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The Nature and Scale of Cognitive Communities of Interest

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by

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ABSTRACT

The Nature and Scale of Cognitive Communities of Interest

by

Daniel W. Phillips

When drawing boundaries of electoral districts, officials often try to respect communities of interest (COIs) by keeping them intact. COIs can be defined socioeconomically, such as an area where a particular ethnic group concentrates, or cognitively, such as a neighborhood or region that people commonly agree upon. My research focuses on the nature and scale of the latter type, called cognitive COIs. I investigate whether people conceive of different scales of cognitive COIs when they are exposed to different map extents of their local area. If they are indeed different, that would point to the existence of different scales of cognitive COIs. I seek to answer this question through two studies. The first splits subjects into three groups and exposes each group to a different map extent; they then draw on the map where they think their COI is located. I find that the size of the COI that they draw depends greatly on map extent. The second study exposes subjects to two different map extents, but all of them receive the same two; they then rank places on the map according to how confident they are that they are in their COI. I likewise find that the size of the COI that they define by their rankings depends on the map extent. These findings indicate that the map induces people to externalize their COI at different scales, confirming

that multiple scales of cognitive COIs exist and officials must be aware of that fact when they are redistricting at different levels of government.

TABLE OF CONTENTS

LIST OF FIGURES

I. Introduction

A. Communities of interest in redistricting criteria

When drawing or redrawing boundaries of electoral districts, officials commonly rely on four criteria: contiguity, compactness, respect for existing administrative regions, and respect for communities of interest (Mann 2005; Handley 2008). While the first three of these criteria are defined relatively easily (with the possible exception of compactness, due to the multiple measures proposed for that criterion), attempts to define a community of interest (COI) have suffered from the ambiguity surrounding the concept (Grofman 1985; Morrill 1987; Cain et al. 2005; Courtney 2008; Handley 2008; McRobie 2008; Medew 2008; Levitt 2011; Mac Donald and Cain 2013). However, the vagueness of this fourth criterion has not prevented jurisdictions across the world from applying it in redistricting. According to a survey carried out by Handley (2008), "19 of the 60 countries that delimit constituencies indicated that respect for communities of interest was a criterion considered by the boundary authority" (p. 275). That selection of countries includes such disparate nations as Australia, Germany, Hungary, Pakistan, Nepal, and Papua New Guinea, all defining the term in slightly different ways. Such definitions range from the very vague "coherent area" and "homogeneity of community" to the more precise "community of economic, social, and regional interests" and "concentration of minority/indigenous populations." So while there is a vague idea throughout the world of such a thing as a COI, different countries hold different ideas of what exactly that looks like.

Unlike the vast majority of the countries surveyed by Handley (2008), the United States has a very decentralized redistricting system, with each state running its own affairs. This means that the degree to which COIs factor into the process varies with the state; some do not consider them at all while others emphasize them a great deal. According to Levitt (2011), 22 states take COIs into account when drawing state legislative districts, and 13 do the same for congressional districts. This practice is most common among states in the Western United States, because they tend to use independent commissions to draw district lines, which use “fair districting criteria” like respect for COIs (May and Moncrief 2011). Even though a fair number of states have provisions for respecting COIs, many have had difficulty enforcing those provisions since they lack a precise definition for the notion (Grofman 1985; Cain, Mac Donald, and McDonald 2005). Some states have tried to buck this trend by laying out a more specific definition, again concentrated in the West. The state of Colorado references “ethnic, cultural, economic, trade area, geographic, and demographic factors.” Alaska, in turn, defined communities by interviewing hundreds of residents on the interests they shared (Cain, Mac Donald, and McDonald 2005, pp. 18–19). One particularly detailed definition for a COI comes from the California Constitution’s list of criteria for the state’s independent redistricting commission, which was formed in 2011:

> A community of interest is a contiguous population which shares common social and economic interests that should be included within a single district for purposes of its effective and fair representation. Examples of such shared interests are those common to an urban area, a rural area, an industrial area, or an agricultural area, and those common to areas in which the people share similar living standards, use the same transportation facilities, have similar work opportunities, or have access to the same media of communication relevant to the election process. Communities of interest shall not include relationships with political parties, incumbents, or political candidates. (California State Constitution, Article XXI, Section 2-d-4)

B. Communities of interest as geographic regions

Among those countries and states that do include respect for COIs as a redistricting criterion, there is clearly a wide disparity in how they define those entities. Despite this lack of agreement, certain common threads appear across various definitions. One is that there is a geographic or spatial element to the concept. Morrill (1987) called the COI "the most geographic [of the redistricting criteria], in the sense that a major concern of geography is to identify the regional structure of a society…the territories with which citizens strongly identify, and whose integrity they want to maintain" (p. 251). Stephanopoulos (2012a) concurred, arguing that people who live nearby tend to have common interests and values (the objective thread, explained below) and also feel more connected to each other (the subjective thread, also below) (pp. 1390–1391). From the very beginning of California's use of the criterion for redistricting, the state very clearly defined it as a territorial concept—a particular area with certain interests (Mac Donald and Cain 2013, pp. 612–613). This remains the case today, as the California Constitution defines COIs as "contiguous populations" (Stephanopoulos 2012c, pp. 287–288). Even Monmonier (2001), though holding that COIs were becoming large and fragmented due to advances in transportation and communication, recognized that geography continued to be relevant today (pp. 152–154). There is thus good reason to think of COIs as geographic regions of some type.

This fact calls for a brief excursus into the topic of regions in geography. Montello's (2003) updated typology of regions can inform this subject. In this essay, he defined geographic regions as pieces of the earth's surface with certain shared properties. Regions can be thought of as roughly two-dimensional features, usually contiguous and compact, with a common theme or character. Montello surveyed textbooks in human and physical geography and concluded that regions could be categorized into four types: administrative, thematic, functional, and cognitive. Administrative regions are those formed by fiat and defined by precise boundaries and uniform membership functions. I propose that this type of region may be further classified into jurisdictions and their divisions. Jurisdictions are regions under the control of a distinct administration, and include countries, states, counties, cities, towns, school districts, and many other special purpose districts. Divisions, on the other hand, are subregions of a jurisdiction created for an administrative use, yet without administrations of their own. Examples of such entities include the Census tracts and blocks of the United States; the electoral districts of a state, county, or city; the voting precincts of a county; the service areas of a police or fire authority; the neighborhoods of a city (as defined for planning purposes); and the parcels of a city. Thematic regions are defined by measurable themes and attributes, such as demographics and economics. Functional regions are determined by various forms of interaction among places, like commuting patterns or trade between cities. “Finally, cognitive regions are produced by people’s informal perceptions and conceptions,” for example, “my neighborhood” or “Southern California” (pp. 176–177). The latter three types of regions lack the potentially precise boundaries and uniform membership functions that characterize administrative regions, meaning that they cannot escape a level of “fuzziness” about their extent, and most seem to have a “core” and “periphery” to them. With these distinctions in mind, one can assess which type of region a COI might be.

If the first common thread among definitions for the COI is its geographic nature, then the second is the objective or thematic aspect of the concept. The basic idea is of “a group of people that share common social and economic interests” (Medew 2008, p. 103). More specific thematic attributes are given in the redistricting law of certain states, like

Colorado and Alaska (as quoted above). California refers to urban, rural, industrial, or agricultural areas, as well as "areas in which the people share similar living standards, use the same transportation facilities, have similar work opportunities, or have access to the same media of communication" (Stephanopoulos 2012c, pp. 287–288). Morrill (1987) noted that "communities are revealed through patterns of work; of residence; of shopping; and of social, religious, and political participation" (p. 251). Mac Donald and Cain (2013) described it as a "clustering of some measurable social or economic characteristic," though stressing that there is a crucial subjective component as well (p. 612). Finally, topographic barriers such as mountain ranges and rivers, as well as important transportation links, are often used to delineate COIs (CRC 2011, p. 27; Stephanopoulos 2013, p. 821). Such references to various socioeconomic attributes suggest that COIs qualify at least as thematic regions, if not also functional regions if transportation and communication links factor in.

A third important thread is the subjective or cognitive element (Chambers 1999; Stephanopoulos 2012a). Geographers and others have long recognized that people tend to identify with the place in which they live (Tuan 1974; Downs and Stea 1977; Hummon 1992; Agnew and Muscarà 2012). Gardner (2002; 2007) and others have argued that this sense of identity is disrupted when district boundaries are constantly redrawn and/or disregard salient communities. When describing the principles many believed should guide boundary reorganization of local government areas in England, Prescott (1965) referenced one stating that "the boundary should be drawn to cater for local sentiment and regional patriotism" (p. 173). Morrill (1990) contended that districts should be meaningful entities with which constituents can identify. Grofman (1993) introduced an idea that he called the "cognizability principle," which refers to the ability of residents to cognize their district by being aware of the general configuration of the boundaries, thereby facilitating their "identification of and with the district" (pp. 1262–1263). Mac Donald and Cain (2013) maintained that residents of a COI "have to perceive and acknowledge that a social, cultural, or economic interest is politically relevant" (p. 612). Perceptions of such interests do not necessarily correlate with demographic attributes, but may instead reflect environmental and cultural concerns, or even things like where parks and fire services are located (ibid, pp. 622–623). It seems then that the beliefs of individuals can be used to identify COIs as cognitive regions.

In sum, a COI can be defined as a geographic region with both objective and subjective elements to it. One may then see it as either a thematic, functional, or cognitive region, with the electoral district itself being an administrative region. Because thematic, functional, and cognitive regions often correlate and the first two are easier to identify than the third because their attributes are more directly measurable, experts tend to just measure the objective and assume the subjective will closely adhere (Stephanopoulos 2012b, p. 1949, n. 217). However, situations may exist where a thematically and functionally homogeneous area is too large or small to constitute one district, in which case cognitive distinctions should be used to ensure that people end up in districts where they feel the strongest sense of attachment to and belonging toward, and are the better represented for it. My research will therefore focus on the nature and scale of these more neglected cognitive COIs, and explore how closely those cognitive regions coincide with the administrative regions.

C. The scale of communities of interest

If a COI can take the form of a cognitive region, one may wonder about the scale of such regions. To be clear, by scale, I mean absolute size, not cartographic scale. So when I refer to larger scales, I am describing larger areas, not smaller areas. Clearly COIs are almost never the exact size of an electoral district; they are not equipopulous, as districts are required to be (Morrill 1987, p. 252). Therefore attempts to respect COIs when drawing district boundaries can never fully succeed; the hope is merely to do the best job possible. Granting the fact that such communities may differ in size from electoral districts, the question arises as to how they compare in size to districts at various scales. Each state in the U.S. is divided into congressional, state upper house, and state lower house districts (except for the seven states that have one set of districts for both houses, and Nebraska, which only has one house). Furthermore, each of these three levels features a wide variation in size. At all levels, districts can range from large, sparse, and rural to small, dense, and urban. This is not to mention the many types of local districts that exist, such as those for county boards of supervisors, city councils, schools, and special purposes. One might wonder whether COIs are relevant at each of these levels, and whether a district may be too large or small for the COI criterion to meaningfully apply.

It is informative to ask whether the criterion to preserve COIs is indeed being applied by authorities at multiple district levels. A quick survey of several jurisdictions in the United States reveals that many do in fact utilize this criterion at different scale levels. As mentioned above, as of 2011, 13 states considered COIs for both congressional and state legislative districts, and an additional 9 states considered it for just state legislative districts (Levitt 2011, pp. 27–28). California's redistricting commission is tasked with drawing districts for Congress, both houses of the State Legislature, and the state's Board of Equalization (taxation), and it uses the same criteria for all four bodies, including respect for COIs (CRC 2011). This is especially notable considering how large and geographically diverse that state is, meaning this criterion is applied for a district spanning huge stretches of the Mojave

Desert just as much as it is for one made up of a few densely-packed neighborhoods in inner-city Los Angeles. Furthermore, even local jurisdictions apply the criterion for their relatively small districts, although they often use neighborhoods as a substitute for COIs. For example, San Francisco and San Diego have employed citizen commissions for drawing city council districts that tried to carefully consider which neighborhoods should land in which districts (Cain and Hopkins 2002). Even the relatively small city of Santa Barbara sought to respect the small COIs within it when determining the boundaries of its city council districts (Johnson 2015). These findings demonstrate that the criterion is used for many different types of districts of various sizes.

Given the application of the criterion at multiple district levels, scholars seem to diverge into two camps regarding whether that application is actually meaningful at all of those levels. In other words, they differ on how large or small a COI can truly be said to be. One camp has asserted that COIs do exist at multiple scales, but are not the same thing at one scale as they are at another. For example, Cain and Hopkins (2002) said that they "tend to be identified with neighborhoods in local government more than at the state or federal level. Statewide, COIs are likely to be defined as agricultural regions, coastal areas, and the like" (pp. 527–528). Morrill (1987) outlined three types distinguished by their scale: at the broadest scale, urban, suburban, and rural communities; at the regional scale, small metropolitan areas and media markets; and at the local level, city districts and large neighborhoods (pp. 251–252). Winburn and Wagner (2010) acknowledged that COIs can be equated with counties but also, and potentially even more significantly, with cities and neighborhoods (pp. 382–383). Lastly, Stephanopoulos (2012a) added that "communities exist, and should be represented in the legislature, at different levels of generality," and that more specific communities can form smaller-scale districts and broader ones can be captured by larger-scale districts like the congressional type (pp. 1432–1433). Thus this camp answers that the COI can take a wide range of scales.

The opposing camp, however, has doubted that COIs can exist at certain scales. Chambers (1999) and Monmonier (2001) were skeptical that they hold at the smaller scales, suggesting that they are larger than neighborhoods. Chambers believed that such communities have to be large in order to command a majority in a district, but he was focusing on those relevant to the congressional type, which are almost always far larger than neighborhoods (pp. 179–180). Monmonier based his case on the improved transport and communication links that have allowed communities to form that are more fragmented and extend beyond one's residential proximity (pp. 152–154). Gardner (2002; 2007) had trouble with the idea that there could be COIs at the larger scales, musing that a congressional district of half a million or more people could hardly be deemed a single, coherent community. May and Moncrief (2011), in their commentary on districts in the Western United States, similarly questioned whether a meaningful COI could be tied to one of the sprawling districts in rural desert environments (p. 40), though Steen (2011) suggested that the fact that such districts are so rural is enough to distinguish them as salient communities (pp. 90–91). In sum, this camp retorts that the COI exists only at a narrow range of scales, and cannot be applied at the largest and smallest ends of the scale spectrum.

The frequent references to the neighborhood in this literature on COIs raise the question of how related the two concepts are. These appear to be similar or at least related concepts, especially when one is focusing on the cognitive COI. But this relationship only seems to apply at a particular scale of COI; a large-scale COI made up of multiple counties is obviously not comparable to a neighborhood. Of course, one must first define what exactly a neighborhood is, which is itself an interesting and rich topic that has been approached in various ways. Scholars have given definitions deriving from more socioeconomic or demographic approaches to more cognitive ones (Nicotera 2007; Taylor 2012; Spielman and Singleton 2015; Bae and Montello 2018). The latter study adopted a cognitive approach by asking residents to indicate where they believe the boundaries of the Koreatown neighborhood to be. If one can define and identify a certain neighborhood as a region, either thematic or cognitive, one can then determine how well it corresponds to a particular scale of COI, whether the two greatly overlap or are even identical.

The debate on the scale range of the COI demonstrates how vague and imprecise the concept really is. COIs may well exist at different scales, but they are different varieties of COI, with different meanings for residents. One can discover the nature of each scale of COI by recognizing it as a cognitive region. Conceptualizing COIs as cognitive regions offers the greatest potential to discover their meaningful extents, precisely because meaning is a cognitive construct. In this research, I pursue this by soliciting people's beliefs about the extent of their COI, giving them the freedom to make it as big or small as they choose. Such a survey can reveal the scales people most commonly use to think of COIs, thereby identifying as precisely as possible a range of scales for these cognitive regions.

One can also conceive of a scale of "sense of place" by which people have different levels or types of place attachment at different scales. For example, an individual might identify very strongly with his or her city, but feel little connection to one's county. Similarly, some people might identify more with their state than their country, while others might feel the opposite. One can even possess a strong "sense of place" at multiple scales simultaneously. Shamai (1991) demonstrated this in a study with Canadian students, finding that they held "nested allegiances" for three different levels of place: country, province, and metropolitan area. However, these students did not feel an equal degree of attachment toward each of these three scales. Rather, they felt a stronger sense of place toward their metropolitan area, followed by their country, and lastly their province. These findings have implications for COI research, because if people can identify with multiple levels of place simultaneously, they can certainly identify with multiple COIs while feeling different levels of attachment toward each.

D. Administrative regions as communities of interest

In addition to the COI criterion, the need to respect the boundaries of already existing administrative regions (primarily jurisdictions like counties or cities, but in some cases their divisions) has long been recognized as an important objective for good redistricting (Morrill 1981; 1987; Grofman 1985; Handley 2008). The requirement is currently used in places ranging from Japan (Moriwaki 2008) to the United Kingdom (Johnston et al. 2008) to California (CRC 2011). While respecting clearly-bounded administrative regions is easier to interpret than respecting the more vaguely-bounded COIs, the two criteria may in fact be closely related. Counties and cities are often considered to be "vital, legal, and familiar communities of interest" (Morrill 1987, p. 251). The residents of such jurisdictions "share a history and collective sense of identity" that help foster a genuine sense of community (Gardner 2002, p. 1258).

Gardner (2007) contended that genuine communities arise where relevant ties form, but those bonds last only in jurisdictions with fixed boundaries. He argued furthermore that "common residency in a working, functioning, self-governing locality by itself can give rise to a political and administrative community of interest entitled to recognition. As the Colorado Supreme Court recently observed, ‘counties and the cities within their boundaries are already established as communities of interest in their own right, with a functioning legal and physical local government identity on behalf of citizens that is ongoing’” (p. 584). Winburn and Wagner (2010) likewise identified counties as important COIs in the redistricting context, in large part because they play such a critical role in the electoral process, from registering voters to mailing election information to administering polling places (p. 375). Bowen (2014) made a similar case with cities, as “residents of the same city share much in common—the same taxation levels, the same public problems, and the same municipal government” (pp. 864–867). These findings suggest that administrative regions may well contribute to the emergence of COIs as cognitive regions, and that the boundaries of the former may also serve as the boundaries of the latter.

However, some scholars have cautioned against completely equating administrative regions with COIs. Winburn and Wagner (2010) recognized that “counties are [not] the only, or even always the most relevant, political community of interest for a citizen” (p. 382). Stephanopoulos (2012a) argued that the two are often different, as when interests and affiliations do not follow administrative boundaries, or when administrative regions contain multiple communities or only parts of communities. He did concede, however, that “the two may sometimes be functionally identical, both because [administrative regions] tend to be inhabited by people with similar socioeconomic characteristics, and because civic ties can foster a sense of kinship” (p. 1432). The consensus appears to be that administrative regions are at the very least useful proxies for COIs, if not in some sense meaningful communities themselves. Whether this is more the case for counties or cities likely depends on locational context; counties are probably more meaningful entities in rural areas than in urban areas.

E. My research plan

My dissertation seeks to investigate the effect of both scale and administrative regions on people's conceptions of their COI. I do so by conducting two studies. The first study seeks to determine the effects of three factors on the cognitive COIs that survey respondents depict. Those factors are the extent of the map given to survey respondents, whether the boundaries of administrative regions are shown to them on the map, and whether they live in an urban or rural locale. This study is an experimental survey of residents of an urban study area and a rural study area, with the manipulated variable being the type of map that residents receive. There are six types of map, because there are three possible map extents with versions that have and lack boundaries. Participants of this first study respond by drawing freehand on the map three different areas representing their COI, one being the area that is *definitely* within their COI, another being the area that is *probably* within their COI, and the last one being the area that is *possibly* within their COI. Requiring a series of drawings enables me to achieve a secondary aim of this study—examining variation within respondents' cognitive COIs by having them depict different levels of confidence, in the same vein as Montello et al. (2003) (also see Montello, Friedman, and Phillips 2014). Another secondary aim is to explore how the cognitive COIs that respondents depict coincide with the existing electoral districts, as a function of scale.

The second study seeks to determine the extent of the cognitive COIs that survey respondents depict, when given free rein to make their region as large or small as they want. Participants respond to this second study by ranking predefined administrative regions on the map according to how confident they are that a given area is within their COI. They do so at three different map scales—one showing large-sized areas (mostly counties), one showing medium-sized areas (mostly municipalities), and one showing small-sized areas (mostly towns). Respondents also indicate how much they identify with the COI they define at each scale, on a five-point rating scale. This enables me to achieve a secondary aim of this study—investigating whether respondents identify with multiple nested COIs at different scales, and if they do, which ones they identify with the most. Like the first study, my second study achieves the additional secondary aim of exploring how the cognitive COIs that respondents depict coincide with the existing electoral districts, as a function of scale. Both studies together allow me to determine whether COIs exist as cognitive regions at multiple scales. If they do, then I can describe the nature of these regions at those different scales, particularly whether they reflect local districts, counties, and cities.

Table 1. Summary of the two studies, including their purposes, methods, and findings.

Study 1: - Investigates whether different people conceive of roughly the same scale of COI when they receive the same map extent, and if that scale is different from the others - Splits survey participants into three groups - Exposes each group to a different map extent - Asks participants to draw on the map where they think their COI is located at, and do so multiple times at different levels of confidence - Demonstrates that different people can conceive of roughly the same scale of COI when they receive the same map type and live in the same urban/rural context
Study 2: - Investigates whether the same person conceives of different scales of COI, and if they identify with each scale of COI equally - Exposes all survey participants to the same sheet - The sheet has two different map extents, with three levels of administrative regions - Asks participants to rank places on the map according to how confident they are that those places are in their COI - Demonstrates that the same person can conceive of different scales of COI when they receive different map types, and identify with each of them
Both studies: - Show that different map extents/types act as stimulants to reveal the existence of different scales of COI - Establish that cognitive COIs do exist at multiple scales, and people recognize that they can belong to all of them

II. Study 1: The effect of map scale constraints on cognitive regions

A. Introduction

The first study investigates whether COIs appear to exist as cogent entities at different scales, as measured by the degree to which people agree on the location and extent of their COI when using different mapping scales. Secondarily, this study examines whether this degree of agreement is influenced by urban/rural residence, and awareness of administrative regions like counties. In this study, I manipulate scale mainly by changing the extent of the map shown to participants. As is typically the case, this change in map extent is accompanied by a change in map generalization. Specifically, I change the number of cities in Santa Barbara County that are visible so that smaller scale maps show more of them. One could conceivably manipulate scale by changing other, non-graphical properties, but this method seems the simplest.

Given the literature on administrative regions outlined above, administrative boundaries are clearly an important factor to consider. It is therefore prudent to examine whether people frame their conception of their COI around these regions when they are visible to them on the map. For example, those who can see the county lines might be inclined to draw the boundaries of their COI to follow those lines because they feel an attachment or sense of belonging with that county specifically. They might also have a tendency to draw a region that has an area that is closer to that of their own county than they might otherwise, or that coincides somewhat more with that county's extent than they might otherwise. I do not expect those who cannot see county lines to exhibit such tendencies, because I speculate that many lack the knowledge of where those boundaries are located without being able to see them. I therefore anticipate some distinction in the way that participants draw their regions based on the visibility condition to which they are assigned.

I look at agreement both within and between mapping scales, and both within and between urban/rural study areas. Such agreement might take the form of consensus among all people despite their differences, or consensus among groups of people precisely because of those differences. This study also assesses how people portray variation within their COI at different levels of confidence. The study deals with three between-subjects factors—whether the participants live in an urban or rural area (two alternatives), whether county lines are present on the survey materials (two alternatives), and what scale of map they are given on their survey instrument (three alternatives)—for a product of 12 conditions. Because the first factor is location-dependent, there are two study areas—an urban study area and a rural one.

I differentiate between urban and rural in order to explore the effect that one's environment has on their perceived COI. In particular, I want to know whether it matters if someone's environment is more urban or more rural. I view this distinction as important because urban residents and rural residents are frequently claimed to comprise vastly different interest groups (Morrill 1987; Steen 2011; Mac Donald and Cain 2013; Stephanopoulos 2013). They are likely to differ substantially in lifestyle, livelihood, values, and outlook on the world. Thus their concerns and attitudes often do not align. The fact that the California Constitution noted this dichotomy first and foremost in its definition for a COI (Section 2-d-4) further speaks to its perceived importance. I therefore wish to test this claim by isolating the two groups into separate study areas, and comparing their results.

Rather than just create three different arbitrary scales of map to present to survey participants, I structure each one so that the map fully contains a certain type of district. I do so in order to achieve the secondary study aim of comparing people's cognitive COIs with the existing electoral districts. Thus each scale of map corresponds to a certain type of district. I opt to consider three types of districts, one each for a different level of government: those used at the congressional level, those used at the state upper house level, and those used at the state lower house level. Almost every state features these three levels of districts; more local levels below these tend to vary more depending on whether counties or towns hold more power. These three levels thus form the basis of my map scales.

In the United States, individual states have widely varying populations and legislature sizes and therefore widely varying district populations (May and Moncrief 2011). Thus the population of a state upper house district can range from about 15,000 in North Dakota to almost a million in California. Residents of those states live in upper house districts that are extreme in size; if they were participants in this study, then using the size of the districts in which these people live to determine one of the three scale levels would not be representative of upper house districts in nationwide. Since residents of California are indeed participants in my study, I decide to use the extent of a *typical* district. I define a typical district as one that approximates the nationwide average of population. This is because districts in the United States conform above all else to strict population standards, since, in the words of Chief Justice Earl Warren, "Legislators represent people, not trees or acres." Thus my approach identifies three districts that adhere as closely as possible to the U.S. average for the population of a congressional, state upper house, or state lower house district. In particular, I aim for each district to reflect the average district population that weights by person rather than state; this weighted average is higher than the raw average for state upper house and lower house districts because more people live in states like California with large state legislative districts.

Table 2. Statistics for typical U.S. districts at three levels of government, across all 50 states.

Scale	# of districts	Average district pop.	Weighted average district pop.
Congressional	435	708,405	709,930
State upper house	1,938	159,007	338,660
State lower house	4,808	63,713	139,362

With those values in the last column in mind, I select three overlapping districts to use as models for the "typical" district at three levels of government: California's 24th Congressional District for the congressional scale, California's 37th State Assembly District for the state upper house scale, and Santa Barbara County's 3rd Board of Supervisors District for the state lower house scale. In this scheme, two of the three districts do not correspond to their stated scale level: What is supposed to be a state upper house district is actually a state lower house district (known in California as a state assembly district), and what is supposed to be a state lower house district is actually a county board of supervisors district. Why would I employ such a scheme with two of the three districts at the "wrong" level? I do so because, while those two districts may not actually serve as a state upper house district and state lower house district, respectively, their populations closely approximate the weighted average populations of those two types of districts.

A state assembly district in California has about the same population as a typical state upper house district nationwide, as measured by a weighted average. This is because California has a large population but a relatively small legislature size (May and Moncrief 2011), so each of its 80 state assembly districts has almost half a million people. Likewise, a county board of supervisors district in California has about the same population as a typical state lower house district nationwide. This is due to the fact that populous California tends to have highly populated counties, and each of these counties can only have five supervisors on its board (with the exception of the City and County of San Francisco). This means that many of the counties have board of supervisors districts with many tens of thousands of people. Thus, I am taking an approach in which the districts surveyed need not actually be the type of district they are intended to stand for, as long as they approximate the population of a typical district of that type.

The three districts that I select do not overlap perfectly, as the board of supervisors districts is not completely contained by the state assembly district, nor is the state assembly district completely contained by the congressional district. Nevertheless, there is a sizeable chunk of land that was covered by each of the three districts at the time of my survey, meaning that residents of this area shared the same congressional district, state assembly district, and county board of supervisors district. I therefore survey the population within just this area in order to make inferences about all three levels of districts. I hypothesize that this group of people would share a lot in common and maybe even belong to the same cognitive COI because the governing authorities lumped them together into the same district not just at one level, or two, but three (even four when counting the state senate district)! Given that these authorities are supposed to respect COIs, per the guidelines in the California Constitution, they may well view this group of people as a COI for them to keep it together at so many levels. The results from my study would hopefully either confirm or reject that hypothesis.

