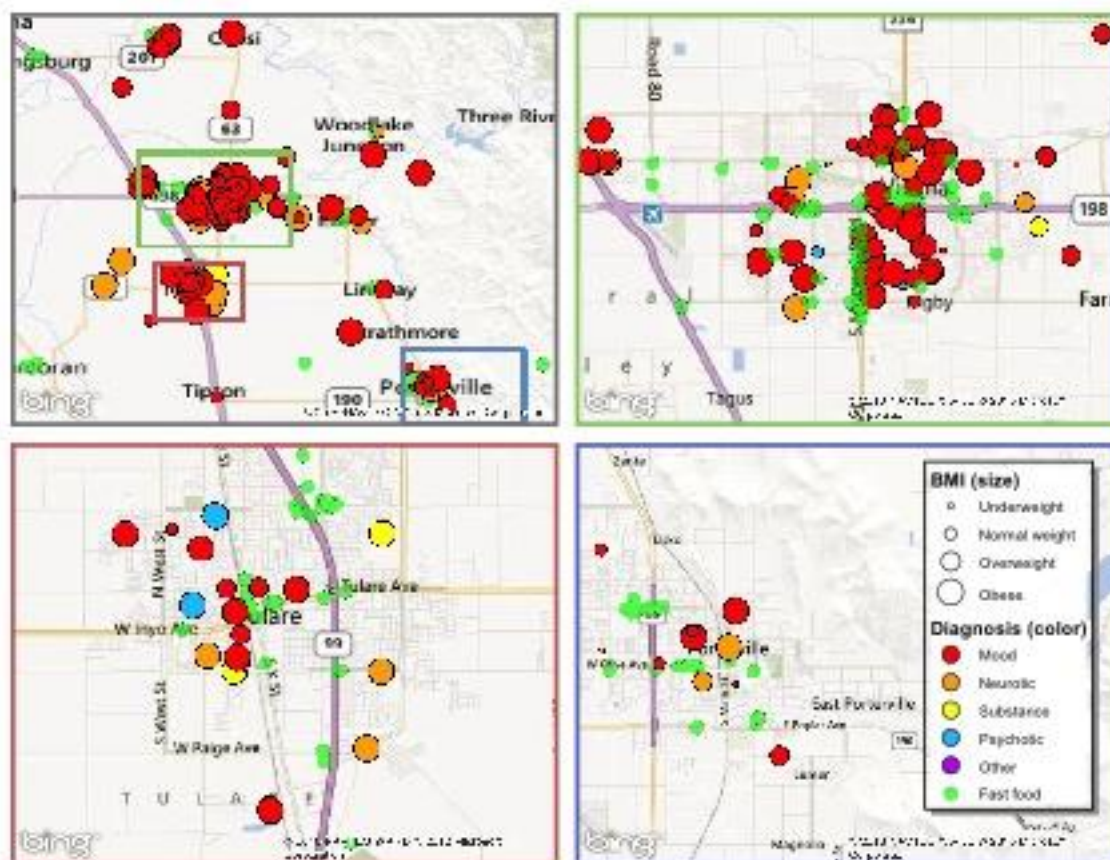
Table 3. Number of FFRs for Each Distance Buffer and Diagnostic Group

Diagnostic Group	BMI <i>M</i> (<i>SD</i>)	Obese (%)	Number of FFRs within 0.25 miles <i>M</i> (<i>SD</i>)	Number of FFRs within 0.50 miles <i>M</i> (<i>SD</i>)	Number of FFRs within 1.0 mile <i>M</i> (<i>SD</i>)	Number of FFRs within 2 miles <i>M</i> (<i>SD</i>)
Depressed (<i>N</i> = 90)	31.23 (7.15)	53.3	0.38 (0.92)	2.32 (3.34)	4.09 (4.29)	23.91 (15.48)
Other primary diagnosis (<i>N</i> = 33)	30.38 (6.88)	57.6	0.43 (0.93)	2.06 (3.37)	3.62 (3.69)	19.09 (14.71)
Total sample (<i>N</i> = 123)	31.00 (7.06)	54.5	0.40 (0.92)	2.22 (3.34)	3.91 (4.06)	22.07 (15.31)