B. Methods

1. Study areas

This study utilized primary data collected by surveying residents of three districts, the details of which are given in Table 3. That table is followed by a map showing the spatial extents of these three districts, and specifically the area in which all three overlap. Each district modeled a certain level of government because its population size was roughly that of a typical district from that level. In addition to their population sizes, I also chose these three districts for convenience's sake, as I lived and worked within the area covered by all three. The districts were also relatively diverse in terms of demographics and economics, with a sizeable number of Hispanics, young people, and working-class people to help balance the majority who were non-Hispanic, older, and/or affluent. And while these districts were all fairly rural in nature, there was a large urban area shared by all three. Thus each district offered the chance to obtain the perspectives of both urban and rural residents, an important feature since I wanted to have an urban study area and a rural study area that each covered all three of these districts.

Table 3. Statistics for districts used in Study 1.

Govt. level modelled	Jurisdiction	Electoral districts	District studied	2010 pop.	Land area	Population density
Congress	United States	House of Reps. in California	24th	702,905	17,941 km^2	39 per km^2
State upper house	California	State Assembly	37th	465,674	8,619 km^2	54 per km^2
State lower house	Santa Barbara Co.	Board of Supervisors	3rd	84,779	2,695 km^2	31 per km^2

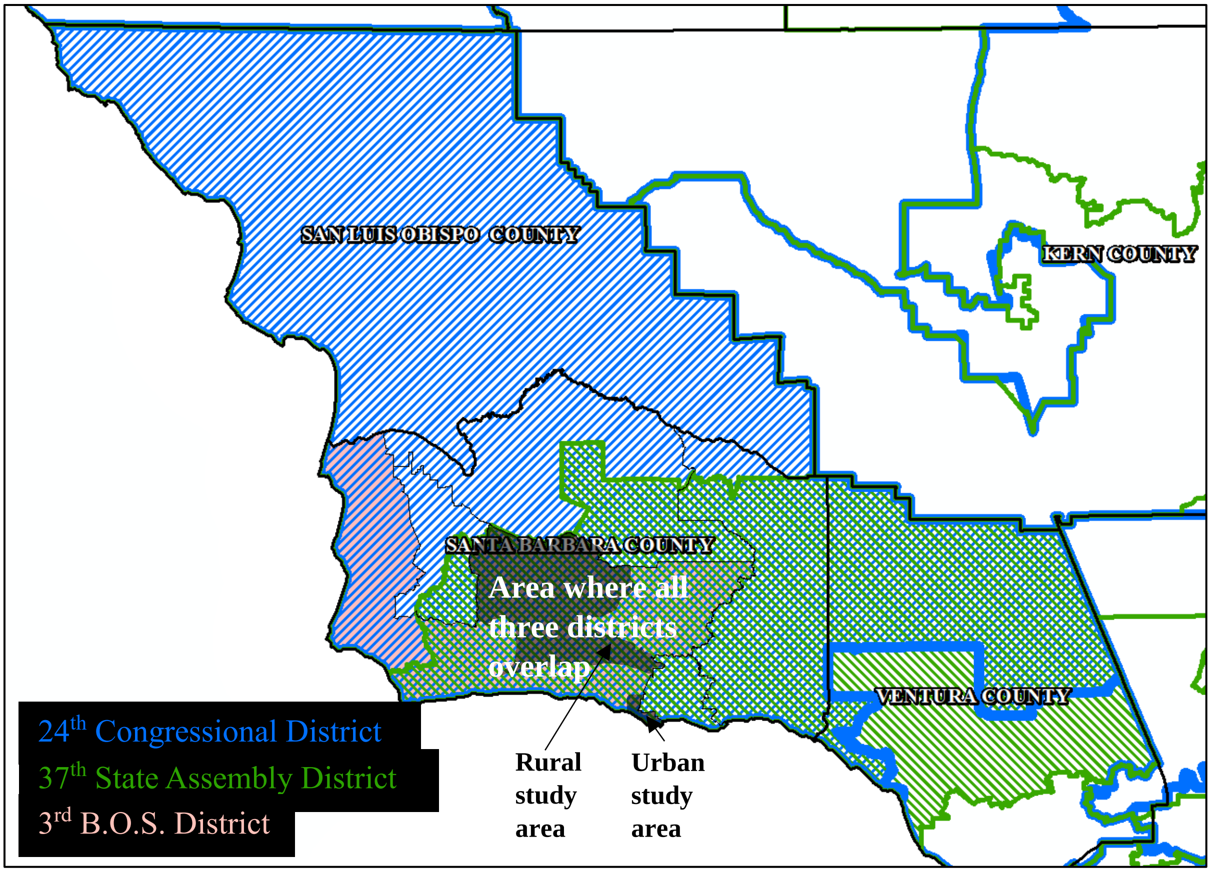

Figure 1. Map of the districts surveyed in Study 1. Different levels of government are symbolized by different colors (see key). The urban and rural study areas are the transparent black areas.

As discussed above, I focused my attention on the area covered by all three district types, which is the area symbolized by blue, green, and pink in Figure 1. Again, residents of this area share the same district at all three levels of government. I divided this area of overlap into an urban study area and a rural study area. The urban study area contained the campus of the University of California, Santa Barbara, the adjacent college town of Isla Vista, and the southern and western portions of the city of Goleta, a suburb of Santa Barbara. The rural study area contained the agriculture-dominated and relatively sparsely-populated Santa Ynez Valley. More information on these study areas, as well as the Census units that made them up, is given in Tables 4 and 5, with the urban area shown first.

Table 4. Statistics for census units surveyed in the urban study area (areal data from USA.com).

Census tract	Block group(s)	Description	2010 pop.	Land area	Pop. density	Number surveyed
29.09	3 (blocks 0–16, 20–24)	Far Western Goleta	1,291	0.6 km^2	2,152	6
29.15	1	UCSB North & West Campuses	580	1.3 km^2	446	6
29.22	1–2, 4 (blocks 6–9, 16–31), 5	UCSB Main & Storke Campuses, Storke Ranch	8,303	4.0 km^2	2,076	36
29.24	1–4	Eastern Isla Vista	5,833	0.4 km^2	14,583	24
29.26	1–3	Central Isla Vista	5,328	0.3 km^2	17,760	24
29.28	1–2	Western Isla Vista	4,089	1.3 km^2	3,145	18
29.30	1–6	Camino Real Marketplace, Ellwood	7,328	4.5 km^2	1,628	36
29.32	2 (blocks 5–36, 39–65)	Winchester	1,375	13.3 km^2	103	6
All tracts	All block groups	UCSB, Isla Vista, Southwestern Goleta	34,127	25.7 km^2	1,328	156

Table 5. Statistics for census tracts surveyed in the rural study area (areal data from USA.com).

Census tract	Block groups	Description	2010 pop.	Land area	Pop. density	Number surveyed
19.01	1 (blocks 89–396), 2–5	Buellton, Los Alamos	7,729	288.0 km^2	27	36
19.03	1–5	Solvang	5,764	23.5 km^2	245	24
19.05	1 (blocks 1–212), 2–3	Los Olivos	3,231	263.1 km^2	12	12
19.06	1–3, 4 (blocks 22–204), 5	Santa Ynez	5,389	236.8 km^2	23	24
All tracts	All block groups	Santa Ynez Valley	22,113	811.4 km^2	27	96

2. Cases

I utilized geographical cluster sampling to select residences to approach for an interview within each study area. This ensured that responses were drawn from residents across the entire study area, so that no particular cluster (or subarea) was overrepresented or underrepresented. Rather, I wanted to ensure that each cluster was sampled in proportion to its population. I used Census tracts as the clusters, collecting some multiple of six responses from each one (e.g., 6, 12, 24, 36) depending on the population of the tract. I collected multiples of six responses to match the different map types that participants received on their survey. Thus I ensured that an equal number of participants within each Census tract received one of the six types of map.

I selected individual residences within a given Census tract to receive a particular type of map by randomly choosing Census blocks, with each block weighted according to its population so that more populated blocks were more likely to be selected. After choosing the Census block, I then randomly chose a particular street making up that block. The street address with the lowest number was the first residence approached, and if the address was multi-unit, the unit with the lowest number was the first approached. I repeated this process with the other five map types and then continued with another set of six, until I had selected a residence to approach for each survey assigned to that Census tract. I surveyed 156 people across the five Census tracts that made up the urban study area, and 96 people across the four Census tracts that made up the rural study area, for a total of 252 participants, a sixth of which (42) received a particular type of map. Overall, 728 residences were approached for a response to this survey; of those, 320 had someone come to the door and 252 agreed to participate, for a response rate of 78.8% among those who came to the door and 34.6% among residences approached. Information about the survey sample is given in Table 6, along with information from the larger-sample American Community Survey.

Table 6. Statistics for survey respondents (relevant 2016 ACS 5-year estimates for surveyed block groups in parentheses).

Study area	Sample size	Average age in yrs.	Average yrs. in area	Race/Ethnicity	Sex
Urban	156 (39,543 tot. pop.)	32.0 (25.4 med. age)	9.5	75 Whites, 45 Hispanics, 28 Asians, 8 others (27.3% Hispanic)	77 males, 78 females, 1 unspecified
Rural	96 (21,695 tot. pop.)	54.2 (46.8 med. age)	27.4	77 Whites, 13 Hispanics, 3 Asians, 3 others (23.5% Hispanic)	40 males, 56 females
Both	252 (61,238 tot. pop.)	40.4 (33.0 med. age)	16.3	152 Whites, 58 Hispanics, 31 Asians, 11 others (25.9% Hispanic)	117 males, 134 females, 1 unspecified

3. Materials

I administered the surveys to participants in a traditional paper-and-pencil format, with a map of their local area printed on the survey sheet. Participants received one of six different types of map: three different map scales each shown with or without county lines, which are the most salient administrative regions in California (as opposed to boroughs, towns, or townships in other parts of the United States). The different map scales were intended to guide the participants into drawing regions of a certain size to compare to a particular level of district in which they live (the 24th Congressional, 37th State Assembly, or 3rd Board of Supervisors District). I chose these map extents in order to encourage participants to draw a COI of a size approximating a certain level of district, so that the relevant electoral district took up a large portion but not the majority of the map (the district was not shown on the map, however). I assumed that survey participants in general would tend to express their opinions in a moderate fashion, neither drawing a region that took up the whole map or even exceeded it, nor drawing a region that took up just a tiny portion thereof. Thus I designed the map to cover an area that would prompt a moderate response that would be similar in size, and thus readily comparable, to that of a particular level of district. I could have opted to explicitly tell them to draw a region approximating the size of a certain level of district, but that would have been a difficult proposition considering that most people have little idea how large a level of district might be in terms of area or population. Even if I had told them this information, they would still have had a hard time determining how much of the map contained a certain area or population.

The largest map scale I named the “state scale.” The map covered the area of a small state (about 100,000 square kilometers), so as to encourage participants to draw a COI about the size of a typical congressional district that would make up a good portion of that area (Figure 2). It included the entirety or majority of ten counties in Central California, and showed two cities in Santa Barbara County. The medium-sized map scale I named the “regional scale.” This map covered the area of a typical-sized intra-state region (about 50,000 square kilometers), so as to encourage participants to draw a COI about the size of a typical state upper house district that would make up a good portion of that area (Figure 3). It included the entirety or majority of Kern, San Luis Obispo, Santa Barbara, and Ventura Counties, and showed five cities in Santa Barbara County. The smallest map scale I named the “local scale.” It covered the area of a typical-sized locality, usually a large county or group of small counties (about 10,000 square kilometers), so as to encourage participants to draw a COI about the size of a typical state lower house district that would make up a good portion of that area (Figure 4). This map extent included the entirety of Santa Barbara County, and showed twelve cities in that county. To show how these three scales of map relate, I include a schematic map of California after presenting the actual maps shown to participants (Figure 5).

Figure 2. Map of the “state scale” extent with county lines shown.

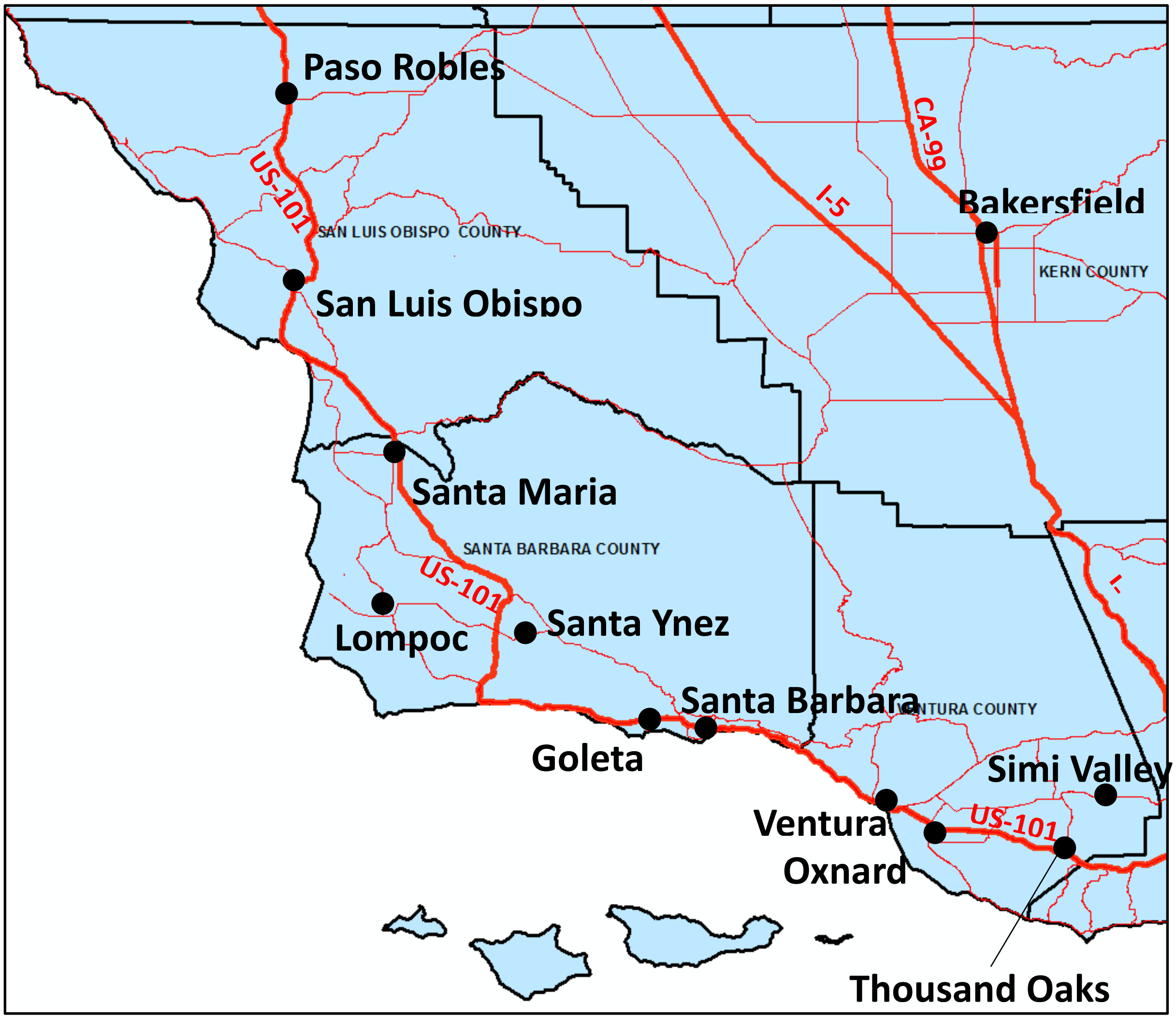

Figure 3. Map of the "regional scale" extent with county lines shown.

Figure 4. Map of the “local scale” extent with county lines shown.

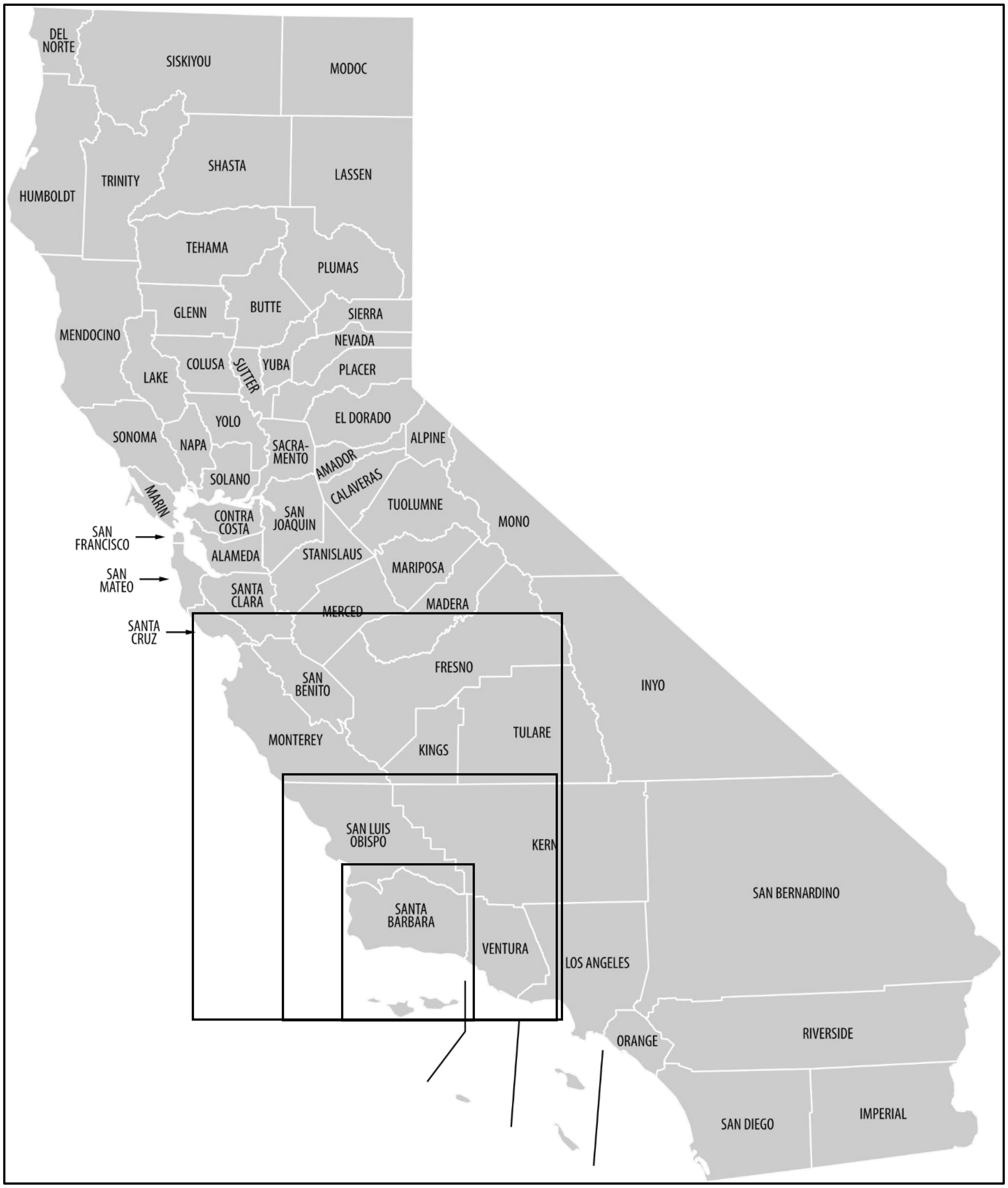

Figure 5. Schematic map of California showing the extents of each of the survey maps. The "state scale" is the largest, the "regional scale" is the next largest, and the "local scale" is the smallest.

Printed above the map was the same definition for all participants: “A community of interest is a group of people who live next to each other and share a common identity and sense of belonging.” This was the same definition used in a previous study I did (Phillips and Montello 2017); it seemed to be widely understood and to communicate well the cognitive aspect of communities I was seeking to capture. It also resembled the definition for a community that many respondents in the Phillips and Montello study gave in response to the open-ended question: “A group of people who interact with each other in close geographic proximity, living together and supporting one another for their mutual benefit.” Below the definition came three instructions to encourage the participants to express on the map varying levels of confidence within their COI. The first instruction read: “On the map below, please draw a line around the area that you believe is *definitely* within your community of interest.” The second read: “Many people believe there is a wider area outside the area that is definitely within their community of interest, an area that is still *probably* within their community of interest. If you believe that there is such an area, please draw a line around it.” And the third read: “Some people might even believe there is yet a further area outside the area that is probably within their community of interest, an area that is only *possibly* within their community of interest. If you believe that there is such an area, please draw a line around it.” These instructions aimed to obtain more nuance in people’s cognitive regions than a single drawn polygon would provide. The definition and instructions were given in Spanish on the reverse side for participants who preferred to use them.

4. Procedure

Since many native Spanish speakers live in the two study areas, I enlisted the service of bilingual survey administrators. These administrators approached the selected residence and sought a response from there. If they could not get a response from there, they moved on to the next-highest-numbered residence on that side of the street until they obtained a response. If that street was exhausted, they then found the lowest-numbered residence on the next street alphabetically that made up that block and repeated the process. Residences with locked gates or “no trespassing” signs were passed over. Survey collection took place on either weekday evenings or weekend middays, since most people were at home during those times. Both study areas were surveyed during roughly the same time frame, spanning from February to July 2018, so as to remove date as a confounding factor for differences observed between the areas. For each residence the survey administrators visited, they introduced themselves to an adult resident as a UCSB student conducting research and asked that person whether he or she would be willing to participate in a quick survey. Those residents who agreed to participate then received the paper map on which to portray their COI. After that, the administrators asked them to provide their age, their racial or ethnic identity (if not obvious), and how long they had been living in the area; they also noted their sex and the street block they lived on.

5. Analysis

Analyzing this study’s results involved three tasks: digitizing the region drawings, computing the area of each region drawn, and calculating degree of agreement among those regions. First I scanned all the region drawings and then digitized the lines in a GIS to create a polygon for each drawn region; this allowed me to calculate the area of each region. Various anomalies found in people’s drawings led to the exclusion of nine cases for all analyses besides one or more qualitative ones. Three participants drew lines around city labels to indicate that their community was that city, instead of drawing an actual region with boundaries, and so their data was not deemed usable except for the types of regions they drew. Five individuals had lived in the area for less than six months, so their data was deemed as less valuable since they did not have much experience in the community. I did, however, include these participants in my analyses of the qualitative properties of the regions that they draw, in case time in the community had an effect on those analyses. This winnowing left 244 cases for analysis of polygons depicting the area that people *definitely* believed was within their COI.

Analysis of polygons depicting the area that people *probably* and *possibly* believed was within their COI was complicated by an unfortunate error committed by one of the research assistants for this project. That research assistant instructed every participant in Census Tract 29.24 to draw three regions, even though the instructions on the survey materials clearly stated that they were not obligated to draw any region besides the "definitely" one if they chose not to do so. This resulted in every person in that tract drawing a "definitely," "probably," and "possibly" region, whether they wanted to or not. While "forcing" these participants to draw all three regions goes against the survey design, this did not wholly invalidate their views on what those communities looked like. Therefore, I conducted my analysis of agreement both with and without the "probably" and "possibly" regions drawn by 23 residents of Tract 29.24, to see whether the results were impacted in any sizable way. I did so only with that analysis because it dealt with the geographic location and extent of people's cognitive communities, and these residents still retained the freedom to draw their region in whatever location and of whatever size they desired. The analysis of area, in contrast, considered the size of the combined "definitely + probably + possibly" cognitive region, which depended on whether a participant elected to draw an additional one or two regions on top of their “definitely” region. Excluding the residents of Tract 29.24 in this and other analyses, all noted in the results, left 221 cases for analysis.

Consensus cognitive COIs were determined by the degree to which residents of a given district agreed about the location and extent of their COI, so that for each community a gradation from a lesser-agreed-upon periphery to a greater-agreed-upon core would be visible, rather than a monolithic average polygon. To determine level of agreement, all the polygons were merged into one GIS shapefile, which served as the input for two operations. First, I computed a count of the overlapping polygons at each point in space. Second, I used that count to produce an output raster with 250×250 meter cells (deemed to be adequate resolution at this scale). This output raster could then be classified based on degree of agreement across points in space. Agreement could range from 0% at points in space contained by no region drawing to 100% at points in space contained by every region drawing (Woodruff 2012). This process resulted in maps of the cognitive COIs salient within each study area, with a gradation of lesser to greater agreement. I then identified an area of a certain level of agreement: 20%+, 40%+, 60%+, and 80%+. Finally, I measured the spatial similarity between these areas and the existing electoral districts.

C. Results

1. Areas of regions drawn by participants

a. Raw area values

First I examine the results of the areal analysis. These results concern the raw areas of the regions that participants draw in the study. To start, I consider the regions drawn by people that they believe *definitely* to be in their COI; this was the only type of region drawn by all participants. The mean areas of these regions are 2,497; 1,773; and 776 square kilometers for participants using the “state scale,” “regional scale,” and “local scale” maps, respectively. Included in these data are three area values for regions that participants do not actually draw on the map, but indicate by writing “LA” or “SF,” as these areas fall outside the map extent. Because there is no actual polygon on these drawings for which I can calculate area, I instead derive the area values from the greater urban areas defined by the US Census for those cities. I assume that these terms in their vernacular sense are not limited to just the city proper.

These mean values are distorted, however, by the fact that a few people draw their region to encompass almost the entire map area, which pulls the averages upward. This is borne out by the large standard deviations of 4,486; 4,263; and 1,865 square kilometers, respectively. Because of the undue influence exerted by these outliers, I winsorize the data by treating all areas larger than three standard deviations above the mean at each scale as being exactly three standard deviations above. There are seven regions overall with such large areas. After doing this, the mean areas decrease to 2,280; 1,514; and 660 square kilometers for the three scales.

These values for the three scales fall well short of the actual areas of the corresponding electoral districts at the three levels of government. The winsorized mean for the “state scale” regions is 15,661 square kilometers smaller than the actual congressional district, while that for the “regional scale” regions is 7,105 smaller than the actual state assembly district, and that for the “local scale” regions is 2,035 smaller than the actual county board of supervisors district. The winsorized mean areas for the three scales are significantly different from one another ($F[2, 241] = 7.79$, $p < .001$). Comparing between pairs of scales reveals where this difference lies. The winsorized mean areas for the “state scale" and "regional scale" are not significantly different from one another (t[149] = 1.59, p = .11). However, those for the "state scale" and "local scale" are significantly different from one another (t[100] = 3.97, $p < .001$), as are those for the "regional scale" and "local scale" (t[118] = 2.63, $p < .01$).

However, these areas only represent the "core" of people's COIs, the regions that people feel are *definitely* within their COIs. What happens to these estimated region areas if we examine people's expanded COI regions drawn to indicate probable regions? One can combine the "definitely" region and the "probably" region (if there is one) drawn by participants into one larger region (often noncontiguous) that people believe is *probably if not definitely* within their COI. I include participants who draw only the sole "definitely" region, but do not include those from Census Tract 29.24 and one with an unfinished survey. After winsorizing, the mean areas of these larger "definitely + probably" regions are 6,888; 4,930; and 1,311 square kilometers for participants drawing on the "state scale," "regional scale," and "local scale" maps, respectively.

The discrepancies between these regions and the corresponding actual districts are smaller but still substantial. The winsorized mean for the "state scale" regions is 11,053 square kilometers smaller than the actual congressional district, while that for the "regional scale" regions is 3,689 smaller than the actual state assembly district, and that for the "local scale" regions is 1,384 smaller than the actual county board of supervisors district. The relationships between the three scales of "definitely + probably" regions are in line with those of just the "definitely" regions. The winsorized mean areas for the three scales are significantly different from one another (F[2, 217] = 9.31, $p < .001$). Again, those for the "state scale" and "regional scale" are not significantly different from one another (t[133] =

1.24, $p = .22$). However, those for the "state scale" and "local scale" are significantly different from one another ($t[77] = 4.31$, $p < .001$), as are those for the "regional scale" and "local scale" ($t[85] = 3.70$, $p < .001$).

But even these areas do not represent the entirety of what people consider possibly to be within their community. Next, I consider the areas of the most expansive assessment of COI. Just as one can combine the "definitely" and "probably" regions, one can combine all three regions drawn by participants into one larger region (often noncontiguous) that people believe is *possibly, if not probably, if not definitely* within their COI. I include participants who only draw one "definitely" region or just "definitely" and "probably" regions, but do not include those from Tract 29.24 and one with an unfinished survey. After winsorizing, the mean areas of these large "definitely + probably + possibly" regions are 13,016; 14,033; and 1,698 square kilometers for participants drawing on the "state scale," "regional scale," and "local scale" maps, respectively.

The discrepancies between these regions and the actual corresponding districts are even smaller (except for the "regional scale") but still notable. The winsorized mean for the "state scale" regions is 4,925 square kilometers smaller than the actual congressional district, while that for the "regional scale" regions is actually 5,414 *larger* than the actual state assembly district, and that for the "local scale" regions is 997 smaller than the actual county board of supervisors district. The relationships between the three scales of "definitely + probably + possibly" regions are in line with those of just the "definitely" regions and the "definitely + probably" regions. The winsorized mean areas for the three scales are significantly different from one another ($F[2, 217] = 3.95$, $p = .02$). Again, those for the "state scale" and "regional scale" are not significantly different from one another ($t[129] =$ –

0.17, p = .86). However, those for the "state scale" and "local scale" are significantly different from one another (t[72] = 3.41, p = .001), as are those for the "regional scale" and "local scale" (t[74] = 2.52, p = .01).

I not only examine how area differs between the three scales of map, but also how it differs between the urban and rural study areas. All of the mean values reported here result from the same data refining process described in the area analysis above, that is, the omission of some problematic data and winsorisation of extreme outliers. These values for the "definitely" regions are 1,208 square kilometers for the urban study area and 1,925 square kilometers for the rural study area, which falls just short of being a significant difference (t[155] = –1.91, p = .06). The values for the "definitely + probably" regions are 4,559 for the urban study area and 4,107 for the rural, which again is not a significant difference (t[196] = 0.45, p = .66). And the values for the "definitely + probably + possibly" are 11,344 for the urban study area and 7,191 for the rural, which yet again is not a significant difference (t[199] = 1.12, p = .26).

However, the analysis above deals with differences between study areas across all three scales. I also look at the differences between study areas within scales. I first consider the "state scale." Here, the mean values for the "definitely" regions are 2,330 square kilometers for the urban study area and 2,197 square kilometers for the rural study area, which is not a significant difference (t[78] = 0.17, p = .87). The values for the "definitely + probably" regions are 8,308 for the urban study area and 4,781 for the rural, which again is not a significant difference (t[57] = 1.60, p = .12). And the values for the "definitely + probably + possibly" are 16,008 for the urban study area and 8,581 for the rural, which yet again is not a significant difference (t[61] = 1.26, p = .21).

I next consider the "regional scale." Here, the mean values for the "definitely" regions are 967 square kilometers for the urban study area and 2,387 square kilometers for the rural study area, which is in fact a significant difference ($t[51] = –2.26$, $p = .03$). The values for the "definitely + probably" regions are 4,470 for the urban study area and 5,548 for the rural, which is not a significant difference ($t[71] = –0.60$, $p = .55$). And the values for the "definitely + probably + possibly" are 16,420 for the urban study area and 10,825 for the rural, which again is not a significant difference ($t[67] = 0.61$, $p = .54$). Last I consider the "local scale." Here, the mean values for the "definitely" regions are 334 square kilometers for the urban study area and 1,186 square kilometers for the rural study area, which is in fact a significant difference ($t[34] = –2.56$, $p = .02$). The values for the "definitely + probably" regions are 812 for the urban study area and 1,988 for the rural, which is again a significant difference ($t[47] = –2.22$, $p = .03$). And the values for the "definitely + probably + possibly" are 1,372 for the urban study area and 2,142 for the rural, which this time is not a significant difference ($t[71] = –1.36$, $p = .18$).

b. Proportional area values

These results concern the proportional areas of the regions that participants draw in the study, relative to the areas of the corresponding electoral districts. I obtain these proportional area values by taking the area of a region that an individual participant draws, and dividing that by the area of the corresponding district. That corresponding district would be the congressional district for a region drawn at the "state scale," the state assembly district for a region drawn at the "regional scale," and the county board of supervisors district for a region drawn at the "local scale." The resulting proportions indicate how the area of a region compares to that of the district corresponding to the map scale on which that region is drawn.

For example, the extent of the “state scale” map is supposed to encourage participants to draw a region about the size of the 24^{th} Congressional District, as a moderate response that takes up much of the map but not all of it would approximate that size. The proportional area value will show how close in size that region comes to the “target” district, with a value less than 100% indicating that the region is smaller than that district, and a value greater than 100% indicating that the region is larger.

As above, I first consider the regions drawn by people that they believe *definitely* to be in their COI. The mean proportional area of these regions is 13.9%, 20.6%, and 28.8% for participants using the “state scale,” “regional scale,” and “local scale” maps, respectively. These mean values are distorted, however, by the fact that a few people draw their region to encompass almost the entire map area, which pulls the averages upward. Because of the undue influence exerted by these outliers, I winsorize the data as I do above. After doing this, the mean proportional areas decrease to 12.7%, 17.6%, and 24.5% for the three scales. These proportional values for the three scales fall well short of the actual areas of the corresponding electoral districts at the three levels of government. The winsorized mean proportional areas for the three scales are not significantly different from one another ($F[2, 241] = 2.41$, $p = .09$). Comparing between pairs of scales reveals where some difference might lie. The mean proportional areas for the “state scale” and “regional scale” are not significantly different from one another ($t[138] = –1.21$, $p = .23$), nor are those for the “regional scale” and “local scale” ($t[138] = –1.11$, $p = .27$). However, those for the “state scale” and the “local scale” are significantly different from one another ($t[106] = –2.09$, $p = .04$).

As above, I next consider the regions drawn by people that they believe *probably if not definitely* to be in their COI. The winsorized mean proportional area is 38.4%, 57.2%, and 48.7% for participants using the “state scale,” “regional scale,” and “local scale” maps, respectively. The discrepancies between these regions and the corresponding actual districts are smaller but still substantial, with those drawn at the “regional scale” coming closest to the actual. However, the mean proportional areas for the three scales are not significantly different from one another (F[2, 217] = 1.02, $p = .36$). No pairing of scales approaches significance either.

I last consider the regions drawn by people that they believe *possibly, if not probably, if not definitely* to be in their COI. The winsorized mean proportional area is 72.6%, 162.8%, and 63.0% for participants using the “state scale,” “regional scale,” and “local scale” maps, respectively. The discrepancies between these regions and the actual corresponding districts are even smaller (for the most part) but still notable. The one exception is the “regional scale,” where the average region is larger than the actual district. And yet, the mean proportional areas for the three scales are not significantly different from one another (F[2, 217] = 2.43, $p = .09$). Those for the “state scale” and “regional scale” are not significantly different from one another ($t[90] = –1.52$, $p = .13$), nor are those for the “regional scale” and “local scale” ($t[79] = 1.73$, $p = .09$), nor those for the “state scale” and the “local scale” ($t[112] = 0.45$, $p = .65$).

I not only examine how proportional area differs between the three scales of map, but also how it differs between the urban and rural study areas. All of the proportional mean values reported here result from the same data refining process described in the area analysis above, that is, the omission of some problematic data and winsorisation of extreme outliers. These values for the “definitely” regions are 12.2% for the urban study area and 28.1% for the rural study area, which is in fact a significant difference ($t[117] = –3.08$, $p < .01$). The values for the “definitely + probably” regions are 42.9% for the urban study area and 55.7% for the rural, which this time is not a significant difference (t[218] = –1.17, p = .24). And the values for the “definitely + probably + possibly” are 110.7% for the urban study area and 85.5% for the rural, which again is not a significant difference (t[205] = 0.66, p = .51). This analysis deals with differences between study areas across all three scales. It is not necessary to delve into these differences within scales because the distributions are identical to those of the raw area values, since each raw value within a certain scale is divided by the same number to yield the proportional value. Therefore, the results of the significance tests are identical to those already reported above.

c. Area values with or without visible administrative boundaries

I next compare the mean area values for the regions drawn by participants using maps with the administrative boundaries shown and those using maps without them. I consider whether the former more closely approximate the area of Santa Barbara County. However, I only examine those results at the “state scale” and “regional scale.” I disregard the “local scale” because there is no appreciable difference between the two versions of the “local scale” map; the version with administrative boundaries only shows those of Santa Barbara County at the map’s far edges. All of the values reported result from the same data refining process described above. These values for the “definitely” regions are 1,690 square kilometers with administrative boundaries and 2,087 square kilometers without them, which is not a significant difference (t[149] = –0.82, p = .41). The values for the “definitely + probably” regions are 4,139 with boundaries and 7,663 without, which is in fact a significant difference (t[100] = –2.26, p = .03). And the values for the “definitely + probably + possibly” are 8,961 with boundaries and 18,171 without, which is not a significant difference (t[93] = –1.55, p = .12).

However, the analysis above deals with differences between boundary conditions across both the "state scale" and "regional scale." I also look at the differences between boundary conditions within scales. At the "state scale," the mean values for the "definitely" regions are 1,935 square kilometers for the map version with administrative boundaries and 2,625 square kilometers for the map version without them, which is not a significant difference (t[61] = –0.90, p = .37). The values for the "definitely + probably" regions are 4,958 with boundaries and 8,928 without, which again is not a significant difference (t[47] = –1.55, p = .13). And the values for the "definitely + probably + possibly" are 12,498 with boundaries and 13,564 without, which yet again is not a significant difference (t[70] = –0.16, p = .87). At the "regional scale," these values for the "definitely" regions are 1,452 with boundaries and 1,575 without, which is not a significant difference (t[81] = –0.21, p = .83). The values for the "definitely + probably" regions are 3,320 with and 6,498 without, which again is not a significant difference (t[50] = –1.72, p = .09). And the values for the "definitely + probably + possibly" are 5,424 with and 22,415 without, which yet again is not a significant difference (t[38] = –1.79, p = .08).

2. Areas of agreement among participants' drawn regions

a. Regions that are *definitely* in participants' COI

Results from the three scale levels show varying areas of agreement among participants about the location and extent of their COI. For the following analysis, I look only at the drawings of "definitely" regions, since every participant draws or at least describes such a region. I calculate agreement at four levels: 20%+, 40%+, 60%+, and 80%+

agreement. For example, an area at the 40% level is contained by the regions of at least 40% of the participants. As expected, the areas of agreement within each class decline in size as one moves toward greater agreement. For this analysis, I include the full extent of the outliers that I winsorize in the areal analysis; their large sizes have no skewing effect here since only their innermost parts that overlap with other regions are taken into account. Thus the outlier-skewed mean areas for the regions are given in Table 7 to reflect the fact that all those outliers I now include.

First I present the agreement areas among all participants in the study, whether they live in the urban study area or the rural study area. As stated previously, all of these people live in the same district at not just one level of government, but three (actually four when one counts the state senate level). They all are residents of the 24th Congressional District, the 37th State Assembly District, and the 3rd Board of Supervisors District (as well as the 19th State Senate District). Therefore, one might assume that these people largely agree about the location and extent of their COI. Yet the results do not bear that out, as is evident in Table 7 and Figures 6–8.

Table 7. Areas of agreement among all individual "definitely" regions, showing how much area that at least a certain percentage of those regions share in common, where they overlap.

	Mean area of indiv. regions	20%+ agreement area	20%+ prop. of mean area	40%+ agreement area	40%+ prop. of mean area	60%+ agreement area	60%+ prop. of mean area	80%+ agreement area	80%+ prop. of mean area
"State scale"	2,497 km^2	2,809 km^2	112.5%	418 km^2	16.7%	0 km^2	0.0%	0 km^2	0.0%
"Reg. scale"	1,773 km^2	1,803 km^2	101.7%	203 km^2	11.4%	<1 km^2	<0.1%	0 km^2	0.0%
"Local scale"	776 km^2	615 km^2	79.3%	64 km^2	8.2%	<1 km^2	0.1%	0 km^2	0.0%

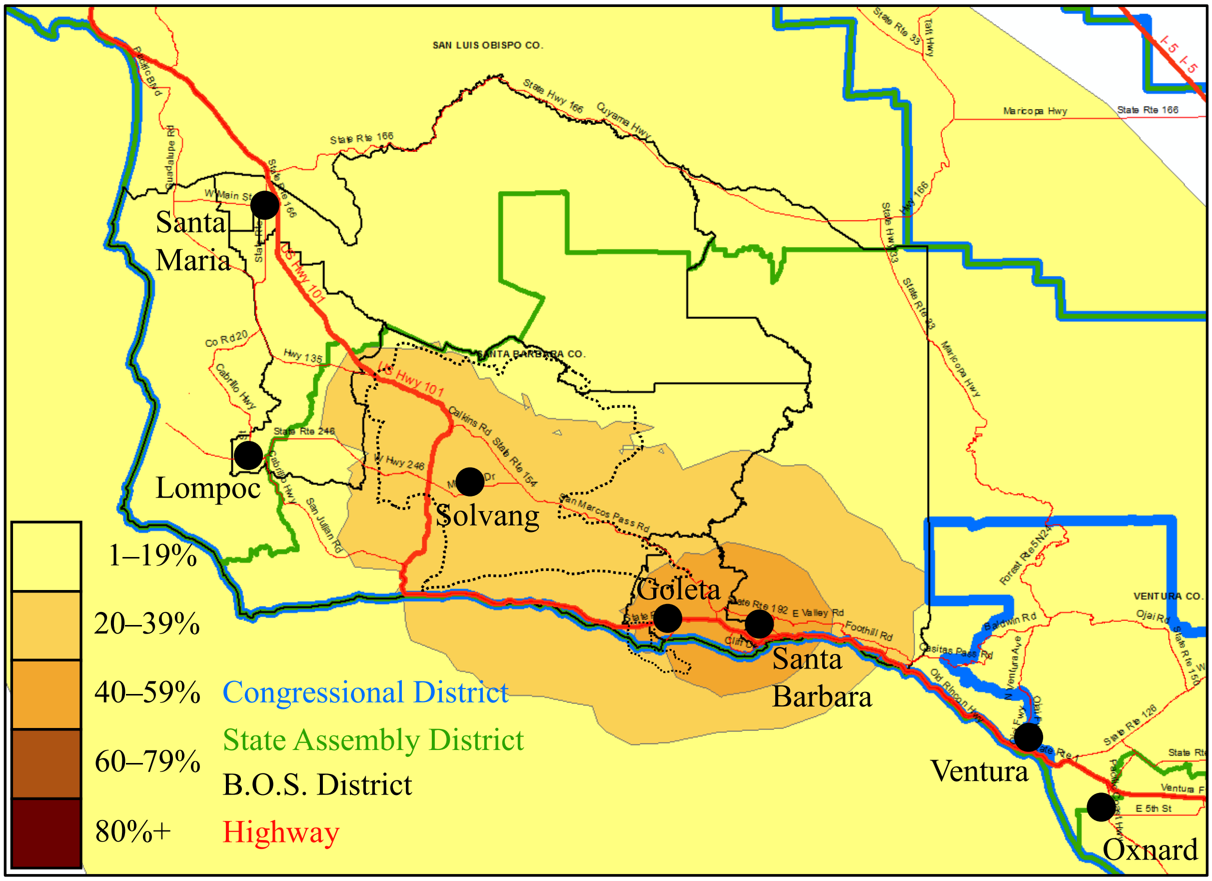

Figure 6. Map of agreement areas among <u>all</u> "definitely" regions at the "<u>state</u> scale." The dotted lines show the boundaries of the urban (southern) and rural (northern) study areas.

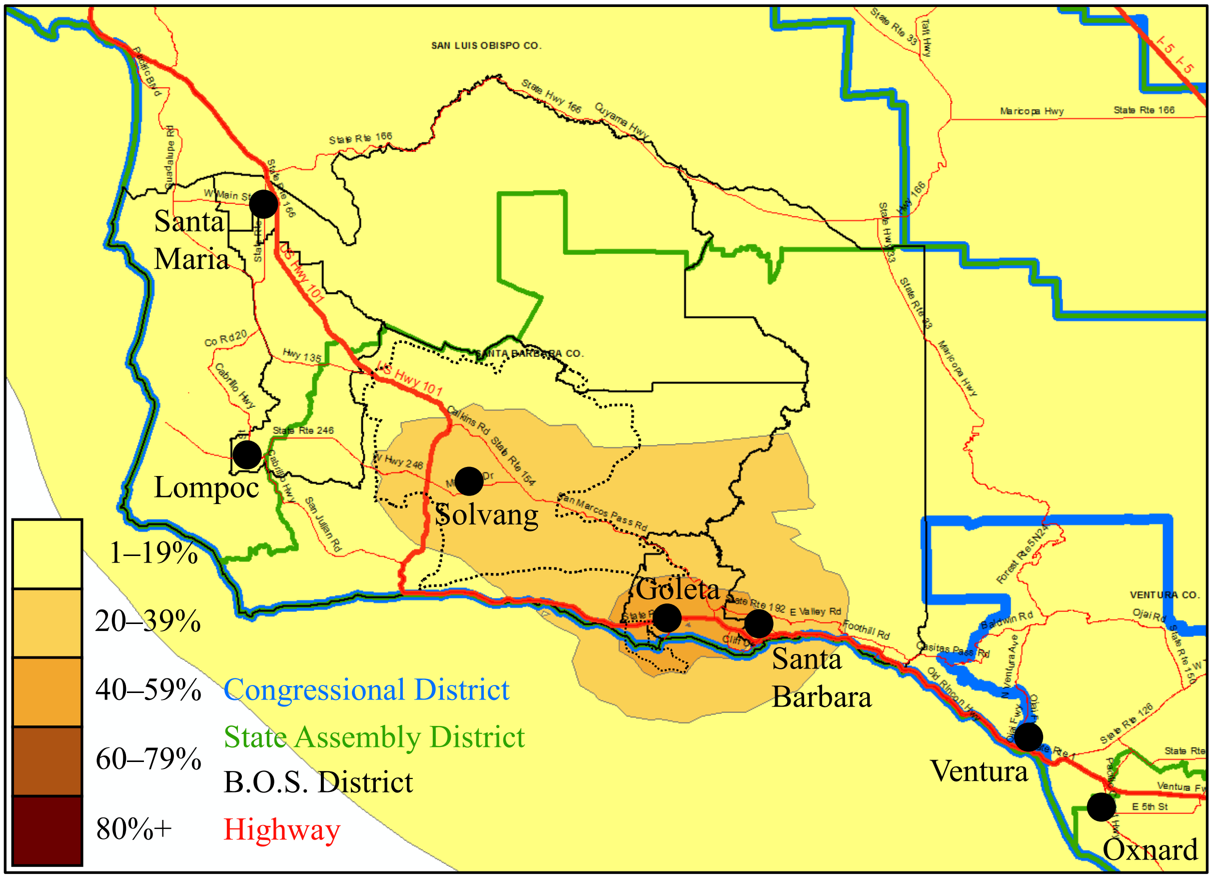

Figure 7. Map of agreement areas among <u>all</u> "definitely" regions at the "<u>regional</u> scale." The dotted lines show the boundaries of the urban (southern) and rural (northern) study areas.

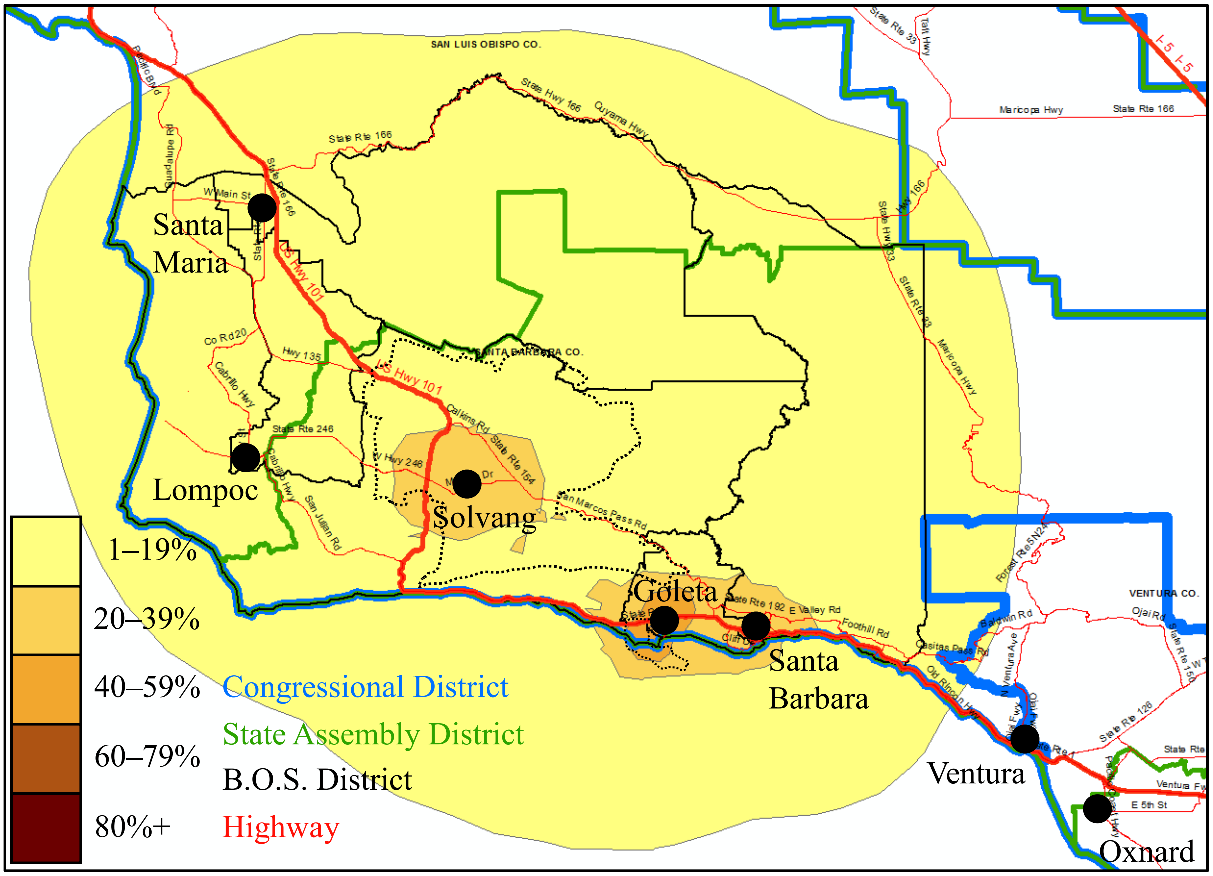

Figure 8. Map of agreement areas among <u>all</u> "definitely" regions at the "<u>local</u> scale." The dotted lines show the boundaries of the urban (southern) and rural (northern) study areas.

What stands out in these results for participants' "definitely" regions is the surprising lack of agreement among them, with only the tiniest areas receiving 60% or more agreement. Those participants using the "state scale" maps have the largest areas of agreement, followed by those using the "regional scale," and followed by those using the "local scale." This is to be expected, as it mirrors the mean area values of the individual "definitely" regions. If I take the areas of agreement and divide them by those mean area values, that proportion stays somewhat constant across the three scales for the 20%+ and 40%+ agreement areas, and exactly constant for the 60%+ and 80%+ agreement areas.

I now examine each scale specifically. Looking at the "state scale," a 20%+ agreement area envelops both study areas, with a 40%+ agreement area around the "South Coast" area of Santa Barbara and Goleta. At the "regional scale," the agreement areas follow the same pattern but are slightly smaller in extent. There is a tiny area of 60%+ agreement in Goleta, however. Finally, at the "local scale," two separate 20%+ agreement areas emerge around the two study areas, with 40%+ and 60%+ agreement areas in the vicinity of Goleta. This reflects the fact that people draw much smaller "definitely" regions when given a "local scale" map, usually only around their own study area. But the overall takeaway is just how little agreement there is when all participants from both study areas are included. However, I might find more agreement when I differentiate the results by study area. Tables 8 and 9 and Figures 9–14 reveal this information.

Table 8. Areas of agreement among individual "definitely" regions in the urban study area, showing how much area that at least a certain percentage of those regions share in common, where they overlap.

	Mean area of indiv. regions	20%+ agree-ment area	20%+ prop. of mean area	40%+ agree-ment area	40%+ prop. of mean area	60%+ agree-ment area	60%+ prop. of mean area	80%+ agree-ment area	80%+ prop. of mean area
"State scale"	2,594 km^2	3,331 km^2	128.4%	835 km^2	32.2%	300 km^2	11.6%	10 km^2	0.4%
"Reg. scale"	1,332 km^2	824 km^2	61.9%	309 km^2	23.2%	82 km^2	6.2%	0 km^2	0.0%
"Local scale"	317 km^2	407 km^2	128.4%	101 km^2	31.9%	49 km^2	15.5%	2 km^2	0.6%

Table 9. Areas of agreement among individual "definitely" regions in the rural study area, showing how much area that at least a certain percentage of those regions share in common, where they overlap.

	Mean area of indiv. regions	20%+ agree-ment area	20%+ prop. of mean area	40%+ agree-ment area	40%+ prop. of mean area	60%+ agree-ment area	60%+ prop. of mean area	80%+ agree-ment area	80%+ prop. of mean area
"State scale"	2,335 km^2	2,911 km^2	124.7%	491 km^2	21.0%	17 km^2	0.7%	0 km^2	0.0%
"Reg. scale"	2,475 km^2	4,076 km^2	164.7%	1,307 km^2	52.8%	351 km^2	14.2%	123 km^2	5.0%
"Local scale"	1,488 km^2	1,417 km^2	95.2%	380 km^2	25.5%	196 km^2	13.2%	48 km^2	3.2%

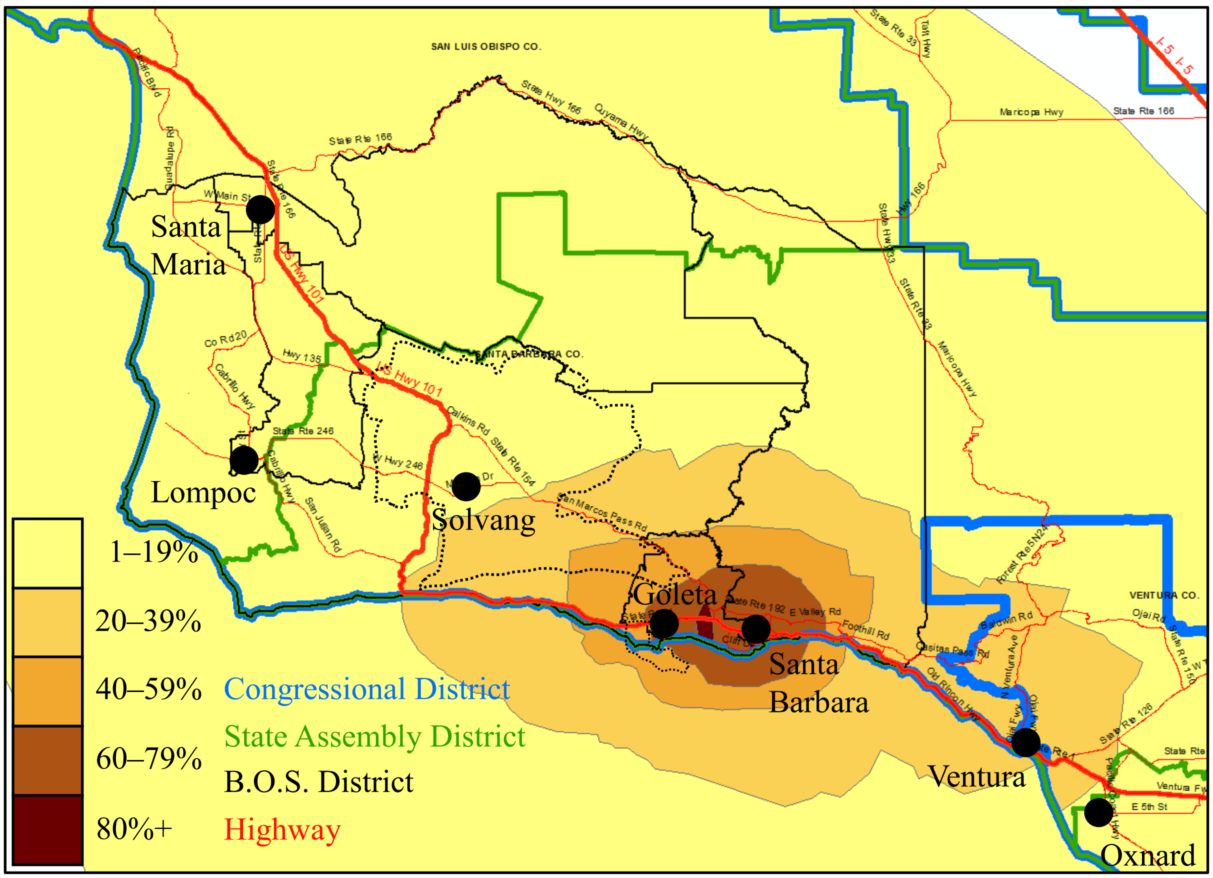

Figure 9. Map of agreement areas among "definitely" regions from the urban study area at the "state scale." The dotted lines show the boundaries of the urban (southern) and rural (northern) study areas.