Table 4. *FFR Density for Each Distance Buffer and Diagnostic Group*

Diagnostic Group	BMI <i>M</i> (<i>SD</i>)	Obese (%)	FFR density within 0.25 miles (frequency per square mile) <i>M</i> (<i>SD</i>)	FFR density within 0.50 miles (frequency per square mile) <i>M</i> (<i>SD</i>)	FFR density within 1.0 mile (frequency per square mile) <i>M</i> (<i>SD</i>)	FFR density within 2 miles (frequency per square mile) <i>M</i> (<i>SD</i>)
Depressed (<i>N</i> = 90)	31.23 (7.15)	53.3	1.75 (4.39)	2.78 (4.07)	1.24 (1.36)	2.12 (4.01)
Other primary diagnosis (<i>N</i> = 33)	30.38 (6.88)	57.6	2.62 (5.40)	6.81 (22.04)	1.25 (1.07)	1.72 (1.20)
Total sample (<i>N</i> = 123)	31.00 (7.06)	54.5	1.98 (4.67)	3.86 (11.95)	1.24 (1.28)	2.01 (3.48)

Figure 3: Obesity status, mental health diagnosis, and fast food density



To test my first hypothesis, a Pearson product-moment correlation coefficient was used to evaluate the relationship between FFR density and BMI score (range 16 to 41). Specifically, this study evaluated the relationship between the highest FFR density observed within the four buffer zones and BMI. The 0.50 mile distance had the highest FFR density with an average FFR density of 3.86 (see Table 4). Therefore, a Pearson product-moment correlation coefficient was calculated using FFR density within 0.50 miles of the participant's residence and BMI. Results revealed that there was no relationship ($r = -.004$, $n = 123$, $p = .961$) between FFR density within the 0.50 mile buffer and BMI.

To examine my second hypothesis, a one-way ANOVA was used to detect a difference between depressed and other primary diagnosis participants on BMI. The independent variable was diagnostic group and was created by assigning a “1” for depressed and “2” for other primary diagnosis. BMI score was the dependent variable. There was no statistically significant difference between “depressed” and “other primary diagnosis” groups on BMI as determined by a one-way ANOVA $F(1, 121) = .072, p = .789$.

To test the third hypothesis, two separate two-way ANOVA’s were conducted that examined the effect of gender and living within close proximity to FFRs (0.25 miles and 0.50 miles) on BMI score. The first independent variable was gender, with two levels, male and female. The second independent variable was close proximity to at least one FFR. The close proximity variable was created for the 0.25 miles distance by assigning a “1” for yes and “2” for no for patients who lived within 0.25 miles of one or more FFRs. The close proximity variable was created separately for the 0.50 mile distance in the same manner as the 0.25 mile close proximity variable. BMI scores were the dependent variable. The first two-way ANOVA was run using the gender independent variable, close proximity (0.25 miles) independent variable, and the dependent variable BMI. The second two-way ANOVA was run using the gender independent variable, the close proximity (0.50 miles) independent variable, and the dependent variable BMI. Results showed that there was no significant interaction between close proximity to FFRs at 0.25 miles and gender, $F(1, 119) = .356, p = .552$ and there was no significant difference in BMI between gender ($p = .294$) and proximity to FFRs at 0.25 miles ($p =$

.836). Similarly, there was no significant interaction between close proximity to FFRs at 0.50 miles and gender $F(1, 119) = .490, p = .485$ and there was no significant difference in obesity between gender ($p = .097$) and proximity to FFRs at 0.50 miles ($p = .539$).

Chapter 4

DISCUSSION

The increase in obesity rates in the US is a multi-factorial problem, occurring at least in part due to an insidious change in our environment where calorie-dense, processed food is more readily available and opportunities for physical activity are lacking (CDC, 2012a). Participants in this study lived in an obesogenic environment with an average of 22.07 FFRs within two miles of their homes. The majority of this sample (54.5%) was considered obese, compared to Tulare County as a whole, with 31% of residents considered obese. The aim of this study was to test the relationships of FFR availability, psychiatric disorders, and gender to the BMI scores of participants in order to better understand their risk for obesity.

There was no relationship found between FFR density and BMI. Past research found that increased access to FFRs has been linked to obesity and related illnesses (Fleischhacker et al., 2010). Although the results of this study did not support past research, this study focused on a sample living in an area that was densely populated with FFRs ($M = 3.86$, $SD = 11.95$ FFRs within 0.50 miles of their residence) and the participants were atypical in that their rates of obesity were higher than rates in the surrounding population. In addition, these participants were selected by referral from their PCP for a psychiatric evaluation; all but four were assigned a psychiatric diagnosis. Thus, these participants were more physically and psychiatrically vulnerable than the general population, and the impact of FFR density may have been difficult to detect due

to lack of variability in the sample; in addition, other factors may have been more salient for this group. More sensitive measures, such as frequency of eating fast food might have been more effective for detecting the impact of FFR; future studies may benefit from including measures of consumption as well as environmental variables.

This study examined the relationship between mental health status and BMI. Specifically, differences in BMI between participants with a primary mood disorder diagnosis and those with other primary diagnoses were examined. Although no differences were detected between these two groups, most participants had diagnoses that included mood and/or anxiety disorders. The high average BMI score and the high rate of obesity in the sample is consistent with past findings that obesity is related to several mental health diagnoses such as depression and anxiety disorders (Calkin et al., 2009; Kessler et al., 2005; Kessler et al., 1996; Simon et al., 2006). Future research should include participants with a wider range of diagnoses as well as a larger representation of psychiatrically healthy participants in order to more effectively test the relationship of psychiatric status to BMI and obesity risk. In addition, data on medications, including psychiatric medications that may influence weight status should be collected.

Although this study did not find a statistically significant difference in BMI between males and females who lived in close proximity to FFRs, the results of this study were consistent with past research that found proximity of FFRs to home or work was not associated with BMI for either males or females (Jeffery et al., 2006). Again, given the high average BMI and the high rate of obesity in the sample, lack of variability in the sample may have made it difficult to detect any impact of FFR proximity on BMI. In

addition, there may be other environmental factors affecting the weight status of participants, such as lack of opportunity to be physically active.

Although this study was not able to identify FFR density or proximity, psychiatric diagnosis, or gender as contributing factors to participants' BMI, future research utilizing GSI to study obesogenic environments and patterns of relationship among risk factors and outcomes may shed light that can guide public health and public policy efforts to mitigate risks and promote salutogenic environments. For example, incentives could be offered to attract farmer's markets and other sources of nutritious food to convenient locations that might reduce demand for fast food; programs to promote food literacy in schools could be initiated; and built environments could be modified to promote walking and other forms of healthful activity within neighborhoods where risk of obesity is currently high. In addition, the high average weight of this sample that was selected for psychiatric risk suggest that efforts to promote integrated care that addresses both physical and psychiatric health in a coordinated fashion might be beneficial.

Limitations

This study had several limiting factors. First, it included only one geographic area to investigate these associations, which may not be generalizable to urban or suburban areas. Second, the sample was recruited for a study focused on telepsychiatry; thus the sample was small and participants' psychiatric diagnostic status reduced variability, making it more difficult to detect hypothesized relationships. Third, data on consumption of fast food, nutritious food, and physical activity were not collected, and a control group was not available (e.g., individuals with no mental health disorder) to compare to the

sample used in this study. Fourth, the food environment data (i.e., FFR density) were collected two to three years after the individual-level data were collected. There may have been fewer FFRs surrounding participants' homes in 2008-2009 compared to 2011 when the data for FFR was collected. Fifth, height and weight data were obtained via self report and may be inaccurate, which would result in error in BMI scores calculated for this study.