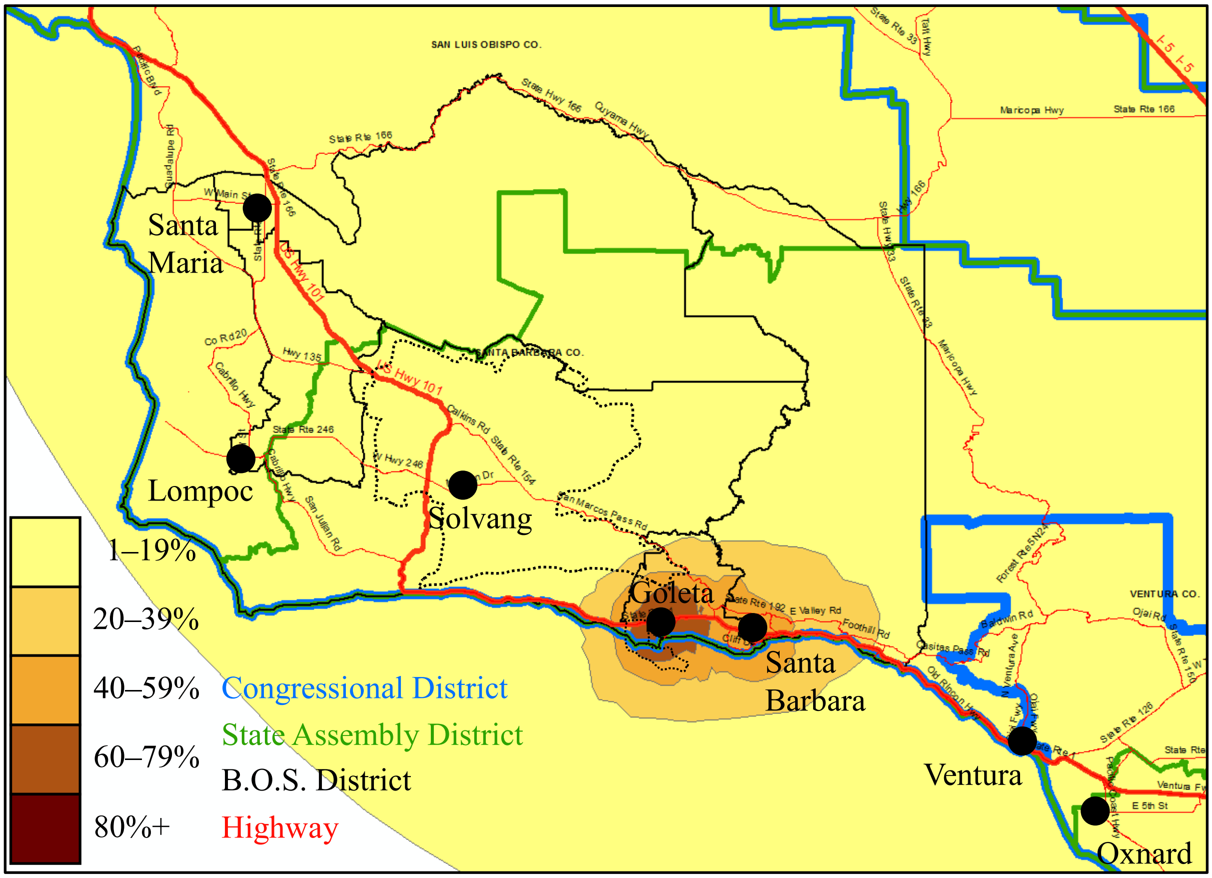

Figure 10. Map of agreement areas among "definitely" regions from the urban study area at the "regional scale." The dotted lines show the boundaries of the urban (southern) and rural (northern) study areas.

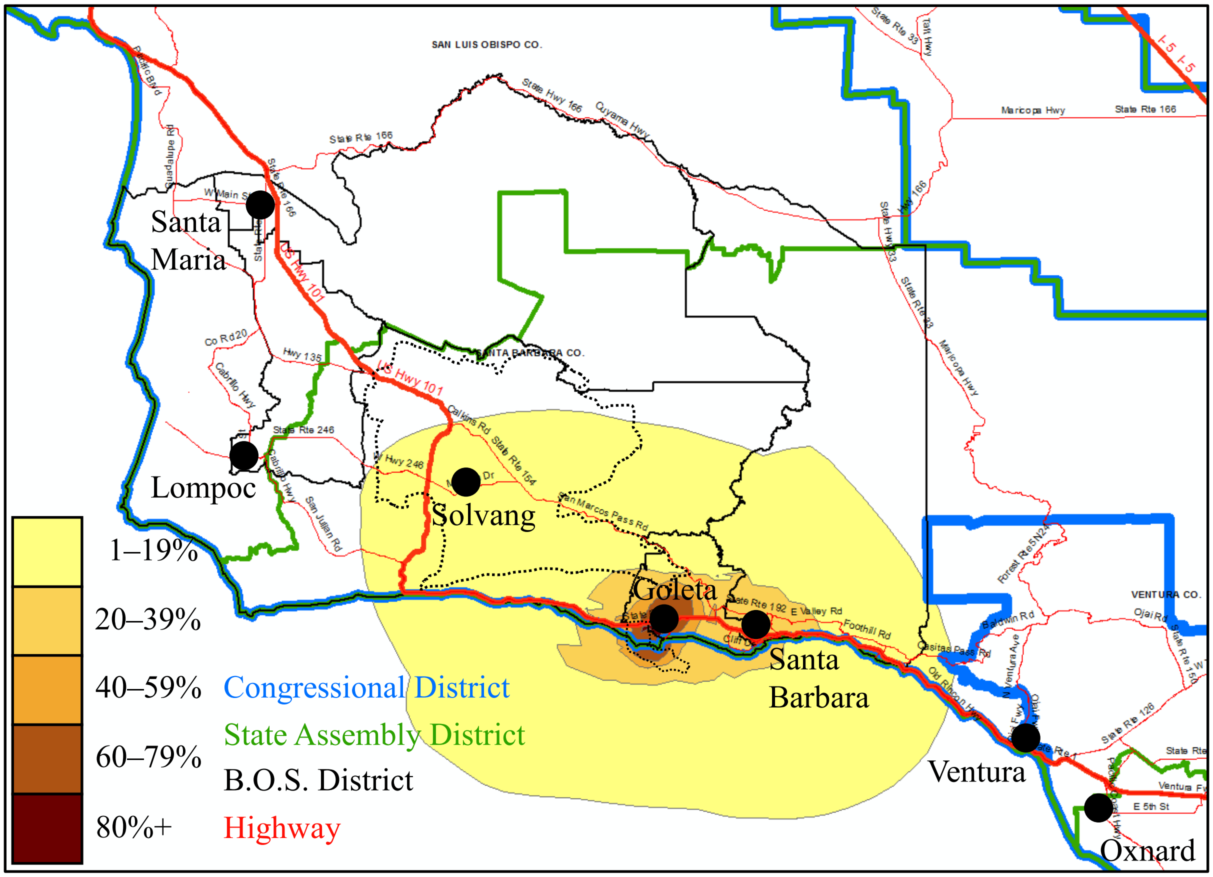

Figure 11. Map of agreement areas among "definitely" regions from the urban study area at the "local scale." The dotted lines show the boundaries of the urban (southern) and rural (northern) study areas.

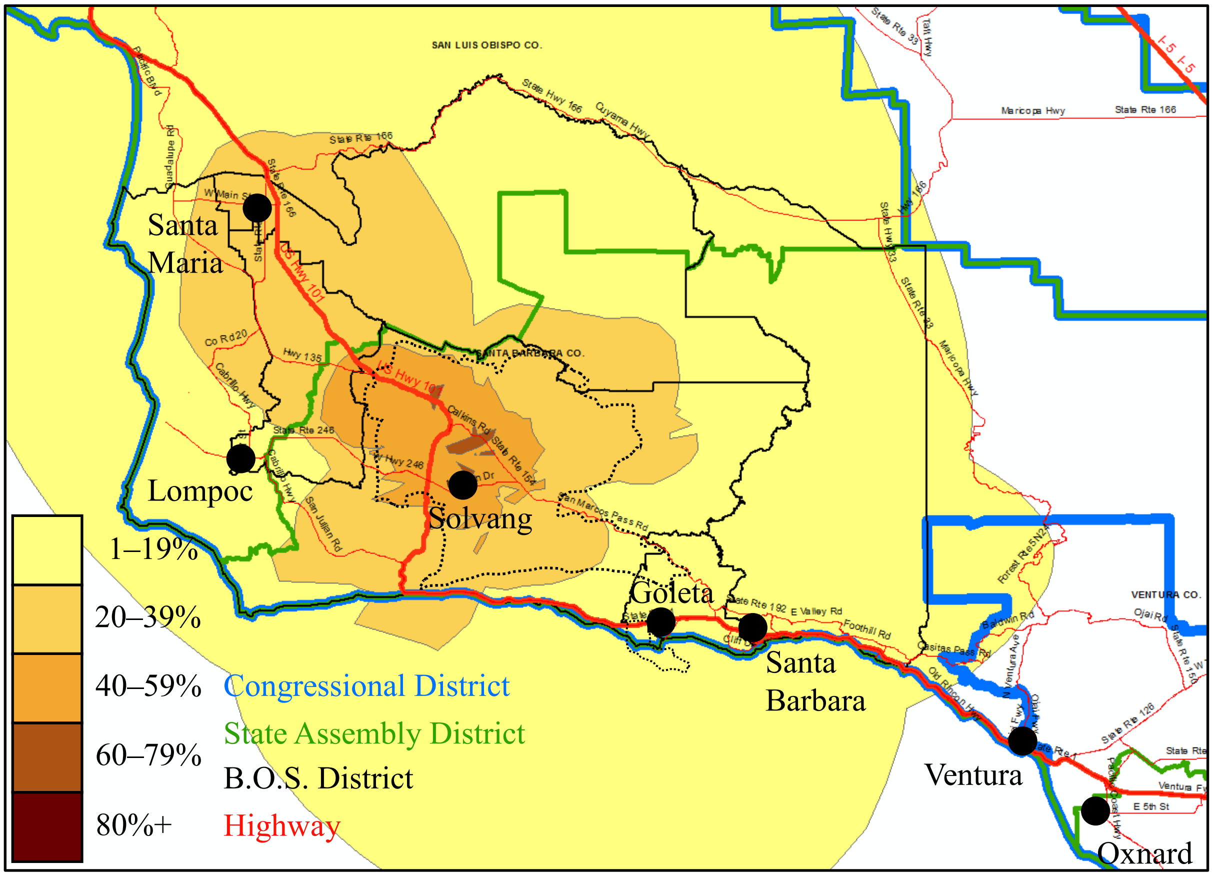

Figure 12. Map of agreement areas among "definitely" regions from the rural study area at the "state scale." The dotted lines show the boundaries of the urban (southern) and rural (northern) study areas.

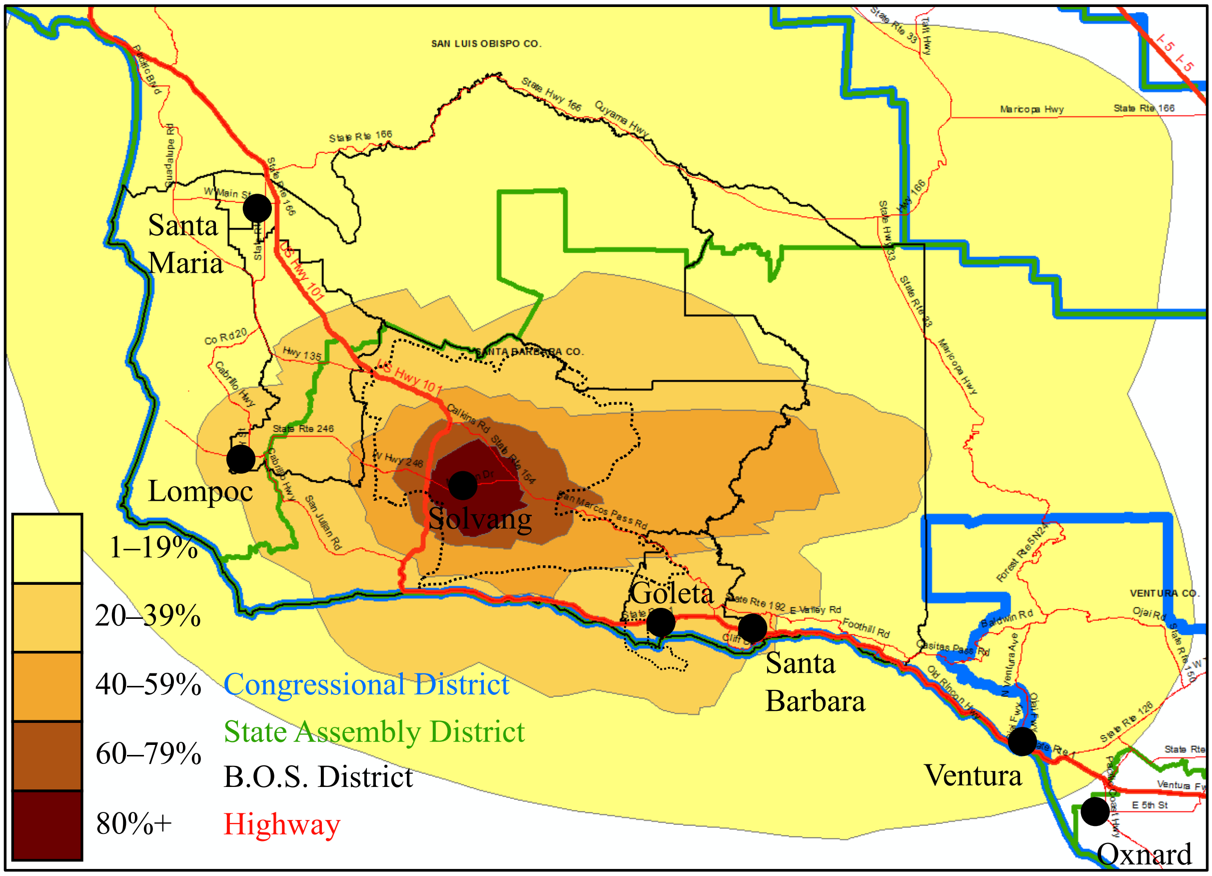

Figure 13. Map of agreement areas among "definitely" regions from the <u>rural</u> study area at the "<u>regional</u> scale." The dotted lines show the boundaries of the urban (southern) and rural (northern) study areas.

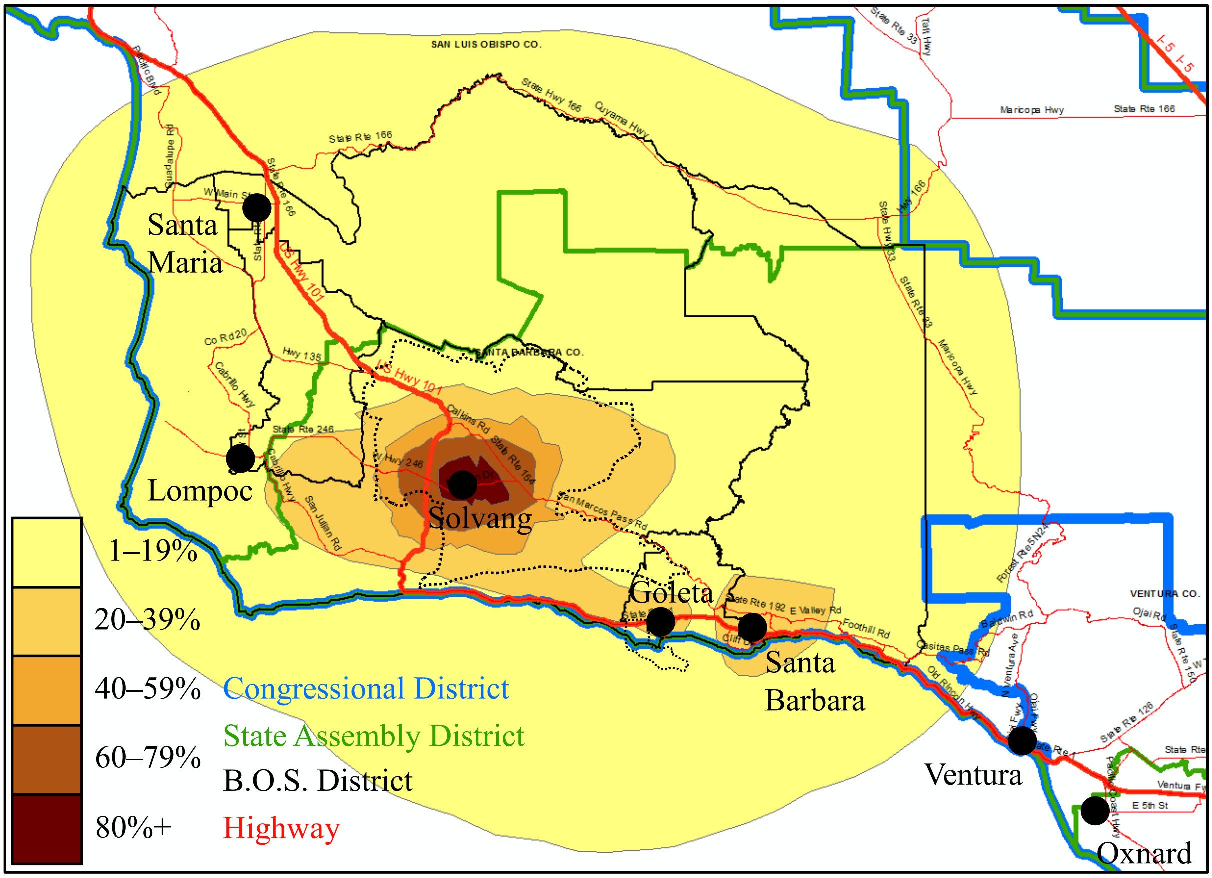

Figure 14. Map of agreement areas among "definitely" regions from the rural study area at the "local scale." The dotted lines show the boundaries of the urban (southern) and rural (northern) study areas.

Treating the results of each study area separately reveals that there is much more agreement among fellow urbanites and ruralites about the location and extent of their COI than there is among residents as a whole. Those in the urban study area agree more that their COI is confined to the "South Coast," but not limited to just the part within their own board of supervisors district, while those in the rural study area agree more that their COI is limited to Santa Ynez Valley and surrounds. This agreement is evidenced by the fact that there are larger areas of 60%+ and at least some areas of 80%+ agreement, in contrast to the results from all participants. This pattern is seen across all scale levels, with the agreement areas generally shrinking when going down in scale. There are exceptions to that general pattern in the rural study area, however. There, the areas of agreement for the "state scale" are less than those for the "regional scale" at all four levels, and less than even those for the "local scale" at the 60%+ and 80%+ agreement levels.

Moreover, the agreement area's proportion of the mean individual region's area does not always stay that constant across scales, as occurs among participants from both study areas combined. For the urban study area, the agreement areas for the "regional scale" are proportionally smaller than they are for the "state scale" and the "local scale," ranging from about half to two-thirds as large. Those for the "state scale" and "local scale" do stay relatively constant across scales, however. For the rural study area, all four agreement areas for the "regional scale" are proportionally larger than those for the "state scale" and "local scale," varying from about twice as large as both scales at the 40%+ level to far larger than the "state scale" but just barely larger than the "regional scale" at the 60%+ level. The other two scales are more similar proportionally at the 20%+ and 40%+ levels, but the "regional scale" becomes much larger than the "state scale" for the 60%+ and 80%+ agreement areas.

b. Regions that are ***at least possibly*** in participants' COI

The preceding analyses only deal with the drawings of "definitely" regions, but this analysis can be expanded to include all regions drawn by participants, whether they be "definitely," "probably," or "possibly" ones. While not every participant drew a "probably" and/or "possibly" region, 70% did (not counting those in Census Tract 29.24), so they are still worth considering. Furthermore, the areal analysis shows that the mean area of the combined "definitely + probably + possibly" regions most closely approximates that of the corresponding electoral districts, which is yet another reason to examine agreement between these largest regions. As above, I calculate agreement at four levels: 20%+, 40%+, 60%+, and 80%+ agreement. I also again include the full extent of the outliers that are winsorized in the areal analysis, and the outlier-skewed mean areas for the regions are given in Table 10.

As noted above, I conducted this analysis both with and without the “definitely + probably + possibly” regions from Census Tract 29.24. I found that the results did not differ much regardless of whether those from Tract 29.24 were included. In light of this fact, in this section I present the results without those 23 cases. I decide to exclude the regions drawn by those participants in this analysis because it is not clear what the extent of their “definitely + probably + possibly” regions would have been had they not been prompted to draw all three. But since they were so prompted, I refrain from comparing them with those who were not.

Table 10. Areas of agreement among all individual “D+P+P” regions, showing how much area that at least a certain percentage of those regions share in common, where they overlap.

	Mean area of indiv. regions	20%+ agree-ment area	20%+ prop. of mean area	40%+ agree-ment area	40%+ prop. of mean area	60%+ agree-ment area	60%+ prop. of mean area	80%+ agree-ment area	80%+ prop. of mean area
“State scale”	16,802 km^2	14,461 km^2	86.1%	4,082 km^2	24.3%	1,002 km^2	6.0%	58 km^2	0.3%
“Reg. scale”	20,204 km^2	12,300 km^2	60.9%	2,974 km^2	14.7%	612 km^2	3.0%	123 km^2	0.6%
“Local scale”	2,095 km^2	2,814 km^2	134.3%	608 km^2	29.0%	121 km^2	5.8%	0 km^2	0.0%

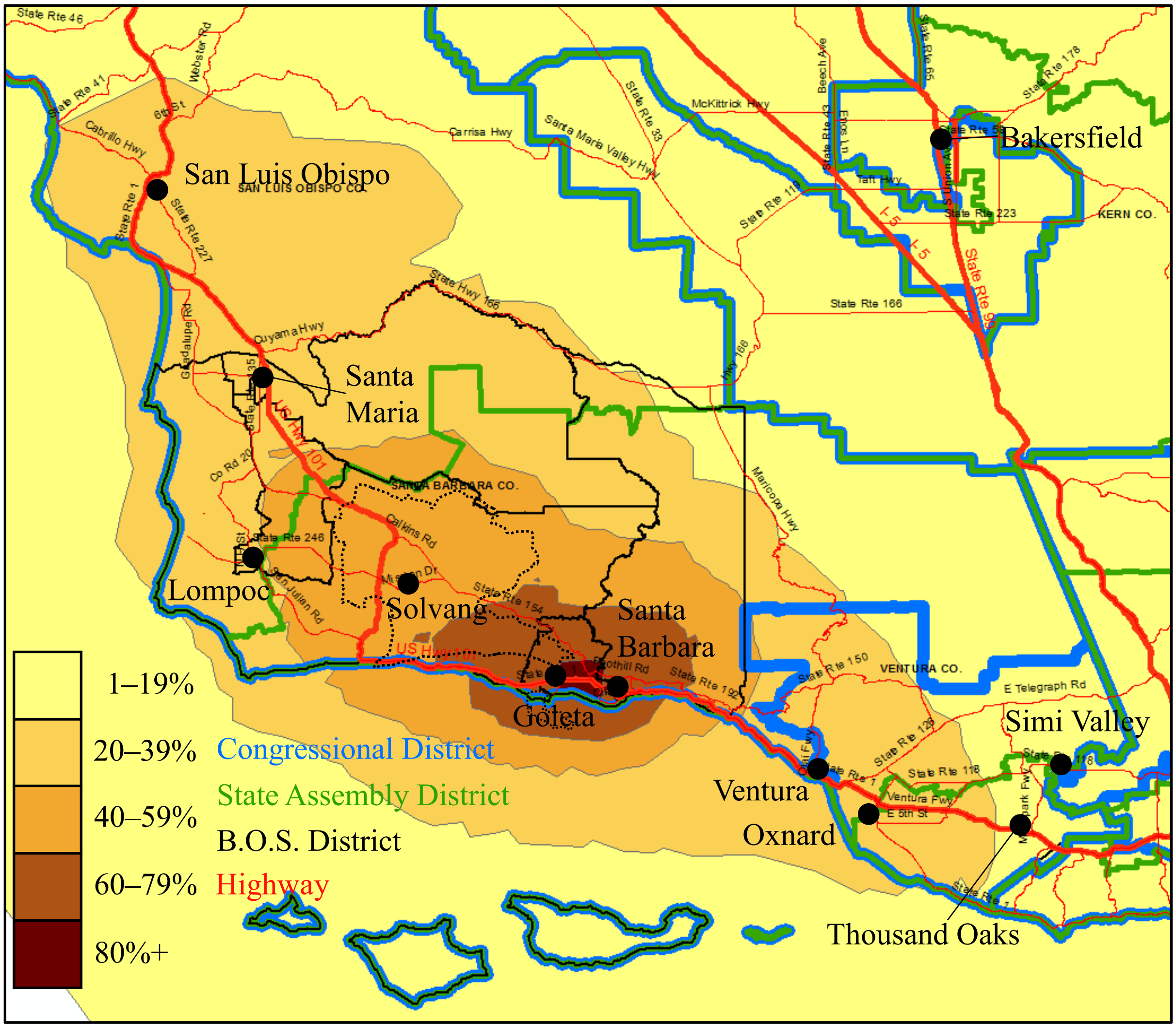

Figure 15. Map of agreement areas among all "definitely + probably + possibly" regions at the "state scale." The dotted lines show the boundaries of the urban (southern) and rural (northern) study areas.

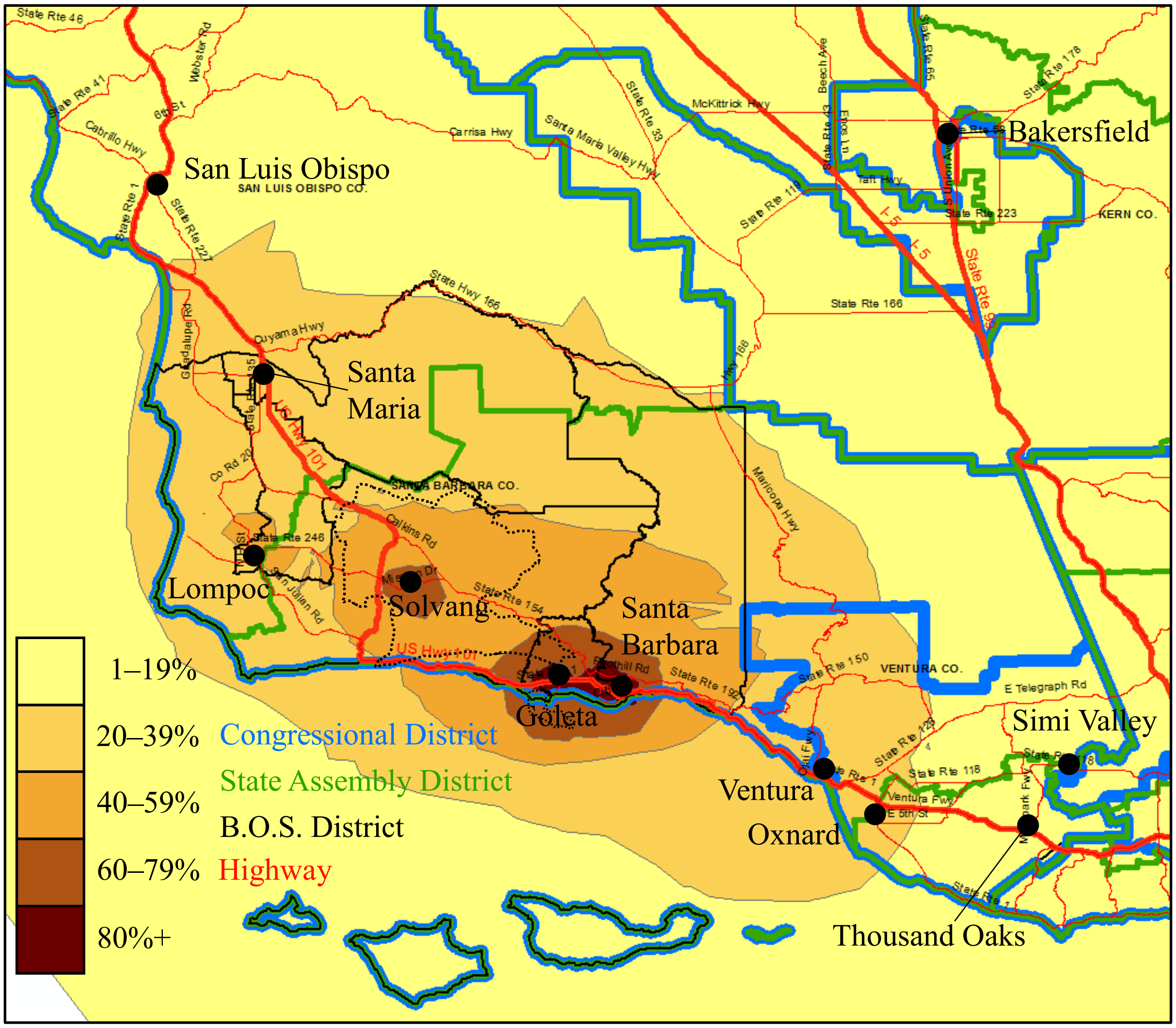

Figure 16. Map of agreement areas among all "definitely + probably + possibly" regions at the "regional scale." The dotted lines show the boundaries of the urban (southern) and rural (northern) study areas.

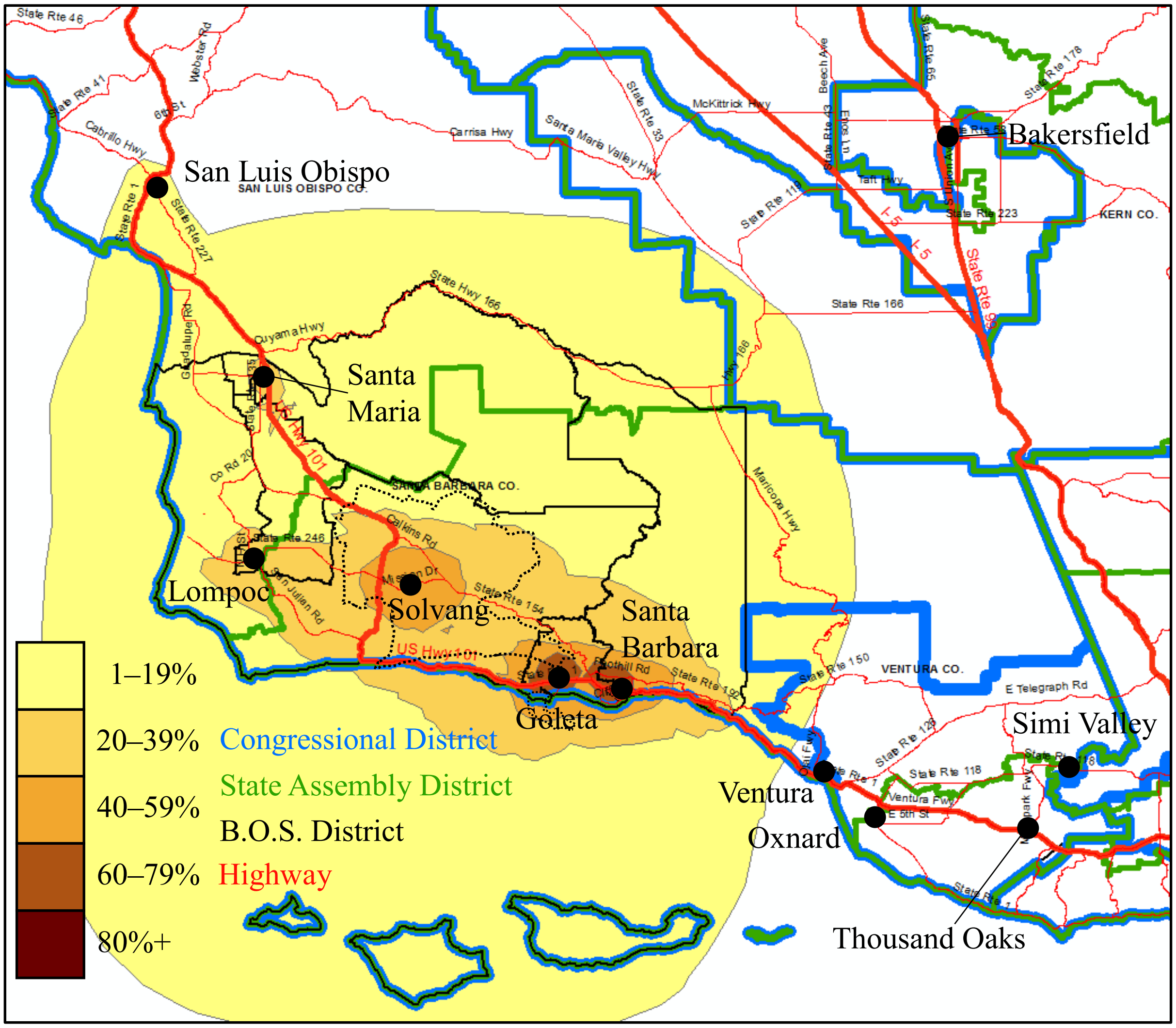

Figure 17. Map of agreement areas among all "definitely + probably + possibly" regions at the "local scale." The dotted lines show the boundaries of the urban (southern) and rural (northern) study areas.

Compared with the results of all "definitely" regions, there is unsurprisingly more agreement among these larger "definitely + probably + possibly" regions. Instead of there being only tiny areas of 60%+ agreement and no areas of 80%+ agreement, here there are significant areas of both levels, except there is no 80%+ area at the "local scale." As with the analysis of only "definitely" regions, those participants using the "state scale" maps in general have the largest areas of agreement, followed by those using the "regional scale," and followed by those using the “local scale.” There is an exception at the 80%+ level, as the area of agreement for the “regional scale” is the largest, followed by that for the “state scale.” Proportionally, the agreement areas for the “regional scale” stand out as the smallest across three of the four levels, tending to be about half as large as those for the “local scale” except at the 80%+ level.

Looking at the “state scale” specifically, a 20%+ agreement area extends from the vicinity of San Luis Obispo all the way down to the Oxnard area, while 40%+ agreement envelops both study areas. Even more agreement can be seen in the “South Coast” area, with 60%+ agreement in most of that area and 80%+ agreement in the small area between Goleta and Santa Barbara known as “Noleta.” At the “regional scale,” the 20%+ and 40%+ agreement areas are similar to those at the “state scale” but slightly smaller. In this case, however, there are two 60%+ agreement areas, one surrounding the “South Coast” and the other including Solvang in the rural study area. At this scale the 80%+ agreement area is slightly larger than that of the “state scale,” enveloping both Goleta and Santa Barbara. Finally, at the “local scale,” a 20%+ agreement area frames central and southern Santa Barbara County, with one 40%+ agreement area in Santa Ynez Valley and another in the “South Coast.” Here the 60%+ agreement is limited to separate small pockets around Goleta and Santa Barbara. Also, there are no areas of 80%+ agreement at this map scale.

Table 11. Areas of agreement among individual “definitely + probably + possibly” regions in the urban study area, showing how much area that at least a certain percentage of those regions share in common, where they overlap.

	Mean area of indiv. regions	20%+ agree-ment area	20%+ prop. of mean area	40%+ agree-ment area	40%+ prop. of mean area	60%+ agree-ment area	60%+ prop. of mean area	80%+ agree-ment area	80%+ prop. of mean area
“State scale”	22,629 km^2	17,074 km^2	75.5%	3,844 km^2	17.0%	1,052 km^2	4.6%	210 km^2	0.9%
“Reg. scale”	27,149 km^2	11,538 km^2	42.5%	1,267 km^2	4.7%	530 km^2	2.0%	231 km^2	0.9%
“Local scale”	1,611 km^2	1,860 km^2	115.5%	447 km^2	27.7%	194 km^2	12.0%	44 km^2	2.7%

Table 12. Areas of agreement among individual “definitely + probably + possibly” regions in the rural study area, showing how much area that at least a certain percentage of those regions share in common, where they overlap.

	Mean area of indiv. regions	20%+ agree-ment area	20%+ prop. of mean area	40%+ agree-ment area	40%+ prop. of mean area	60%+ agree-ment area	60%+ prop. of mean area	80%+ agree-ment area	80%+ prop. of mean area
“State scale”	8,724 km^2	13,247 km^2	151.8%	5,193 km^2	59.5%	2,128 km^2	24.4%	6 km^2	0.1%
“Reg. scale”	10,872 km^2	12,829 km^2	118.0%	5,979 km^2	55.0%	1,308 km^2	12.0%	268 km^2	2.5%
“Local scale”	2,689 km^2	4,046 km^2	150.5%	1,379 km^2	51.3%	316 km^2	11.8%	175 km^2	6.5%

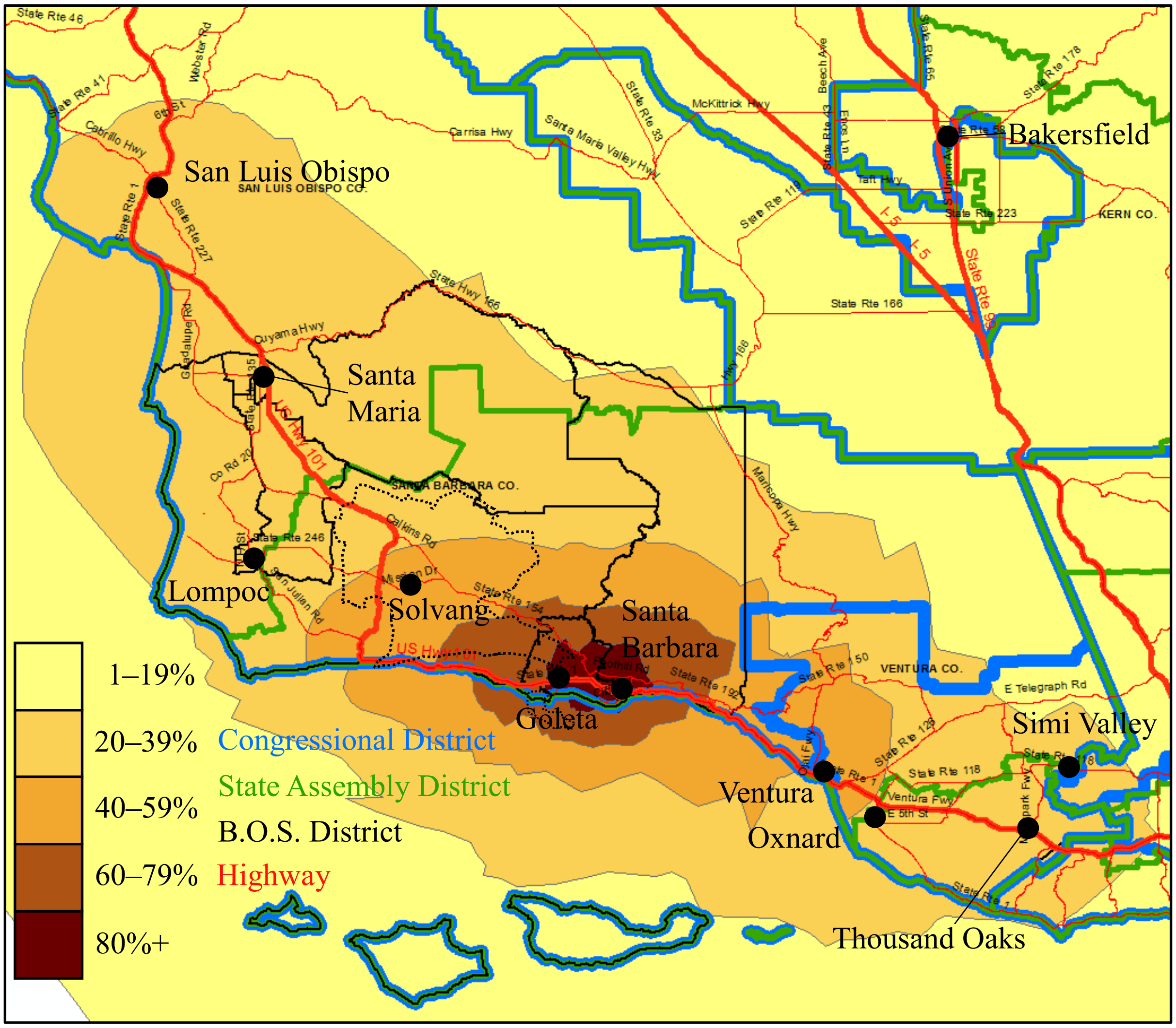

Figure 18. Map of agreement areas among "definitely + probably + possibly" regions from the urban study area at the "state scale." The dotted lines show the boundaries of the urban (southern) and rural (northern) study areas.

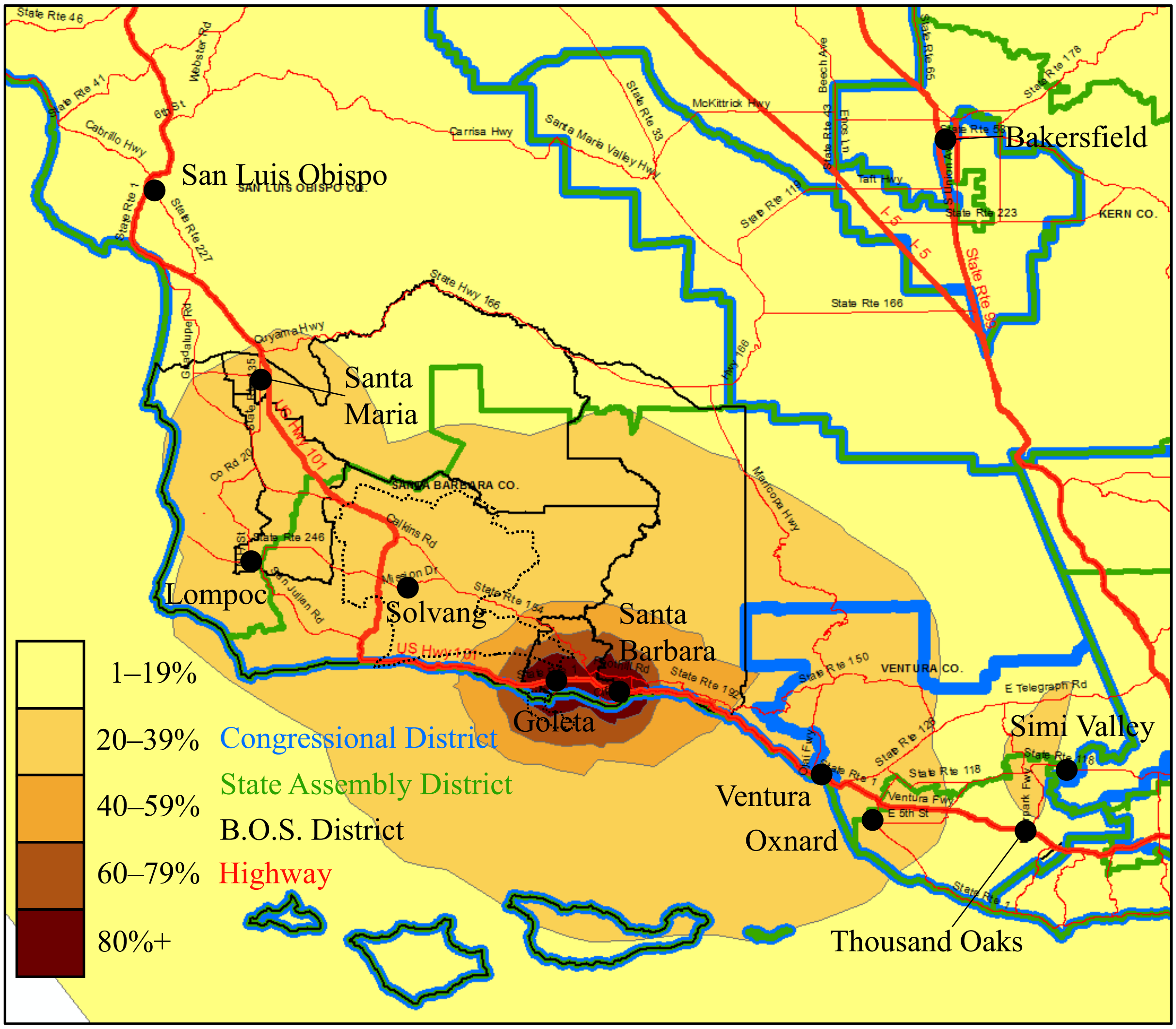

Figure 19. Map of agreement areas among "definitely + probably + possibly" regions from the urban study area at the "regional scale." The dotted lines show the boundaries of the urban (southern) and rural (northern) study areas.

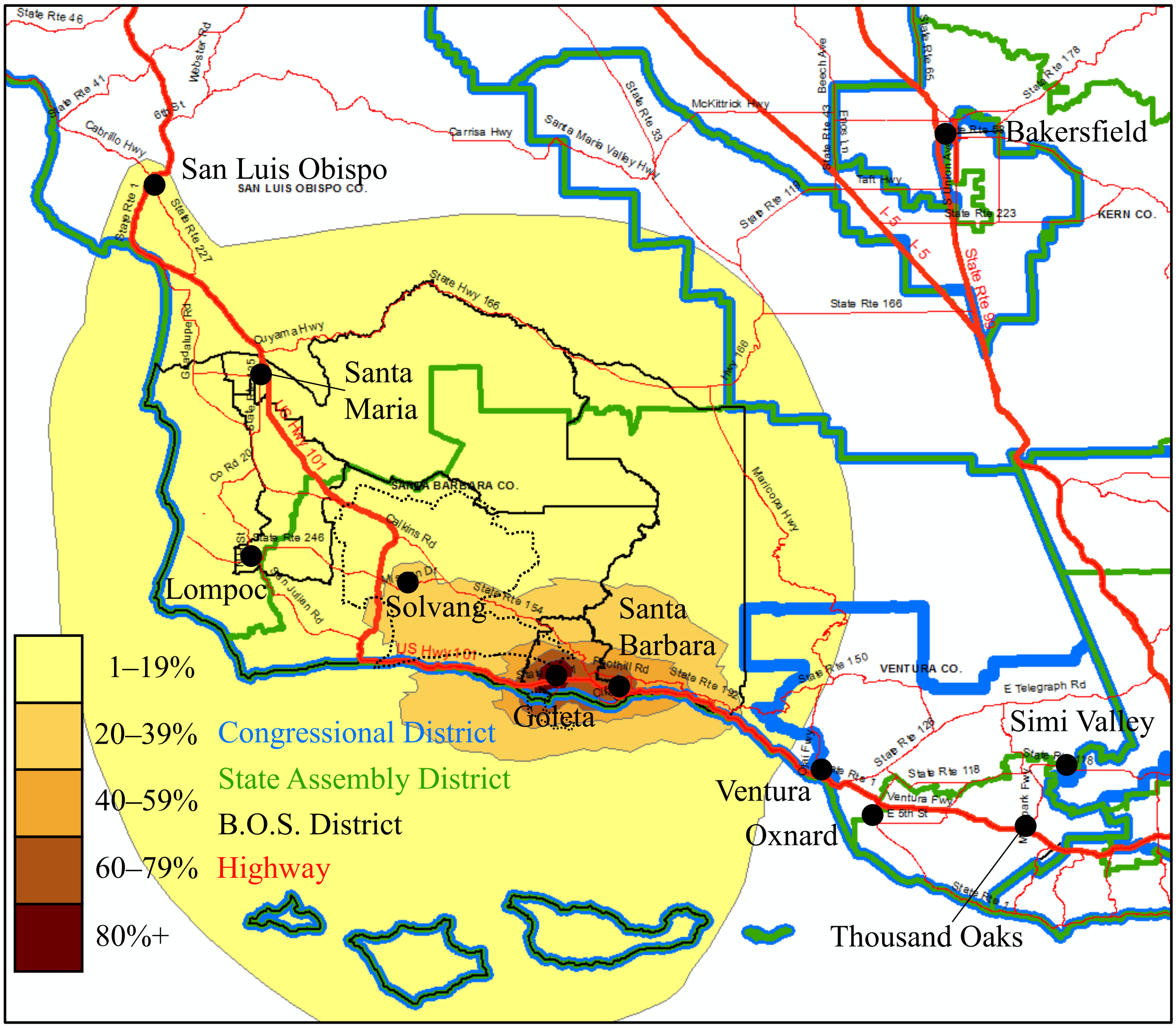

Figure 20. Map of agreement areas among "definitely + probably + possibly" regions from the <u>urban</u> study area at the "<u>local</u> scale." The dotted lines show the boundaries of the urban (southern) and rural (northern) study areas.

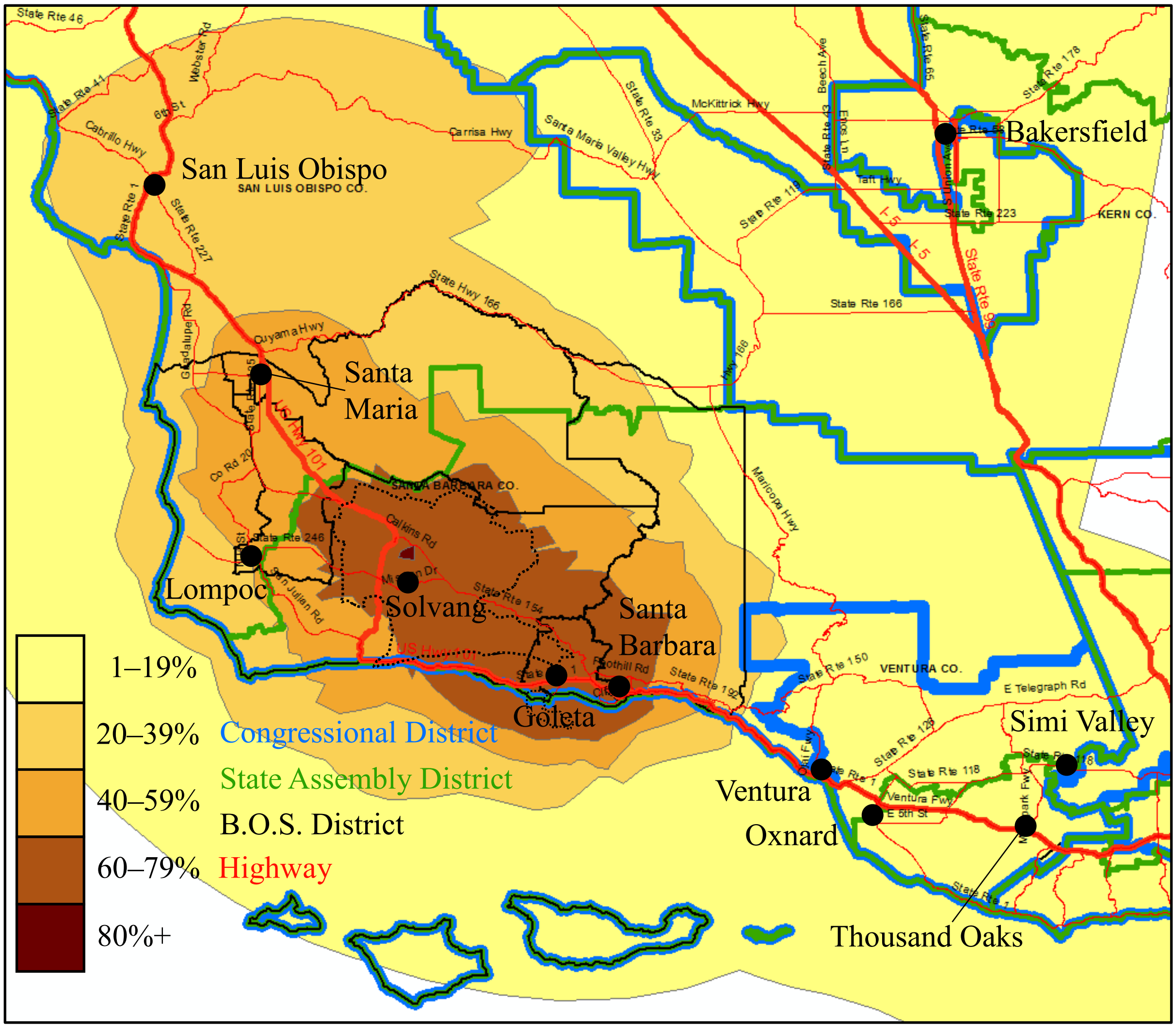

Figure 21. Map of agreement areas among "definitely + probably + possibly" regions from the rural study area at the "state scale." The dotted lines show the boundaries of the urban (southern) and rural (northern) study areas.

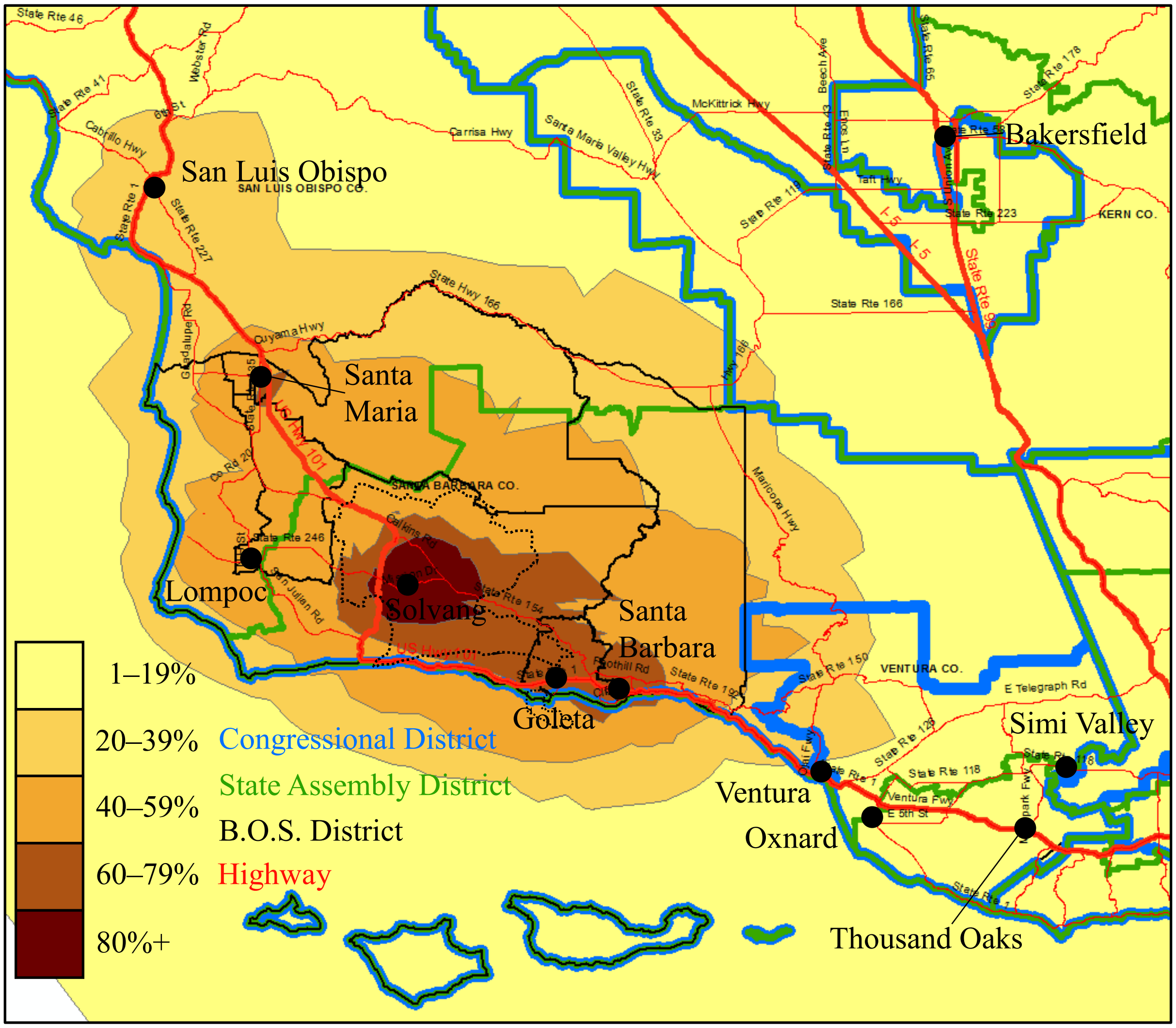

Figure 22. Map of agreement areas among "definitely + probably + possibly" regions from the <u>rural</u> study area at the "<u>regional</u> scale." The dotted lines show the boundaries of the urban (southern) and rural (northern) study areas.