Nevertheless, this research contributes to a growing body of science, which aims to determine the relative influence of neighborhood fast food environments on population health. Only a few studies have been published measuring the associations between local food environments and health outcomes. Although this study did not have any significant findings, the design of this study is consistent with other investigators who have collected similar data on FFR in proximity to a residential home, mental health status, and BMI. However, a larger sample size may be needed in order to identify the effect of FFR density, proximity to FFRs, and mental health status on BMI.

Future Research

Clarifying the social and cultural influences on the relationship between obesity, mood disorders, and other mental health diagnoses will require additional research in populations with a broader range of race/ethnicity, educational attainment, and income. It is likely that some of the methods for addressing the obesity epidemic would benefit from being tailored to specific groups in order to address cultural, regional, economic, and lifestyle differences. In addition, multiple research design strategies (observational, longitudinal, and experimental) will be needed in order to clarify the multiple factors

affecting population trends in weight and obesity and in order to elucidate the direction of causal relationships. For example, a longitudinal design to explore the questions in the current study would be useful to observe whether changes in FFR access or availability of psychiatric status or availability of psychiatric care correspond to changes in BMI.

Several studies have examined the relationship between BMI and living in an area that promotes physical activity (Berke, et al., 2007; Kligerman, et. al., 2007). The results of these studies revealed that when adults live an area that is conducive to walking and being physically active, their BMIs are lower compared to adults who live in an area where walking is not available (Berke, et al., 2007; Kligerman, et. al., 2007). Exercise has also been found to be beneficial for mental health. Including exercise and activity in future studies would help to clarify the benefits of activity for BMI and emotional well-being.

Implications

Novel multidisciplinary, preventive, therapeutic approaches, and social changes are needed in order address the complex interplay of genetic, behavioral, economic, sociocultural, environmental factors that have contributed to the current obesity epidemic. Obesity rates are increasing annually, increasing risk for obesity-linked illnesses, including diabetes, cardiovascular disease, and psychiatric disorders (CDC, 2011). Several studies have shown that individuals with mental illness (especially depression and anxiety disorders) are at greater risk for obesity (Calkin et al., 2009; Kessler, Chiu, Demler, Merikangas, & Walters, 2005; Kessler et al., 1996; Simon et al., 2006).

Integrated care models that address behavioral, emotional, and physical health in a coordinated fashion would benefit many patients.

One major contributing factor to the increase in obesity is how eating patterns have changed over the years. Americans are eating more processed foods and eating out more frequently. The patients in this study lived in an area with a high density of FFR where making healthy eating decisions may be difficult because fast food is so readily available. Rural or poor neighborhoods can improve access to affordable fruits and vegetables by incorporating more farmers' markets into their communities. There is no single solution to the obesity epidemic, but with the help of policymakers, incentives can be offered to help promote a healthy environment. For example, a policymaker might propose a mandate like a prohibition on new FFRs near schools or a requirement that food retailers stock fresh fruits and vegetables (Frye, 2012). Also, grocery stores that carry fresh fruits and vegetables tend to be more prevalent in higher-income neighborhoods because city officials believe that there is more opportunity to make a profit compared to low-income neighborhoods (Frye, 2012). Incentives such as those offered through the Pennsylvania Fresh Food Financing Initiative (FFFI), can increase the number of grocery stores in low-income neighborhoods by providing financing for supermarkets that cannot be filled solely by conventional financial institutions (Pennsylvania Fresh Food Financing Initiative, 2013). The FFFI provides families with a wide variety of nutritious food choices. The lower cost foods help those living on a fixed budget to purchase higher quality foods (Pennsylvania Fresh Food Financing Initiative, 2013). Finally, policymakers can help promote physical activity by offering incentives

for housing developers to build recreational parks, build sidewalks and bicycle friendly streets, and install bicycle lockers in front of buildings (Frye, 2012). It is possible to decrease the obesity rates in the US and policymakers can help promote a healthy lifestyle by creating an environment that makes healthy eating and physical activity more feasible for disadvantaged neighborhoods.

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