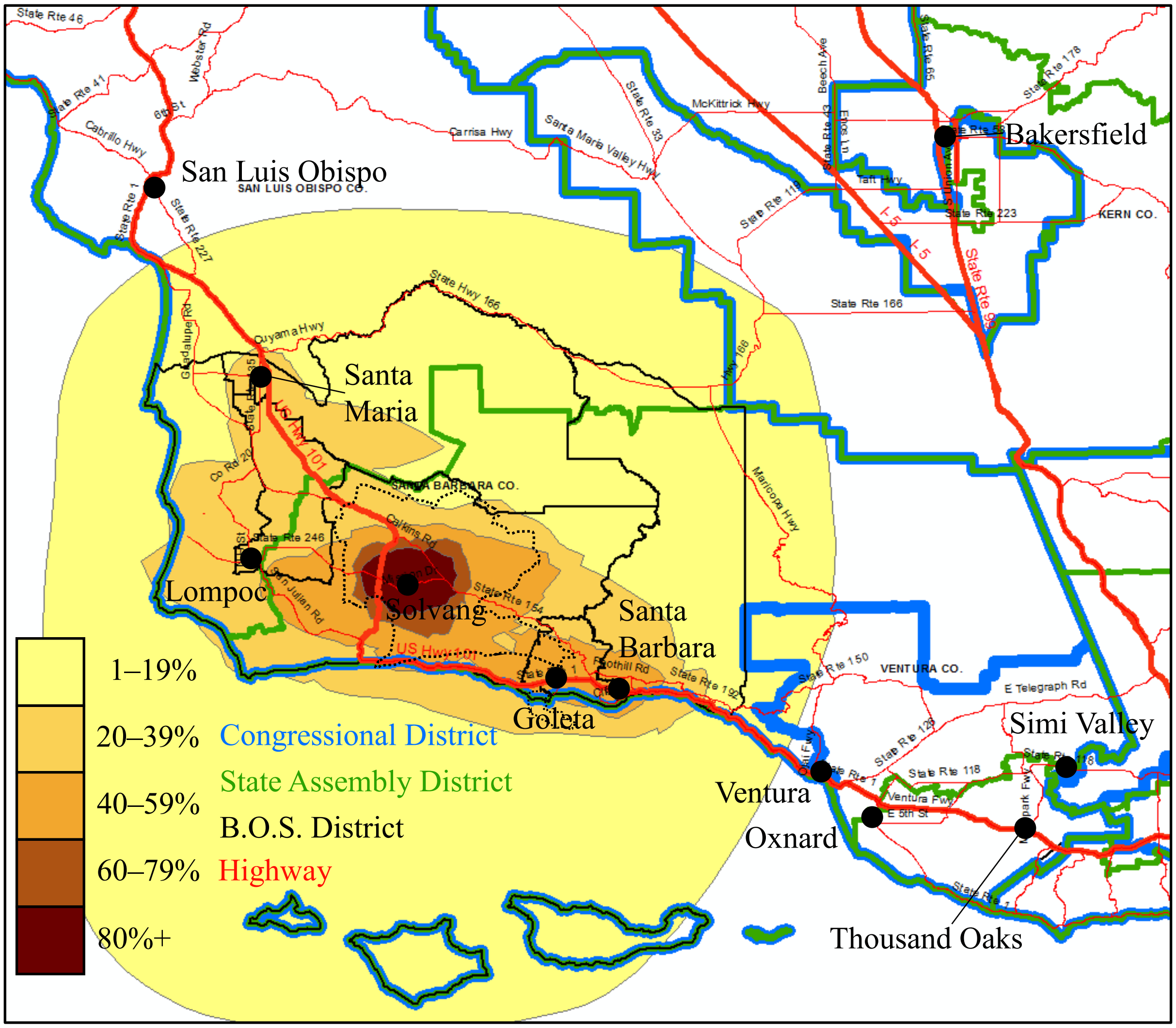

Figure 23. Map of agreement areas among "definitely + probably + possibly" regions from the rural study area at the "local scale." The dotted lines show the boundaries of the urban (southern) and rural (northern) study areas.

Just as with the "definitely" only analysis, examining the results of each study area separately reveals greater agreement among fellow urbanites and ruralites about the location and extent of their COI. This is again evidenced by the fact that there are large areas of 60%+ and 80%+ agreement, in contrast to the results from all participants. There are even areas of extremely high agreement of 90–100%. Yet again, this is a pattern seen across all scale levels, with the agreement areas generally shrinking when going down in scale. There are exceptions to that general pattern in the rural study area, however. There, the area of agreement for the “state scale” is less than that for the “regional scale” at the 40%+ level, and far less than that for both the “regional scale” and “local scale” at the 80%+ level.

Here too, the proportional sizes of the agreement areas do not stay constant across the three scales. For the urban study area, the agreement areas for the “regional scale” are proportionally smaller than those for the “state scale” and the “local scale,” ranging from about a third as large to only a sixth as large as the “local scale” at different levels of agreement. Those for the “state scale” are smaller than the “local scale,” varying from more than half to less than half as large. For the rural study area, no clear patterns appear. The agreement area for the “local scale” is basically tied for the largest at the 20%+ level, then it becomes the smallest at the 40%+ and 60%+ levels, only to become the largest again at the 80%+ level. What can be said here is that the 20%+ and 40%+ agreement areas stay somewhat constant with each other across scales, but this consistency breaks down at the 60%+ and 80%+ levels.

Those in the urban study area agree more that their COI is confined to the “South Coast,” with sizeable areas of 60%+ agreement across all scales. Notable is the fact that not insignificant areas of 80%+ agreement exist even at the “local scale,” which is not the case across all participants. This pattern exists in the rural study area as well, except that the area of 80%+ agreement is quite tiny. Those in the rural study area agree more that their COI is centered on Santa Ynez Valley, not the “South Coast.” Yet enough of these rural dwellers extend their COI to also include the “South Coast” for a 60%+ agreement area to take in that locale at the “state scale” and “regional scale,” and a 40%+ agreement area to take it in at the “local scale.” The COIs defined by urban and rural dwellers appear then to be quite different.

3. Spatial similarity between cognitive COIs and administrative regions

a. Between cognitive COIs and electoral districts

Next I show how an individual cognitive COI quantitatively compares spatially to its corresponding electoral district. I do so by overlaying the cognitive region and administrative region in order to determine their overlap. I can then examine how similar the regions are to each other using a spatial similarity index that assesses the degree of overlap between the two, which depends on their relative locations, sizes, and (to some degree) shapes. Several such indices have been invented, each with its unique formula for computing spatial similarity (Frontiera, Larson, and Radke 2008). However, a number of these have difficulties with them that make them less attractive for use, such as taking a different form depending on the case or situation. For example, one measure uses one function if a region is completely contained by another and a different function if it is not. A simple and intuitive index with only one function in all cases is that developed by Hill (1990), which is:

$$\text{Spatial Similarity} = 2 \times O/(Q + D)$$

where Q and D are the areas of the two regions in question and O is the area of their overlap. Hill's index ranges from 0, meaning the regions do not overlap at all, to 1, where they are exactly the same location, size, and shape.

In order to calculate spatial similarity using Hill's index, it is necessary to determine the area of both the cognitive region and the administrative region. However, this is not as simple as it might seem. Finding the area of these two types of regions depends on how one chooses to define their extent. When defining the cognitive region, I can choose to use the "definitely" region only or the larger "definitely + probably + possibly" one. Here I decide to use the latter because that type of region is more comprehensive and tends to better approximate the size of the corresponding electoral district; this does unfortunately necessitate leaving out the results from Census Tract 29.24. This means that in this analysis I compare the areas of the "definitely + probably + possibly" regions that participants drew on maps at the "state scale," "regional scale," and "local scale" with that of the 24th Congressional District, the 37th State Assembly District, and the 3rd Board of Supervisors District, respectively. The areas of the individual regions are the true ones, not winsorized, since in an analysis of spatial similarity it is important to assess actual shapes and not artificially reduced ones.

Defining the extent of a given administrative region becomes complicated when it borders a large body of water, as is the case for all three electoral districts in this study. Should the region's coastal boundaries be the coastline itself, or does it make sense to extend those boundaries into the water a certain distance to ensure that key features that district residents care about are included? Such attributes can include fisheries, offshore oil reserves, shipping lanes, and various coastal resources. I opt to take the latter approach, since people do care about such marine issues, but also because only a handful of participants draw a cognitive region with boundaries limited to the coastline. Rather, most participants draw cognitive regions that extend into the water (among those whose region is not completely inland), suggesting that many people view the adjoining waters as an integral part of their COI. Furthermore, administrative regions often include a certain stretch of the ocean as part of their legal territory. For example, the boundaries of the board of supervisors districts extend four miles out to sea. For all these reasons, I decide to define the area of each administrative region as its land area plus the area of the water within 12 nautical miles (22.2 kilometers) of the coastline, the "territorial waters" within U.S. sovereignty.

This decision results in a much larger total area for each of the three electoral districts, especially the congressional and state assembly districts, so that each includes the mainland and its adjacent territorial waters. Those total areas do not include the six nearest Channel Islands and their surrounding waters, however. Even though all these islands are part of the state assembly district if not also the congressional district, they are distant, difficult to access, and unpopulated, and so hold little meaning for the residents of these districts. The total area of each district with the exclusion of the islands is given in Table 13, along with the average area of the individual cognitive regions drawn by participants at the corresponding scale level, the average area of overlap for each of those regions, and the average spatial similarity for each.

Table 13. Average spatial similarity between electoral districts and individual cognitive regions drawn by participants at corresponding scale levels.

Electoral district	Total area of district (*D*)	Corresponding scale level	Average area of cognitive region (*C*)	Average area of overlap (*O*)	Average spatial similarity: 2×*O*/(*D*+*C*)
24th Cong.	24,418 km^2	"State scale"	17,029 km^2	6,008 km^2	0.281
37th S.A.	10,919 km^2	"Reg. scale"	20,204 km^2	3,390 km^2	0.281
3rd B.O.S.	6,016 km^2	"Local scale"	2,095 km^2	963 km^2	0.177

The table reveals that participants' cognitive regions cohere with the corresponding electoral district to a moderately low degree at the "state scale" and "regional scale," with a spatial similarity index value just below 0.3. At the "local level," however, the index value is even lower, below 0.2. The index values for the three scales are significantly different from one another (F[2, 217] = 5.43, $p < .01$). But as the means make clear, this difference lies solely between the "local scale" and the two larger scales. The mean index values for the "state scale" and "regional scale" are nowhere close to being significantly different from one another ($t[145] = 0.01$, $p = .99$), but there is a significant difference between those for the "state scale" and "local scale" ($t[133] = 2.88$, $p < .01$), as well as between those for the "regional scale" and "local scale" ($t[146] = 3.04$, $p < .01$).

b. Between cognitive COIs and Santa Barbara County

I also conduct a spatial similarity analysis to see how the two map visibility conditions compare in that regard. At interest here is the effect that administrative boundaries have on the cognitive regions drawn by participants. Since Santa Barbara County is the most prominent administrative region on the map, and where all study participants reside, it makes the most sense to assess the spatial similarity between that county and the two types of cognitive regions. In this case, those two types are regions drawn by participants with visible access to the boundaries of Santa Barbara County, and those without it. I use the broadest definition of "definitely + probably + possibly" regions drawn by those using both the "state scale" and "regional scale" map. The total area of Santa Barbara County with the exclusion of the islands is given in Table 14, along with the average area of the individual cognitive regions drawn by participants with and without administrative boundaries visible, the average area of overlap for each of those regions, and the average spatial similarity for each.

Table 14. Average spatial similarity between Santa Barbara County and individual cognitive regions drawn by participants with and without administrative boundaries visible.

Administrative boundary condition	Total area of county (D)	Average area of cognitive region (C)	Average area of overlap (O)	Average spatial similarity: $2 \times O/(D+C)$
With	10,532 km^2	9,533 km^2	3,390 km^2	0.312
Without	10,532 km^2	27,889 km^2	3,899 km^2	0.317

The table reveals that participants' cognitive regions cohere with the corresponding electoral district to a moderately low degree in both conditions, with a spatial similarity index value just above 0.3. The mean index values for the two conditions are not significantly different from one another ($t[145] = –0.13$, $p = .89$). In sum, there is no clear difference between the conditions in how well the aggregated cognitive COIs spatially relate to Santa Barbara County.

4. Qualitative properties of regions drawn by participants

a. Number of regions

For each survey participant, I assess how many regions they choose to draw, whether those regions are overlapping, and the topology and shape of those regions. All participants draw at least a “definitely” region. Not counting participants from Census Tract 29.24 and one with an unfinished survey, 159 out of 227 (70%) also draw a “probably” region, and 78 (34%) draw a “possibly” region as well. While each participant has the opportunity to draw a maximum of three types of regions, the mean number that participants actually draw is 2.0. What might affect how many regions a participant chooses to draw? One possibility is the number of years one has lived in the community, in that those who have lived there longer may have built up enough experience to be more confident about the extent of their COI, and thus only feel the need to draw a “definitely” region. Another possibility is how old one is, in that those who are older may have characteristics that make them less patient and thus less willing to draw multiple regions.

Therefore, I predict that the number of regions that participants choose to draw correlates negatively with both their time in the community and their age. I do indeed find negative correlations with both variables, but only one of the two is a significant one. The correlation between number of regions drawn and time in the community is the one that is not a significant relationship ($r[225] = –.09$, $p = .17$). That between number of regions drawn and age is significant, however ($r[225] = –.22$, $p < .001$). This means that the older a participant is, the fewer number of regions that person tends to draw, and he or she is more likely to forgo a "possibly" region if not also a "probably" one.

b. Overlap between regions

The next issue I examine is how the regions that participants draw overlap each other. I consider regions as overlapping if they nest within each other, meaning that one region surrounds another. An example of such overlapping regions would be a "definitely" region nesting within a larger "probably" region, and that "probably" region in turn nesting within an even larger "possibly" region. Of those 159 participants who draw multiple regions, 73 (46%) participants draw their regions in this way. On the other hand, 48 (30%) draw entirely non-overlapping regions, with their "definitely" region around one city and their "probably" or "possibly" regions around another. Some (10%) have mostly- or partially-overlapping regions, while others (14%) have a mixed combination, for instance, overlapping "definitely" and "probably" regions but a separate "possibly" one. I also investigate whether there is a relationship between the study area one lives and whether one's regions overlap, if one draws multiple regions. I assign dummy values of 1 and 0 to the urban and rural study areas, respectively, then assign a value of 1 for wholly overlapping, 0.75 for mostly overlapping, 0.5 for partially overlapping, and 0 for not overlapping. I find that there is a weak positive correlation between the two, as urban dwellers tend to draw overlapping regions more than rural dwellers, but the relationship falls just short of being significant ($r[158] = .15$, $p = .06$).

c. Topology of regions

The issue of topology concerns the manner in which people's drawn regions are spatially connected (or not connected). This is related to the issue of overlap, but somewhat different in that I am interested in which particular regions connect in which ways. Also, it is possible for adjoining regions to be connected in space but not overlapping, with a single common border between them. The most common type of topology among survey participants is a solitary "definitely" region, drawn by 67 (30%) of them. The second-most-common type is a "definitely" region connected to just a "probably" one, drawn by 62 (27%). The third-most-common is a "definitely" region connected to both a "probably" region and a "possibly" one, drawn by 42 (19%). The other types of topology are unconnected "definitely" and "probably" regions (9%); unconnected "definitely," "probably," and "possibly" regions (6%); and a mixed combination of connected and unconnected ones (9%).

d. Shape of regions

I classify region shape as either "ovaline," "feature-based," "other," or "undefined." I define these regions in the following way. If the region resembles an oval, I classify its shape as "ovaline." If its edges closely follow features of the environment such as highways or the coastline, I call it "feature-based." If the region has some other type of shape like a rectangle or semicircle, it is classified as "other." Finally, a region may lie outside the extent of the map; I classify those as "undefined." Here I include participants from Census Tract 29.24, since their being compelled to draw multiple regions has no bearing on the shape of the regions they draw. The vast majority of participants draw region(s) that are "ovaline," 214 out of 252 (85%). Only 10 draw region(s) that are "feature-based," 4 draw those that are "other," and 1 gives an "undefined" region. The remaining 23 (9%) draw a mixed combination of shapes, with one region being a certain shape and another region being a different shape or "undefined." In sum, most people do not draw regions with boundaries that carefully follow particular features (and none draw regions with boundaries that follow those of administrative regions, if present on their map), but rather draw regions that are roughly oval in shape. To reemphasize, no participant uses the administrative boundaries as a baseline for the boundaries of their own region.

D. Discussion

This first study seeks to determine the effect of three factors on the cognitive COIs that survey participants draw: the scale of map, the visibility of administrative boundaries, and the study area where one lives. It also assesses variation within those regions by asking them to draw their regions at three different levels of confidence. Finally, this study investigates how those regions coincide with the existing electoral districts. I find that map scale has a large effect on the geographic area of people's cognitive COIs, at all levels of confidence. Meanwhile, the study area largely determines the location and extent of their cognitive COIs, as measured by how much they agree with one another, at all levels of confidence. That is, people who live in the urban study area have a very different conception of their COI than those who live in the rural study area do. On the other hand, the visibility of administrative boundaries does not affect those aspects, except at the medium level of confidence. Lastly, I find that their cognitive COIs coincide with the larger scale districts better than the smallest, most localized district.

1. Areas of regions drawn by participants

I find that participants draw "definitely" regions with significantly different areas at the three map scales. They do the same with their fuller "definitely + probably" regions, as well as with their fullest "definitely + probably + possibly" regions. This confirms that map scale did greatly influence the size of region that people draw. While the extent of the map image on which respondents draw their regions does obviously constrain how large a region can be drawn (it cannot go beyond its edges), it does not constrain how small a region can be drawn, so the fact that I find such disparities is meaningful. It shows that people have a tendency to draw regions that take up some of but not all, or even most of, the map space. When this tendency is consistent across scales, regions drawn at different scales will have different geographic sizes because the map scales themselves have different geographic sizes. Yet this graphical explanation for the observed differences in sizes may only be a partial one, as a more theoretical explanation exists.

People may conceive of COIs at different scales when presented with different information. Those shown multiple counties that take up the size of a typical state or region may be prompted to consider a different scale of COI than those shown just a single county. This might explain why I find that the areas of regions drawn at the "local scale" tend to be the most distinct among the three scales, that is, the most different from the other two. That is because the "local scale" is the only one that shows just one county, while the two other scales show multiple counties. People may have a radically different conception of their COI when forced to narrow their focus to these smaller confines, one more on the scale of a city, town, or valley. Those shown multiple counties, on the other hand, are not so forced and may understand their COI as a larger entity such as the county as a whole.

When comparing between the areas of regions drawn by participants from the different study areas, I find that the "definitely" regions drawn by urban dwellers tend to be smaller than those drawn by rural dwellers. Given that the urban study area is much smaller in geographic size than the rural study area (see Figure 1), I should expect that urban dwellers would generally draw a smaller COI to reflect that smaller study area. However, something else might also be at work here. Rural dwellers probably conceive of their COI as extending over a larger area of space, as they tend to live farther apart from each other. This tendency is reflected by the fact that ruralites are less likely to discuss neighborhood problems amongst themselves (Nation, Fortney, and Wandersman 2010), which may relate to the concept of community of interest. Fraser et al. (2013) find that urbanites often think of their neighborhood as the area that is directly proximate to their residence that they frequent the most, which would indicate a smaller COI due to the higher density of amenities and facilities in the urban context. It therefore makes sense that I find a larger COI for ruralites.

This tendency for participants from the urban study area to draw smaller regions does not apply to their "definitely + probably" and "definitely + probably + possibly" regions. This is probably because these larger regions are less likely to be limited to just one's study area but rather encompass much of if not the whole of Santa Barbara County, meaning whether one's study area is urban or rural matters less. Furthermore, it does not apply at the "state scale," even with the "definitely" regions, because at that scale the two study areas are so small in size relative to the whole of the map that any difference between them no longer matters much. At this scale, even the "definitely" regions are unlikely to be limited to just one's study area but rather encompass much of if not the whole of Santa Barbara County, so one's study area matters little. In other words, urbanites and ruralites agree on the extent of their COI at the scale of a typical state, as they both share the same "state" no matter where they might live within it.

Across all types of regions and all scales, I find a consistent pattern of participants drawing a region that is smaller in size than its corresponding electoral district. The survey instructions prompt participants to first "draw a line around the area that you believe is *definitely* within your community of interest." As they read these instructions and see the word "definitely" italicized, they must feel compelled to identify and define a narrow area that includes only what they are most confident lies within their COI. This explains the tendency to draw a "definitely" region that takes up only some of the map extent—an extent designed to ensure that the corresponding electoral district takes up much of it. When asked to expand upon that narrow area, the larger region that they draw will by definition come closer in size to the electoral district. In addition to this graphical explanation, a more conceptual explanation presents itself.

It appears that electoral districts have been created that exceed the core areas people identify with. This is because districts must comprehensively cover a certain administrative region, whether it be a state or a county. In other words, every piece of land must fall within some district, no matter how sparsely populated or seemingly insignificant that land might be. This means that many if not most districts contain land that is remote, rugged, rural, and/or barely settled. Such land is unlikely to be included in the core areas that people identify with, because those cores will naturally focus on the areas where the population concentrates, where people are much more likely to live, work, and socialize. Therefore, it is not surprising to find that these core areas are dwarfed by the full extent of the districts.

I also consider participants' region areas as a proportion of the area of the corresponding electoral district. When I do so, I find no significant difference between scales for all three types of regions. These findings indicate that the average region that participants draw at each scale has about the same proportion of its corresponding electoral district's area, regardless of region type. For example, the typical region drawn at the "state scale" takes up roughly the same proportion of the congressional district's area as a region drawn at the "regional scale" does the state assembly district. This means that across scales regions take up a consistent amount of the area of the corresponding electoral district. It thus further confirms hypothesis that people draw a region that takes up a similar chunk of the map space, no matter the scale.

There is, however, one notable exception to this general conclusion on the proportional areas of participants' regions. I find that there is a significant difference between the "state scale" and the "local scale" for their "definitely" regions. Those drawn at the largest scale tend to be smaller than those drawn at the smallest one, relative to their corresponding electoral district. Moreover, those drawn at the "local scale" are closer to the size of their corresponding electoral district, though the mean area is still only a quarter of the electoral district's area. This finding may argue for COIs—at least the cores of which that people are most confident about—being most relevant or appropriate at the "local scale," and least at the "state scale." While core COIs drawn at the "local scale" are still much smaller than the county board of supervisors district (that is, a typical state lower house district), they are closer in size to that district than those drawn at the "state scale" are to the congressional district. This is not to say that COIs only exist or matter at the "local scale," only that when it comes to their cores, the correspondence with the electoral district is greater at that scale. This suggests that state lower house districts are likely to be made up of a handful of core COIs, about four, while congressional districts tend to be composed of twice that many.

I note one last finding regarding proportional areas. That is, the proportional difference between the urban and rural study areas is significant for "definitely" regions, but not the two larger region types. Apparently it is only at this narrowest conception of COI that participants from the different study areas conceive of differently-sized regions. They may feel inclined to narrow their focus to an area about the size of the study area itself, and since the rural study area is larger in size than the urban one, participants from the former are prone to draw larger “definitely” regions across all three scales. Overall, urban and rural dwellers define COIs of broadly similar sizes, except at the narrowest definition.

Finally, I find no significant difference between the areas of “definitely” regions drawn with and without administrative boundaries visible, nor between the areas of “definitely + probably + possibly” regions drawn with and without them visible. I do, however, find such a difference between the “definitely + probably” regions with visible boundaries and those without visible boundaries. Those of that type with visible boundaries tend to be smaller than those without. Contrary to expectations, it is those without that tend to be closer in area to Santa Barbara County, though they tend to be slightly greater. Perhaps then, the administrative boundaries serve to contain participants’ region drawings, acting as a kind of barrier in their minds within which they should limit their region’s extent. Evidently they only feel the need to do so with this medium type of region, as the typical “definitely” region is too small for the county lines to factor into their decision making, while the broadest region is too large.

2. Areas of agreement among participants’ drawn regions

When I consider the degree to which participants agree about where they draw their “definitely” regions, I find that they actually agree very little. Despite the fact that all of them reside in the same district at three levels of government, there is little trace of a common COI between them, regardless of the scale of map used. At the “state scale,” no area of 60%+ agreement even exists, while at the “regional scale” and “local scale,” that area is negligible. This is similar to what I found in my study of city council districts in Santa Barbara (Phillips and Montello 2017), where the area of 60+ agreement was less than half a square kilometer. In this study, I find at all scales a large area of 20%+ agreement that envelops both study areas and a smaller area of 40%+ agreement around the urban study area. There is more agreement around the urban study area simply because more participants live there and so a majority of those I survey are more likely to include at least part of that area in their COI. But the main point here is that even though all the participants of this study are lumped together into the same district not once but three times, they do not seem to share a common COI.

When I examine the results separately for each study area, I no longer observe the lack of agreement that I do for those for all participants. Whereas for all participants the area of 60%+ agreement is slim to none across scales, for exclusively urban dwellers or exclusively rural dwellers, this area is quite substantial and takes up dozens if not hundreds of square kilometers. The 20%+ and 40%+ agreement areas are also larger within each study area than they are for all participants. These results indicate that, while no common COI exists among all study participants, one does exist among those in the urban study area, as well as among those in the rural study area. While it is true that people who live closer to each other are more likely to share a COI, I believe that there is something more going on here. There are good reasons to believe that these two groups of people qualify as two distinct cognitive COIs.

One reason is that these groups are physically separated from each other by both distance and terrain. Tens of miles and a rugged mountain range divide them, making interaction between the two more difficult. Another reason is that the people themselves have a number of characteristics that set them apart from each other, as indicated by the divergence in dominant economic sector, voting patterns, and demographics between the two. The urban area is defined by an education and high technology dominated economy, strong Democratic preferences, and a younger populace including many students. The rural area is defined by an agriculture and tourism dominated economy, more Republican preferences, and an older populace including many retirees. Moreover, because more of the urbanites are college students and relatively new to the area, there is a great disparity in time in the community. All of these factors are spatially correlated with urbanness, so I cannot conclusively conclude whether urbanness itself or something else is responsible for these disparate community conceptions. Further studies might hopefully tease that out, but the point remains that these two groups share more in common within each other than between each other. One might wonder why such different communities were lumped together into the same electoral district in the first place, and at four different levels of government!

Despite these differences between study areas, one commonality remains to suggest why these two study areas might belong together in the same district after all. Looking at the rural study area specifically, one can see that participants there have some tendency to include the urban study area in their COI in addition to their own study area. This is evidenced at the "regional scale" and "local scale," where the 20%+ agreement area extends into Goleta and even Santa Barbara. However, urban dwellers do not return the favor, as none of their agreement areas cover much if any of the rural study area, no matter the scale. Thus it appears that rural dwellers are more prone to incorporate the urban area into their COI than urban dwellers are to incorporate the rural area into theirs. I suspect that this is because rural dwellers are more reliant upon and therefore more likely to frequent the urban area than vice versa. There are certain services and amenities that the rural dwellers sometimes need that they must travel to the urban area to obtain, such as bulk goods from a store like Costco, certain medical services, and serving jury duty at the county courthouse in Santa Barbara. Goleta is also home to the nearest major airport to Santa Ynez Valley. Even more importantly, the urban area is a major employment center, especially because the University of California, Santa Barbara is located there, and many of these jobs are held by people who commute from the rural area where housing is generally cheaper. For all these reasons, the rural area depends on the urban area to a large degree that suggests that lumping them together does make some sense.

While urban dwellers tend to leave the rural study area out of their COI, that COI is not just confined to their own study area. Across all three scales, a large segment of the COI commonly agreed upon by these participants extends beyond the board of supervisors district in which they live, to take in other areas of Goleta as well as Santa Barbara. Rather than draw a COI region that includes those in the rural study area with whom they share the same district at multiple levels of government, most of these people instead draw a region that envelops the whole greater urban area called the "South Coast," whether inside their board of supervisors district or not. In fact, at each of the three scales the majority of the 60%+ agreement area actually falls outside those district boundaries, where no participant surveyed actually lives. People in the urban study area evidently feel much more affinity toward their common urbanites in other districts than they do the ruralites in their own. It is therefore clear that urbanness, and/or other factors related to it, influences the way that people conceive of their cognitive COI, overriding the position of the district boundaries.

When I consider the degree to which participants agree about where they draw their more expansive "definitely + probably + possibly" regions, I find that they agree more than they do about their "definitely" regions. This is to be expected, though, as these larger region types are more likely to overlap in places, leading to more opportunities for agreement among them. While with the "definitely" regions there are few if any areas of 60%+

agreement, here such areas appear at all three scales and take up a good deal of space at the "state scale" and "regional scale;" there are even some areas of 80%+ agreement at these scales. These higher agreement areas are found around the urban study area, again, simply because more participants live there. So one can make the case that at this more expansive definition of a COI, more agreement exists across all participants that they do indeed share a COI, though that COI extends to other board of supervisors districts in the county as well.

The greater amount of agreement I observe with this expanded definition of COI increases all the more when I differentiate by study area. The 60%+ and 80%+ agreement areas all become larger and more pronounced when looking at the results for each study area. This confirms what I find when looking at just the "definitely" regions, that there are separate urban and rural COIs that share more in common internally than externally. Those COIs are just larger and more inclusive when they are amalgamated from the most expansive "definitely + probably + possibly" regions. Besides that aspect, the expanded COIs follow the same patterns that the narrowed COIs do. That is, more people in the rural area include the urban area in their COI than people in the urban area include the rural area in theirs. Those in the urban area rather opt to include the whole Santa Barbara / Goleta area in their COI. Thus it is clear that urban and rural dwellers have very different ideas about the location and extent of their COI.

3. Spatial similarity between cognitive COIs and administrative regions

How well do the expanded COIs coincide with the existing electoral districts? I find that they do so moderately poorly at the "state scale" and "regional scale," and quite poorly—significantly worse—at the "local scale." The "local scale" COI is so spatially dissimilar from its corresponding electoral district—the 3rd Board of Supervisors District—

because many urban dwellers believe that their cognitive COI extends beyond that district of their own to include all of the “South Coast” area, the whole Santa Barbara / Goleta urban area. This is not the case with the congressional and state assembly districts, though, as only some participants believe that their cognitive region extends beyond the bounds of those districts into areas of Ventura County (outside the congressional district) or northern Santa Barbara County and southern San Luis Obispo County (outside the state assembly district). So those two districts coincide better with people’s commonly-agreed-upon COIs than the board of supervisors district does.

Nevertheless, the average spatial similarity between participants’ regions and the electoral districts is not very high to begin with, even at the “state scale” and “regional scale.” This means that the typical region that a participant draws at the “state scale” and “regional scale” will only be about three-tenths as spatially similar as the congressional district and state assembly district, respectively. The typical region that a participant draws at the “local scale” will only be about one-sixth as spatially similar as the board of supervisors district. I explain above why there is so little spatial similarity at the “local scale,” but that still leaves the two larger scales. At the “state scale,” the *median* region drawing (the average is skewed by extreme outliers) is almost a quarter the size of the congressional district. Participants at this scale tend to draw a region that is contained within Santa Barbara County, but the district encompasses not only that county but San Luis Obispo County and a sparsely settled swatch of northern Ventura County. At the “regional scale,” the median region drawing is also almost a quarter the size of the state assembly district. Participants at this scale tend to draw a region that is contained within the portion of this district that is within Santa Barbara County, but the district also covers much of Ventura County, including its sparsely populated northern section. So in general participants' region drawings tend to be more limited in scope than their corresponding electoral districts.

But this explanation for why the spatial similarity is so low at the larger scales points to a weakness in the methodology of this analysis. Hill's (1990) index assesses the spatial similarity of two particular regions by considering the pure geographical area of each of those two regions as well as the overlap between them. This rests on the assumption that all of that area is equally important for determining spatial similarity. But that assumption may not necessarily be valid when dealing with electoral districts that are designed to incorporate a certain amount of *people*. Those portions of a district's area that include more people may reasonably be considered more important when comparing that district to a COI. Therefore, a good case can be made that the densely populated areas should be weighted more than sparsely populated areas. If I were to weight the district area in such a way, the spatial similarity index at the "state scale" and "regional scale" would probably be higher. For example, the typical cognitive region at the "state scale" gets a low index score for not including San Luis Obispo County, which makes up close to half the district area but only about a third of its population. And the typical cognitive region at both the "state scale" and "regional scale" gets a low index score for not including northern Ventura County, a large area but with practically no people.

So why not just take Hill's index and use population instead of area? I give two reasons for why it is best to stick to area, one methodological and one conceptual. The methodological reason is that determining how much area each participant's region takes up is a simple task to compute in a GIS, but determining how many people live in each region is daunting. The finest resolution at which the Census tabulates population is the block, but even this is not fine enough to neatly follow the boundaries of each participant's region drawing. And this is not even to mention the overlap portion. Having to do this for each participant would be very labor intensive. The conceptual reason is that a portion of a district does not necessarily matter less just because fewer people live there. It may contain an important natural resource, or provide a critical water source. Maybe such an area is crucial to the local economy because of the tourists that it might attract, or the agricultural production that takes place there. Indeed, all of these elements can be found in the sparsely populated portions of all three electoral districts. For these reasons and more, in this context one cannot think of a district solely in terms where its population is located.

Finally, I consider what spatial similarity analysis can tell me about what effect the visibility of administrative boundaries might have. I find that the "definitely + probably + possibly" regions are just as spatially similar to Santa Barbara County when county lines are visible on the map as when they are not. But I should not expect to find much difference here because I already find that this most expansive definition of COI does not significantly differ in area for the two visibility conditions. This spatial similarity analysis serves to confirm that finding. So overall the effect of the administrative boundaries on how participants draw their regions appears to be very minimal.

4. Qualitative properties of the regions drawn by participants

I can tease out some interesting findings from the qualitative properties of the regions that participants draw. First, the proportion of participants who draw a particular type of region decreases with each lesser level of confidence. Every participant draws a "definitely" region, but only seven-tenths draw a "probably" region, and just a third draw a "possibly" region. This is to be expected, though, because if the amount of "possibly" regions were to exceed that of “probably” regions, it would mean that many participants skip the second level of confidence for the third. So the large majority of participants follow at least the “definitely” then “probably” scheme, and about half of those add a “possibly” region as well. Furthermore, the study instructions do not seem to be a cause of confusion, with virtually every participant understanding their intended purpose of representing internal variation. This therefore demonstrates that people have little trouble conceiving of a cognitive region at different levels of confidence, affirming the findings of Montello et al. (2003).

But the fact that three-tenths of participants choose to only draw a “definitely” region shows that some people have very firm beliefs about the bounds of their COI, to the extent that they are confident that no area outside those bounds is probably or even possibly within that COI. Time in the community might make someone more sure about their COI so that one only draws a “definitely” region, but while there is a negative correlation suggesting that those with more years in the community draw fewer regions, it is not large enough to merit significance. What does significantly—and negatively—correlate with number of regions a participant chooses to draw is that person’s age. Perhaps older people tend to be more sure of themselves in general, or they are just more eager to get the survey over with by drawing as few regions as possible. Such lack of flexibility and/or patience might then explain why older participants might want to move more quickly through my survey.

Second, participants vary in the way their regions spatially relate. No consensus exists among participants who draw multiple regions, as to whether those regions should be contiguous or noncontiguous. While most expand their COI by drawing areas of lower confidence directly around areas of higher confidence in contiguous fashion, many others opt to expand their COI by drawing areas of lower confidence in separate locations, usually around cities that are several tens of miles away. Perhaps they do so because they misunderstand the survey instructions. To reiterate, those instructions state: “Many people believe there is a wider area outside the area that is definitely within their community of interest, an area that is still probably within their community of interest. If you believe that there is such an area, please draw a line around it.” Some participants may understand the phrase “outside the area” to require spatially separated regions for different levels of confidence, so that a “probably” region cannot overlap with a “definitely” one, nor a “possibly” region overlap with either of the other two. However, I intend that phrase to allow participants to draw a region with a spatial extent that goes beyond that of the region draw previously, hence the qualifier “wider area,” whether it totally envelops that earlier region or occupies a different space entirely. In other words, some may take instructions meant to be inclusive of both contiguous and noncontiguous regions as actually being restrictive to the latter. I have no way of knowing this, of course. All those who draw noncontiguous regions may do so out of a genuine desire—not out of compulsion—but this gnawing possibility demonstrates the importance of very clear instructions, or confirming participants’ intentions.

Third, participants in this study overwhelmingly prefer to draw a COI with an oval-like shape than to draw a COI whose boundaries follow features like roads or the coastline. Crucially, for the purposes of this study, no participant draws their COI boundaries to follow those of an administrative region like Santa Barbara County. What might explain this marked tendency? One obvious possibility is that it takes much longer to carefully trace a line on a map like a road or county boundary, as opposed to simply drawing an oval shape. Most people probably do not care to spend that much time on a task like this. Another, more interesting, possibility is that people do not think of their COIs in a very exact way, but rather they are more roughly-defined areas in their minds. This conforms to the idea that these COIs are indeed cognitive regions, because such regions are defined by nonuniform membership function in which a core that strongly exhibits characteristics of that COI gradually transitions into a periphery that only weakly does so (Montello 2003). So people do not care so much about defining a boundary in an exact way because it does not really matter to them if it shifts slightly this way or that; the membership function essentially remains just as weak. As long as they draw their region so that it fully includes the core of their COI—as they perceive it—it suffices to just draw an oval shape, with the unstated implication that the line they draw is a convenient falsehood, a stand-in for what they surely realize is a rough transition zone away from one's COI and into another.

III. Study 2: Identification with multiple nested cognitive regions

A. Introduction

The second study, like the first, investigates whether COIs appear to exist as cogent entities at different scales, as measured by the degree to which people agree on the location and extent of their COI when using different scales. Moreover, this study also assesses how people portray variation within their COI at different levels of confidence. Lastly, this study also manipulates scale by changing the map extent presented to participants. In particular, it shows them two map versions, one that covers just their county, and another that covers a wider stretch of the state. So just as in the first study, the second study solicits people's conceptions of their COI by exposing them to different graphic properties.

This study differs from the first in three main respects. For one, instead of changing the map generalization by changing which cities are shown, it changes which administrative regions are shown. Generally, the map that covers the county shows collections of Census block groups, while the map that covers a wider region shows Census county subdivisions as well as counties themselves. These three types of regions across the two maps serve as reference points for the participants, but also as data points for them to indicate their COI at three different scales. I ask participants to indicate their COI by ranking one or more region(s) of each of the three types, as described below. So I aim to give people the opportunity to identify three different scales of COI, as defined by which regions at each level they decide to rank.

For two, instead of the experimental design being between-subjects, this study is within-subjects. Rather than assigning participants to different map scale conditions, here I expose each participant to the same map conditions. I present the three types of regions to each participant in the same order, going from the smallest scale to the largest. This change in study design allows me to determine whether, and the extent to which, people identify with multiple COIs at different scales. This is because I can ask participants to define a cognitive COI three different times. First I have them indicate a COI within the confines of their county; this COI would approximate the population of a county board of supervisors district, which in this study models a typical state lower house district as in the first study. Then I have them indicate a COI within the confines of their larger region; this COI would approximate the population of a state assembly district, which in this study models a typical state upper house district as in the first study. Finally, I have them indicate a COI also within the confines of their larger region, but approximating the population of a congressional district. In this way I can examine whether people identify with multiple nested COIs, just as they can possess a strong "sense of place" at three different scales simultaneously, as shown by Shamai (1991). At each scale my participants will indicate their COI not only by defining it on a map, but also by giving that COI a name and rating that COI according to how much they identify with it. That way I can assess whether people tend to identify with one scale of COI more than another.

For three, while this second study examines variation in confidence like the first study does, the approach here is considerably different. Instead of drawing freehand three different regions representing different levels of confidence, participants in this study assign rankings to any number of predefined administrative regions. They give their first ranking to the region that they are most confident is within their COI, their second ranking to the region that they are second-most confident is within their COI, and so on. I created these regions by grouping together certain Census units while following a specific set of criteria, outlined below. These areas serve as the “building blocks” of participants’ COIs, and I leave up to them just how many of these “blocks” will form their COI; some may opt to rank only one region and have that be the sole constituent unit of their COI, while others may rank dozens of regions. Nevertheless, most participants rank at least a few of these regions, thus allowing me to assess a gradation in confidence within each person’s COI.

The appeal of ranking administrative regions, rather than drawing freehand as before, lies in the ability to precisely measure the population (in addition to the area) of an individual’s COI. While calculating the area of a region drawn freehand is simple enough, there is no easy way to estimate the population of such a region. People’s freehand boundary lines do not at all follow those of the Census units from which relatively precise demographic information is obtained. Therefore, attempting to estimate how many people live within the bounds of these drawn regions involves a tedious and haphazard process of first determining how many Census units lie wholly within those bounds, the total population thereof, how many Census units lie partially within those bounds, and some kind of fraction of the population thereof. For the latter type of Census unit, the proportion of its area that lies within the bounds could be used as a proxy for population proportion, but this is fraught with issues, especially when a given unit’s population is not close to evenly distributed.

Administrative regions avoid all these challenges when they are composed of Census units. The downside is that the boundaries of the Census units—and by extension the boundaries of the regions that they compose—are defined by the Census for that agency’s purposes, rather than the residents themselves. Furthermore, as much as I strive to follow strict objective criteria, it is ultimately arbitrary how many of these areas I create and which Census units I group to create them. However, the effect of this arbitrariness can be reduced if the “building blocks” are made small enough to provide adequate resolution for people to define a COI that is roughly the size and shape they wish (which I believe they are, as explained below). Ultimately, I believe this is a tradeoff worth making for the sake of having a relatively accurate picture of how many people live within someone’s cognitive COI. With this knowledge in hand, I can discover the average population of people’s COI at each scale.

The use of administrative regions in this study offers another benefit, which is the ability to compare a region’s population with how it is ranked. Since each region’s population is readily available from Census data, one can discern the overall relationship between population and how often or how highly those regions are ranked. This might be informative because one would generally expect to find a high positive correlation between population and ranking. This is because the more populated a region is, the greater the number of survey participants live there. Since participants are more prone to rank the region in which they live, such a region is more likely to be ranked both frequently and highly. If such a strong relationship is so predictable, then what is the point of even looking at this? My aim is to detect any meaningful exceptions to this general pattern, to discern whether it is purely a matter of population that some regions are ranked more than others. If some regions are ranked more or less than their population would suggest, that may indicate that other factors come into play when people are deciding which areas belong in their COI. If I can identify common themes that these outliers share, this will throw more light on what those other factors besides population might be.

B. Methods

1. Study areas

The second study, like the first, utilized primary data collected by surveying residents of a certain area, but focused on two counties rather than the overlap between three electoral districts: San Luis Obispo and Santa Barbara Counties. I chose these counties for the same reasons that I chose the districts for the first study, that is, their convenience, demographic and economic diversity, and mix of urban and rural environments. I also chose these counties because they covered districts from three levels of government, which would allow me to compare the COIs at each scale level with a corresponding electoral district. At the time of the survey, those counties overlapped with California's 24th Congressional District almost entirely, and also California's 35th (entirely) and 37th (partially) State Assembly Districts. Each county also contained five board of supervisors districts to compare to the smallest scale of COI.

2. Cases

As in the first study, I utilized geographical cluster sampling to select residences to approach for an interview within each study area. This ensured that responses were drawn from residents across the entire study area, so that no particular cluster (or subarea) was overrepresented or underrepresented. Rather, I wanted to ensure that each cluster was sampled in proportion to its population. The clusters were identical to the administrative regions that participants were asked to rank on their map. I collected some amount of responses from each region depending on its population. To be clear, these regions played two roles in my study, as both the sampling clusters for surveying participants, and the very regions that those participants ranked when receiving a map of their county. I created these regions by linking Census block groups to form what I called “town-scale units” (TSUs), because most of them constituted a small town or large neighborhood. I linked together these TSUs into larger “municipal-scale units” (MSUs), most of which encompassed a city with its hinterland. Finally, I linked together these MSUs into even larger “county-scale units” (CSUs), most of which were in fact counties.

To create these regions or “units,” I used Census block groups as my “building blocks,” as they were the smallest Census units with recent population data. To form a TSU, I either defined one block group as a TSU in itself if sufficiently large in area and rural in character, or linked contiguous block groups together until the combined area encompassed a widely-recognized town, neighborhood, or community. For this task, I relied on both demographic information as well my knowledge of cognitive regions informed by two decades of living in the area. I also followed a set of criteria to ensure that these TSUs were kept small enough to provide high enough resolution for the survey participants, as explained in the study introduction above.

The first criterion in priority was that the TSU should have an area of at least 5 square kilometers, so that it would not be too small for a participant with poorer eyesight to see on the map. The second criterion was that it should have a population of no more than 25,000 people, so that it would not be too large of a “building block” for the small resolution desired. I violated this second criterion twice, however, in order to observe the higher priority first criterion, so Isla Vista / UCSB and West Central Santa Maria had slightly more than that number. The third criterion was that it should have a population of at least 2,500, unless the area of that unit is at least 50 square kilometers. This served the purpose of ensuring that the TSU would not be too small of a town or neighborhood (in population) for most participants to recognize, except in situations where its area is large enough to compensate for its meager population. This exception allowed me to keep the huge block groups in mountainous and rural areas intact.

In the end, I created 38 TSUs in San Luis Obispo County with an average population of 7,372, and 41 in Santa Barbara County with an average of 10,805. Tables 15 and 16 give various information about these TSUs. This includes the name I gave each one; the number of block groups that made it up; its population, area, and density; how many participants I surveyed from that TSU; as well as the status that determined whether and how I surveyed each one, which I explain below.

Table 15. Statistics for "town-scale units" (TSUs) that I defined in San Luis Obispo County.

Name	# of block groups	Population (ACS 2017)	Land area (km^2)	Pop. density (per km^2)	Participants surveyed	Status
Cal Poly / Grand	4	12,581	19.1	659	6	Urban
Callender / Halcyon Mesa / Los Berros	4	7,745	39.1	198	4	Urban
Cambria	5	5,934	30.7	193	3	Urban
Cayucos	3	2,847	10.4	274	1	Urban
Central Arroyo Grande / Village	5	7,372	15.0	491	4	Urban
Central Paso Robles / Downtown	5	7,122	6.3	1,130	4	Urban
Central San Luis Obispo / Downtown	10	13,054	9.5	1,374	7	Urban
Creston Area	1	2,233	221.2	10	1	Rural
Cuesta College / Camp San Luis Obispo	2	4,545	67.0	68	0	Restricted
East Arroyo Grande Outskirts	2	3,530	172.2	20	2	Rural
East Atascadero / Downtown	11	19,579	30.0	653	10	Urban
East Nipomo Outskirts	1	1,591	774.2	2	1	Rural

Table 15, cont. Statistics for “town-scale units” (TSUs) that I defined in San Luis Obispo County.

Name	# of block groups	Population (ACS 2017)	Land area (km^2)	Pop. density (per km^2)	Participants surveyed	Status
East Paso Robles	9	23,411	62.6	374	12	Urban
East San Luis Obispo / Johnson / Laurel	4	7,421	13.5	550	4	Urban
Far South San Luis Obispo Outskirts / Avila Beach / Edna	3	3,898	178.1	22	2	Rural
Grover Beach	8	13,524	5.7	2,373	7	Urban
Lake Nacimiento Area / Camp Roberts	3	4,425	541.5	8	0	Restricted
Los Osos / Baywood Park	10	15,124	31.4	482	8	Urban
Los Osos Valley / Montaña de Oro	1	1,420	193.0	7	1	Rural
Lopez Lake/Canyon/Mtn.	1	557	219.6	3	0	Rural
Morro Bay	9	10,676	24.2	441	5	Urban
Nipomo	6	16,117	28.0	576	8	Urban
North San Luis Obispo / Foothill / Santa Rosa	6	10,138	15.3	663	5	Urban
Oceano	4	7,238	5.2	1,392	4	Urban
Pismo/Shell Beach	8	8,019	27.2	295	4	Urban
Pozo / California Valley / Carrizo Plain	1	738	2,489.0	0	0	Rural
Rural North Coast / San Simeon	1	1,459	751.5	2	1	Rural
Rural Northeast County / Shandon	4	8,974	1,683.7	5	5	Rural
San Miguel	1	2,635	5.7	462	1	Urban
Santa Margarita Area	2	3,039	300.9	10	2	Rural
South San Luis Obispo / Tank Farm / Airport	2	3,661	26.8	137	2	Urban
Templeton	3	7,271	26.8	271	4	Urban

Table 15, cont. Statistics for “town-scale units” (TSUs) that I defined in San Luis Obispo County.

Name	# of block groups	Population (ACS 2017)	Land area (km^2)	Pop. density (per km^2)	Participants surveyed	Status
West Arroyo Grande / Fair Oaks	7	11,827	9.3	1,272	6	Urban
West Atascadero	5	7,818	13.5	579	4	Urban
West Atascadero Outskirts	3	5,721	169.4	34	3	Urban
West Nipomo Outskirts	1	2,876	136.9	21	1	Rural
West Paso Robles Outskirts	2	4,706	291.9	16	2	Rural
West San Luis Obispo / Madonna / Laguna	5	9,293	12.3	756	5	Urban

Table 16. Statistics for “town-scale units” (TSUs) that I defined in Santa Barbara County.

Name	# of block groups	Population (ACS 2017)	Land area (km^2)	Pop. density (per km^2)	Participants surveyed	Status
Buellton	3	5,139	11.9	432	3	Urban
Carpinteria / Summerland / Toro Canyon	14	17,932	135.5	132	9	Urban
Cathedral Oaks/San Marcos Foothills	6	7,464	87.9	85	4	Urban
Central Goleta Valley / Old Town / Fairview	12	13,275	14.9	891	7	Urban
Channel Islands	1	6	779.1	0	0	Rural
Cuyama Valley / San Rafael Mountains	1	941	3,024.0	0	0	Rural
Downtown Santa Barbara / Oak Park / Upper East	17	17,595	5.3	3,320	9	Urban
East Central Santa Maria	10	18,100	5.2	3,481	9	Urban
East Goleta Valley / Noleta / Turnpike	12	20,769	10.4	1,997	11	Urban
East Lompoc	13	17,950	10.0	1,795	9	Urban

Table 16, cont. Statistics for "town-scale units" (TSUs) that I defined in Santa Barbara County.

Name	# of block groups	Population (ACS 2017)	Land area (km^2)	Pop. density (per km^2)	Participants surveyed	Status
East Lompoc Valley / Purisima Hills	1	536	204.3	3	0	Rural
East Orcutt / Bradley	18	22,381	15.9	1,408	11	Urban
East Santa Maria / Pioneer Valley	7	11,550	11.6	996	6	Urban
East Santa Maria Valley	1	1,136	67.2	17	1	Rural
Eastside / Laguna	11	13,724	5.2	2,639	7	Urban
Far South Santa Maria / Airport	8	14,714	22.6	651	8	Urban
Gaviota / Refugio / El Capitan	1	499	217.2	2	0	Rural
Guadalupe / Casmalia / West Santa Maria Valley	4	7,581	167.0	45	4	Urban
Hope Ranch / More Mesa	3	3,240	12.6	257	2	Urban
Isla Vista / UCSB	14	27,708	6.4	4,329	14	Urban
Los Alamos Area	2	2,175	408.9	5	1	Rural
Los Olivos Area	3	2,595	323.9	8	1	Rural
Mission Hills	3	4,535	8.6	527	2	Urban
Montecito	9	9,460	55.8	170	5	Urban
North Santa Maria / Preisker Park	10	19,912	26.4	754	10	Urban
Riviera / Eucalyptus Hill / Mission Canyon	13	14,625	33.0	443	7	Urban
Santa Barbara Mesa / Campanil	13	12,221	10.3	1,187	6	Urban
Santa Ynez Area / Chumash Reservation	3	3,767	32.5	116	2	Urban
Santa Ynez Mountains / Lake Cachuma / San Marcos Pass	1	878	242.1	4	0	Rural

Table 16, cont. Statistics for “town-scale units” (TSUs) that I defined in Santa Barbara County.

Name	# of block groups	Population (ACS 2017)	Land area (km^2)	Pop. density (per km^2)	Participants surveyed	Status
Sisquoc/Garey Area / Orcutt Hills	1	1,613	370.2	4	1	Rural
Solvang Area	6	7,369	29.8	247	4	Urban
South Santa Maria / Minami Park	7	17,392	19.2	906	9	Urban
Upper State / Hope / San Roque / Samarkand	11	14,686	7.3	2,012	7	Urban
Vandenberg Air Force Base	2	6,450	426.4	15	0	Restricted
Vandenberg Village	6	7,541	29.9	252	4	Urban
West Central Santa Maria	16	27,846	5.3	5,254	14	Urban
West Goleta Valley / Ellwood / Storke	11	17,034	26.7	638	9	Urban
West Lompoc	16	22,575	12.1	1,866	11	Urban
West Lompoc Valley / Lompoc Hills / Jalama	1	730	508.2	1	0	Rural
West Orcutt / Old Town	5	5,871	10.5	559	3	Urban
Westside / Bel Air / Hidden Valley	16	21,481	6.1	3,521	11	Urban

Overall I surveyed 360 residents across the two counties, but I excluded three TSUs with restricted status from my sample. Two of them—Cuesta College / Camp San Luis Obispo and Vandenberg Air Force Base—had populations that were mostly prisoners or military personnel living within guarded gates. Another one—Lake Nacimiento Area / Camp Roberts—also had a large guarded military contingent, plus a civilian population living in a collection of private gated communities. Therefore, having no access to these populations, I did not include them as part of my statistical population. However, those TSUs still showed up on survey map materials, as the residents of the non-restricted TSUs who were surveyed may still have wished to include those areas as part of their COI.

In order to determine how many participants to survey in each of the remaining TSUs, I first subtracted the total population of the three restricted TSUs from that of the two counties combined. I then calculated each remaining TSU's proportion of that statistical population. Finally, I multiplied that proportion by the number of participants I intended to survey—360—in order to come up with an amount to survey from each TSU (besides the restricted ones) that was proportional to its population. I used the largest remainder method to distribute the fractional remainders as simply as possible. Some TSUs had such small populations that I did not survey a single participant from those areas, while others were so populous that I surveyed more than a dozen of their residents.

The procedure in which I surveyed residents of the non-restricted TSUs depended on whether I deemed their status urban or rural. The urban TSUs were those that had a population density greater than 25 people per square kilometer, while the rural TSUs were those that had a density less than that. In the experience of surveying, that threshold turned out to be the point below which surveying became much costlier in time and money due to the large spaces involved, as well as the greater likelihood of encountering houses or even whole neighborhoods with private, restricted access. In order, then, to reduce that cost, I adopted a sampling procedure for rural TSUs that was different from the one I used for urban ones. But first, I outline the procedure utilized for the urban TSUs that made up the vast majority of all those TSUs surveyed.

In order to select individuals from an urban TSU for participation in the survey, I randomly selected from the Census units that made up that TSU. I weighted each Census unit according to its population so that I was more likely to randomly select a more populated one. To illustrate, there were three block groups that composed the TSU of Buellton, labelled 3, 4, and 5 by the Census. Because I needed three participants from Buellton, I had to select from those block groups three times, so I selected 5, then 4, then 4 again. I then had to select three blocks within those block groups, so I selected one block in Block Group 5 and two blocks in Block Group 4, because I selected that twice. After selecting a certain block, I then randomly chose a particular street making up that block. The street address with the lowest number on that street was the first residence approached on that street, and if an address was multi-unit, the unit with the lowest number was the first approached.

The procedure for a rural TSU differed in that once I selected a block group (in the same manner in which I selected one for an urban TSU), I then selected from among only the densest blocks within that block group. I took the densest blocks (with a minimum of 10 residents) in the block group that totaled to at least 100 people per participant needed. To determine which blocks I would select from, I first took the block with the highest population density, then the one with second-highest, and so on until I had isolated enough blocks to reach the necessary total population. I then followed the same procedure from there as I followed with an urban TSU in order to select a block, a street on that block, and an address on that street. The whole idea behind only choosing among the densest blocks in these rural TSUs was to cut down on the time and cost spent surveying by avoiding the wide open spaces and gated farms and compounds typical of the sparsest blocks. That way I could survey people in these rural TSUs faster and easier than otherwise, while still ensuring that I would obtain the perspectives of these ruralites.

Overall, I surveyed 139 people in San Luis Obispo County and 221 people in Santa Barbara County, for a total of 360 participants. I approached 2,355 residences for a response to this survey; of those, 834 had someone come to the door and 360 agreed to participate, for a response rate of 43.2% among those who came to the door and 15.3% among residences approached. Information about the survey sample is given in Table 17, along with information from the larger-sample American Community Survey.

Table 17. Statistics for survey respondents (relevant 2017 ACS 5-year estimates for surveyed block groups in parentheses, which includes children not surveyed in this study).

Study area	Sample size	Average age in years	Average years in district	Race/Ethnicity	Sex
SLO County	139 (280,119 total pop.)	48.8 (39.0 median age)	27.7	115 Whites, 16 Hispanics, 7 Asians, 1 other (22.2% Hispanic)	74 males, 65 females
SB County	221 (442,996 total pop.)	45.7 (33.7 median age)	26.8	122 Whites, 83 Hispanics, 10 Asians, 4 others (44.8% Hispanic)	114 males, 107 females
Both counties	360 (723,115 total pop.)	46.9 (35.8 median age)	27.2	237 Whites, 99 Hispanics, 17 Asians, 5 others (36.1% Hispanic)	188 males, 172 females

3. Materials

I administered the surveys to participants in a traditional paper-and-pencil format, using a double-sized survey sheet with a map printed on both sides. On the front side they viewed a map of their county, so residents of San Luis Obispo County received a map of that county, and residents of Santa Barbara County received one of that county. On the back side they saw a map of the larger region, but this map also came in two versions. One version showed Central California and much of Northern California, and the other showed much of Southern California. Which version of the back map that a participant received depended on whether that person said that they were from Northern or Central California (in which case they received the first version), or from Southern California (in which case they received the second version). If someone did not come from California at all, that person was asked which part of California that they identified with the most.

As I did in the first study, the map scales were designed to guide the participants into drawing regions of a certain size to compare to a particular level of district in which they live (congressional, state assembly, and board of supervisors district). I assumed that survey participants in general would tend to express their opinions in a moderate fashion, neither defining a region that took up the whole map or even exceeded it, nor defining a region that took up just a tiny portion thereof. Thus I designed the map to cover an area that would prompt a moderate response that would be similar in size, and thus readily comparable, to that of a particular level of district. I could have opted to explicitly tell them to draw a region approximating the size of a certain level of district, telling them to stop ranking once they hit a certain population threshold, but I decided to leave it up to the participant as to how large their COI would be, so that I could investigate that factor as another variable of interest.

The county map on the front side of the survey sheet showed the TSUs that I predefined. Thin lines marked their boundaries, and labels gave their names. Next to each label appeared a small white box in which participants were asked to write their ranking. These boxes minimized confusion during data entry as it was clear which unit the ranking referred to. One area in San Luis Obispo County—the San Luis Obispo area—and two areas in Santa Barbara County—the Santa Barbara area and the Santa Maria area—were too densely populated for me to fit all the labels and boxes while maintaining clarity and legibility. Therefore, I blew up these areas in larger insets and positioned them over unpopulated areas of the county. Finally, at the corner of the map appeared a large white box in which the participant wrote a common place name that would describe their COI, how long they had lived in that COI, and how much they identified with that COI on a five-point scale from “Very much” to “Not at all.”

The regional map on the back side of the survey sheet showed the MSUs and CSUs that I predefined. Thin lines marked the boundaries of the MSUs, and labels gave their names. Next to each label appeared a small white box in which participants were asked to write their ranking. Thick lines marked the boundaries of the CSUs, and bold labels gave their names. There were no boxes for the CSUs, as the chance of confusion was minimal with these larger units. To create the MSUs, I linked contiguous TSUs together, and to create the CSUs, I linked contiguous MSUs together. Most of these CSUs were single counties. I followed similar criteria in creating the MSUs and CSUs as I did for the TSUs. First and foremost, the unit had to be wholly contained by one county. Second, MSUs had to have an area of at least 50 square kilometers (500 for CSUs). Third, MSUs could have a population of no more than 250,000 (2,500,000 for CSUs). Finally, MSUs had to have a population of at least 25,000 (250,000 for CSUs), unless one had an area of at least 500 square kilometers (5,000 for CSUs). One area in Northern California—the San Francisco Bay Area—and one in Southern California—the Los Angeles area—were too densely populated for me to fit all the labels and boxes while maintaining clarity and legibility. Therefore, I blew up these areas in larger insets and positioned them over the ocean part of the map. Finally, two large white boxes appeared at the corners of the map, one for participants to give their information for the COI that they defined with MSUs, and one for the COI that they defined with CSUs. All map versions are shown in Figures 24–27.

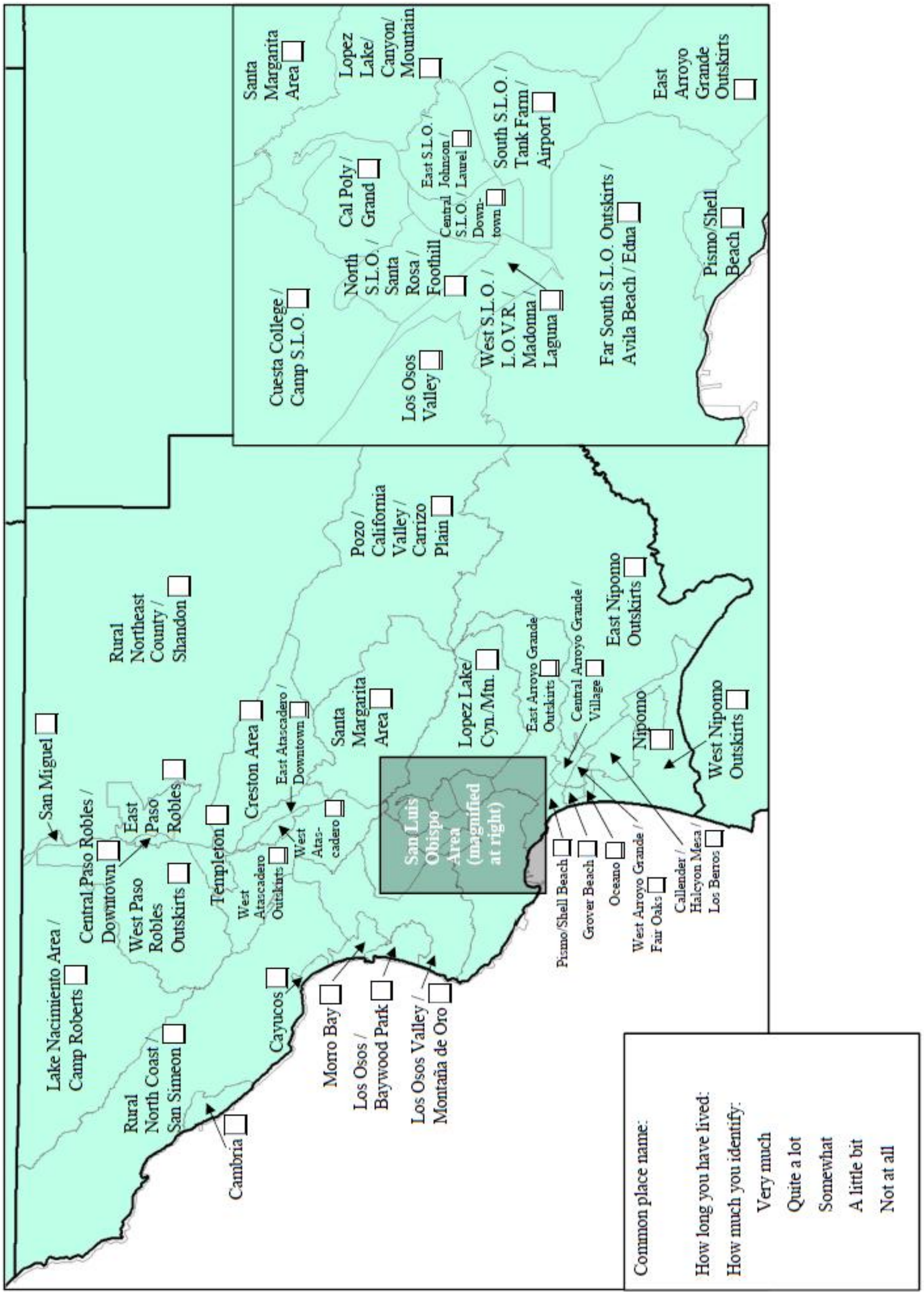

Figure 24. Map of San Luis Obispo County used in Study 2.

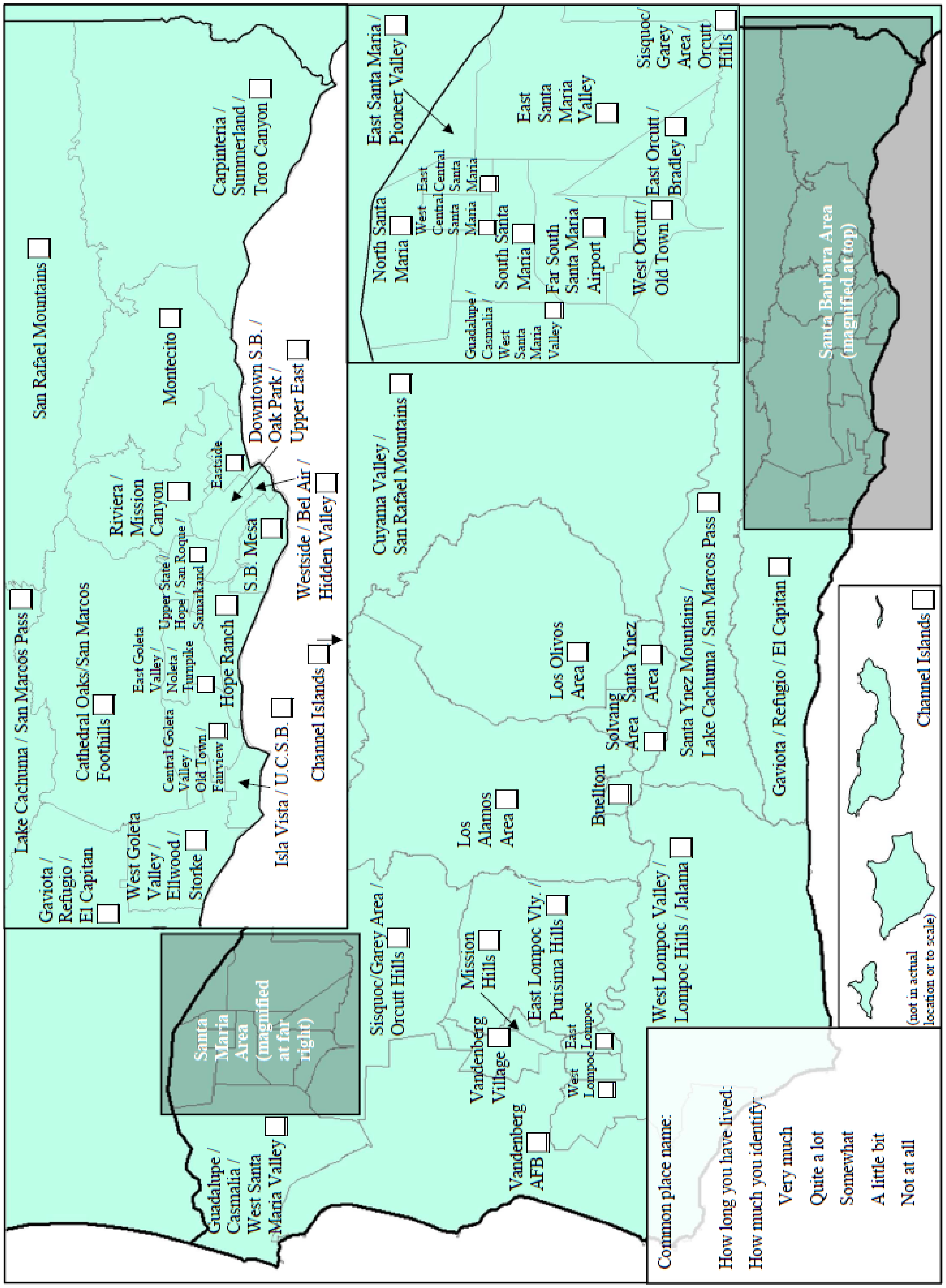

Figure 25. Map of Santa Barbara County used in Study 2.

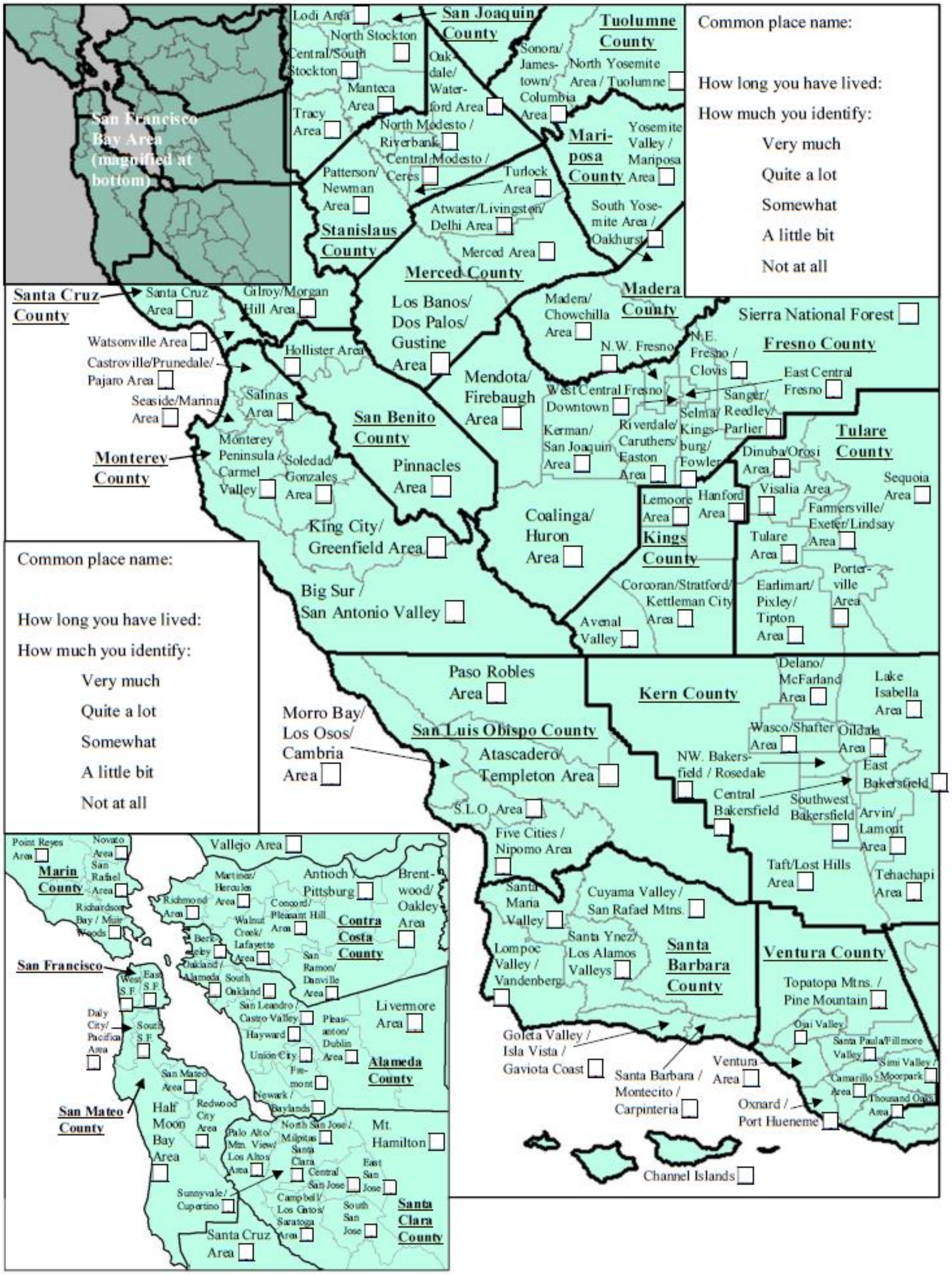

Figure 26. Map of Northern and Central California used in Study 2.

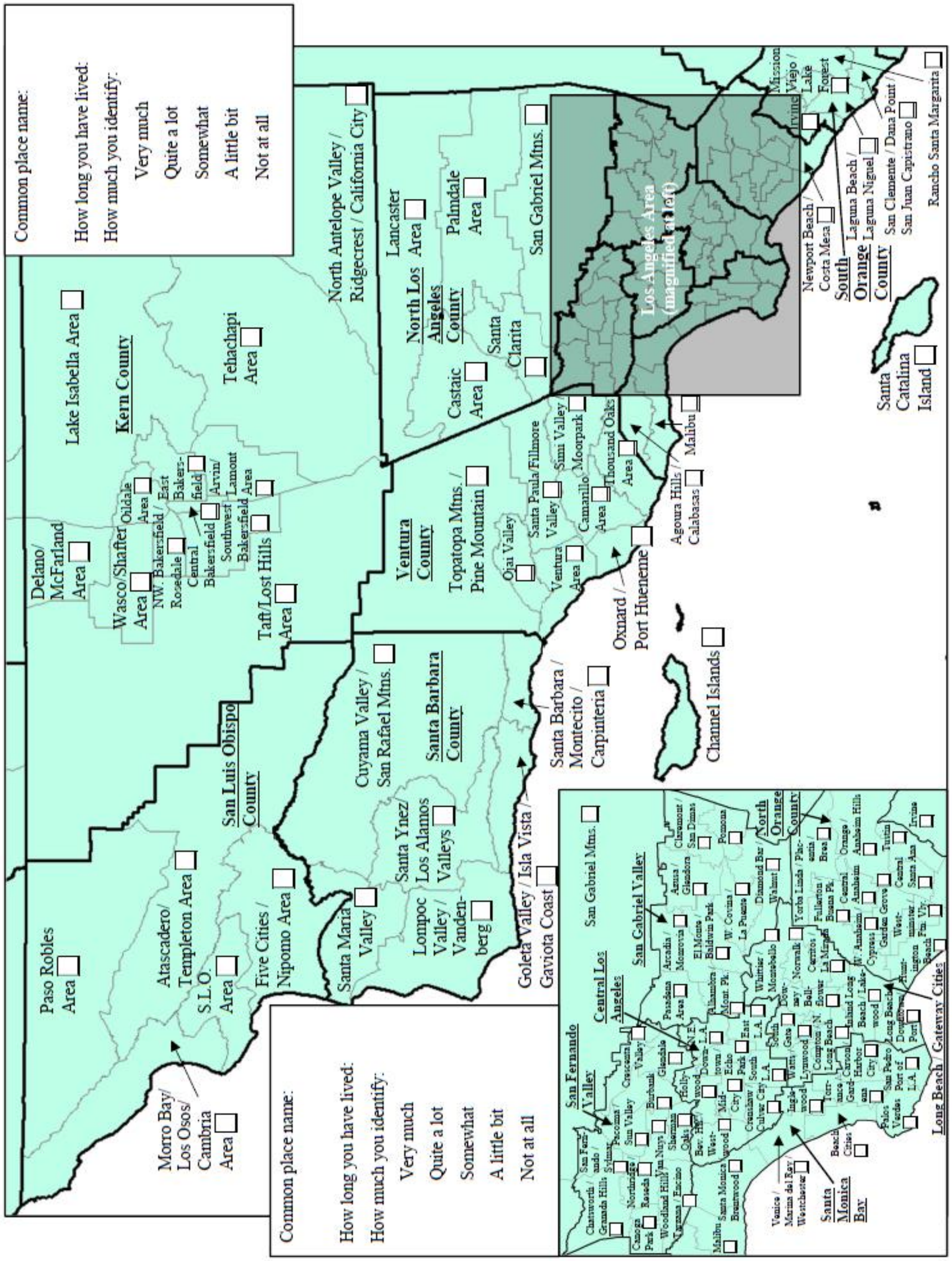

Figure 27. Map of Southern California used in Study 2.

4. Procedure

Since many native Spanish speakers lived in the study area, I enlisted the service of bilingual survey administrators in certain parts with higher concentrations of Hispanics. Monolingual English-speaking survey administrators, including myself, surveyed in other parts of the district. In our survey sessions, we first approached the selected residence and sought a response from there. If they could not get a response from there, we moved on to the next-highest-numbered residence on that side of the street until we obtained a response. If that street was exhausted, we then found the lowest-numbered residence on the next street alphabetically that made up that block and repeated the process. Residences with locked gates or “no trespassing” signs were passed over. Survey collection took place on either weekday evenings or on weekends, since most people were at home during those times. Different parts of the study area were surveyed during roughly the same time frame, spanning from May 2019 to January 2020, so as to remove date as a confounding factor for differences observed between the parts.

For each residence that we visited, we introduced ourselves to an adult resident as a UCSB student conducting research and asked that person whether he or she would be willing to participate in a quick survey. Those residents who agreed to participate were first asked whether they considered themselves to be from Northern, Central, or Southern California. Their response determined which version of the back-side map they received. They were then shown the front-side map, told that the map showed their county divided up into several smaller areas, made aware of which area they lived in, and asked to rank some of those areas according to how confident they were that a given area was in their COI. We defined a COI as “a region filled with people who live next to each, have similar characteristics, and share a common identity." They were instructed to rank their areas by putting a "1" for the area that they were most confident was in their COI, a "2" for the area they were second-most confident was in their COI, and so on. We made clear to them that they did not have to rank every single one of the areas, but only as many as they felt were in their COI. Once they had finished ranking, we then had them indicate a common place name for their COI (often clarifying, "a name that people commonly call your community"), and then asked them to write how long they have lived in their COI (using the actual name that they gave for it), and how much they identify with that COI. We then turned the sheet over and told them the following: "This map is similar to the last map, but just shows a larger area. You are located here [pointing to the MSU in which the participant was living] in [the MSU's name]. I would like you to do the same task as you did before, just at a larger scale." After they did this, we asked them to replicate the task once more with the CSUs that shared the same map with the MSUs. Finally, we asked them to provide their age and racial or ethnic identity (if not obvious); we also noted their sex and the street block they lived on.

5. Analysis

a. Rankings given by participants for units to define their COI

In analyzing the actual rankings made on the survey maps, I first had to grapple with how to quantitatively assess each predefined region or "unit." One option was to compute a mean value for each unit from all the rankings that participants gave that unit. Thus the units with the lowest mean value would be the ones that participants tended to rank higher. However, this method of analysis would be inappropriate because I did not require each participant to rank every single unit. Therefore, if some unit had been ranked by only one person, but ranked first by that individual, that unit would be treated by such an analysis as the highest-ranked unit overall. This clearly would be misleading, so I opted for a different method of analysis.

Instead, I computed mean scores for all units by transposing the highest ranking, 1, to a maximum score of either 5 (for CSUs) or 10 (for MSUs and TSUs). Then all subsequent rankings were transposed accordingly, so that the second-ranked unit would be 4 or 9, the third would be 3 or 8, and so on. This transposition caused higher-ranked units to be reflected as higher numbers. By using a maximum possible score, I was able to handle the difficulty of different people ranking different numbers of units. I chose maximum scores of 5 and 10 because the vast majority of participants ranked no more than 5 CSUs and 10 MSUs and TSUs. If a participant ranked more than the maximum number of units, those ranked past 5 or 10 were scored as 0. However, relatively few participants ranked this far. Only 6.5% of them ranked more than 5 CSUs, while 6.9% ranked more than 10 MSUs, and 15.4% ranked more than 10 TSUs. If someone gave multiple units the same ranking, those units all received the median score between them. So for example, if a participant's COI were to consist of one CSU ranked first, three CSUs ranked second, and another ranked third, the one ranked first would be scored as 5, the ones ranked second would all be scored 3, and the unit ranked third would be scored as 1.

b. Spatial similarity between cognitive COIs and electoral districts

In order to assess the spatial similarity between participants' cognitive COIs and the existing electoral districts, I had to decide how to define the extent of those COIs. There were a few ways I could do this. One approach would be to look at the percentage of participants who ranked a given unit, and identify a COI made up of contiguous units that are all ranked by at least some threshold percentage. However, this posed the difficulty of deciding whether to look at the percentage of all participants or some subgroup such as within a certain county or part of a county. It also required me to arbitrarily choose that percentage threshold or "cutoff" line. Another approach would be to take the mean transposed score for a given unit, and identify a COI made up of contiguous units that all have scores past a certain threshold, but the two problems with the first approach applied with this one also. A third approach would avoid the arbitrariness of the first two by identifying COIs from correlations between units. This method would consider how similarly participants from different units ranked all the units available to them on the survey map. The more similar their rankings were, the higher the correlation would be between them. This method would analyze how residents of each unit related to those of every other unit. Therefore, I did not have to analyze different groups of participants.

Furthermore, it made good conceptual sense to identify COIs using this method. Those units whose residents agreed very much about how they ranked their units likely belonged to the same cognitive COI, as those residents shared similar beliefs about the extent of their COI. So a pair of units with a high positive correlation between them very likely shared a COI, but a pair of units with a low positive correlation or even a negative one probably came from different COIs. This could extend beyond pairs to include groups of several units that all correlated highly with one another, so that they formed a network where the links between the nodes were correlations between units with values greater than 0.5 (granted, this was an arbitrary threshold). Such a network would constitute a closed system, and thus a distinct and self-contained COI, where no such links to any other systems existed.

Having identified COIs at different scales, I could then compare their spatial extent with those of the existing electoral districts. One thing to note is that participants could only assess the degree to which some predefined units belonged to their COI. They had no ability to define a COI very finely by drawing a boundary line on a map as those in Study 1 could. Therefore, it would not have been fair to assess spatial similarity between a group of units forming a COI and the actual district with which it overlaps the most. Instead, I assessed spatial similarity between that group of units and the group of units that best approximated the extent of that district. The latter group included all units that fell completely within a given district. For a unit that spanned different districts, I counted it as being completely within the district where most of its population lived. That way, I could compare one group of whole units representing the COI with another such group representing the district.

I calculated spatial similarity using Hill's (1990) index, but with population as the measurement of a region's spatial extent rather than area, which is what is typically used as demonstrated in Study 1. I just considered population for two main reasons. First, I considered a unit spanning two different districts to be wholly part of the district where most of its population lived. This meant that a unit could have most of its area in one district but be counted as being within another if most of its people lived in the latter. Second, I wanted to determine the overlap between the two regions in actual people/voters. That is because a COI is first and foremost a "group of people" (as the definition given to participants reads), so I was principally interested in how many of that group reside in one district or another. The design of this second study allowed me to discern that, because it involved ranking areas with known populations. This was not feasible with the first study, where the populations of different regions was more uncertain.

c. Degree of identification with different scales of COI

I also considered the degree to which participants identified with COIs at different scales. To do so, I transformed the verbal scale given to participants into a numeric scale by assigning a value of “5” to “Very much” and a value of “1” to “Not at all.” This enabled me to compute a mean value for each scale of COI. The higher the mean value, the more that people tended to identify with that COI, in general.

d. Names given by participants for their COIs

Lastly, I examined the names that participants gave for their COI at different scales. This involved developing a coding system to standardize and categorize each response. To standardize the names, I rephrased any responses that were unique or vague in order to reduce and refine the total number of names to be categorized. There were several steps in this standardization process. For one, abbreviations or shortenings were expanded into the full intended name, like “SB County” to “Santa Barbara County” and “SoCal” to “Southern California.” For two, references to the cities of “San Luis Obispo” and “Santa Barbara” were clarified as “San Luis Obispo Only” and “Santa Barbara Only” to distinguish them from the county names. For three, names for places beyond the Central Coast region, like “North Los Angeles” and “Bay Area,” were renamed as “Beyond.” For four, names like “My Community” and “My Heritage” (which were discouraged by the survey instructions but sometimes insisted upon anyway) were renamed as “Personal.” Finally, uncommon names like “Coastal Ag” and “Los Alamos” were renamed as “Other.” Once this process was complete, I categorized the resulting 32 standardized names into 10 categories. Three of these categories carried over from the previous step, those of “Beyond,” “Personal, and “Other.” The remaining seven categories, on the other hand, funneled the 29 standardized names besides those three. I decided to base these seven categories on the general spatial scale of the standardized names. They thus ranged from the largest-scale “State” to the smallest-scale “Sub-City.” For example, “California” would be categorized as “State,” while “Santa Barbara Neighborhood” would be classified as “Sub-City.” Table 18 visualizes how the standardized names funneled into the categories.

Table 18. Standardized names and categories for names given for COIs.

Standardized name	Category
California	State
Northern California	Sub-State
Central California	Sub-State
Southern California	Sub-State
Central Coast	Coast
Coastal California	Coast
West Coast	Coast
South Coast	Coast
Tri-County	Multi-County
San Luis Obispo County	One County
Santa Barbara County	One County
North San Luis Obispo County	Sub-County
South San Luis Obispo County	Sub-County
North Santa Barbara County	Sub-County
South Santa Barbara County	Sub-County
San Luis Obispo Only	Sub-County
Five Cities	Sub-County
Nipomo	Sub-County
Pismo Beach	Sub-County
Atascadero	Sub-County
Paso Robles	Sub-County
Santa Barbara Only	Sub-County
Goleta	Sub-County
Santa Maria	Sub-County
Lompoc	Sub-County
Santa Ynez Valley	Sub-County
San Luis Obispo Neighborhood	Sub-City
Santa Barbara Neighborhood	Sub-City
Santa Maria Neighborhood	Sub-City
Beyond	Beyond
Personal	Personal
Other	Other

C. Results

1. Rankings given by participants for units to define their COI

a. Rankings given by residents of both counties for county-scale units

Results from rankings for units across the three scale levels can show agreement among participants about the location and extent of their COI, in that units ranked by a greater percentage of participants indicate greater agreement that that unit is in their COI. In this section, I look first at the results for rankings of county-scale units (CSUs). I consider two sets of results: the percentage of participants who rank a certain CSU at all, and the average transposed score that participants give to that CSU. The first set represents how often a CSU is included in people's COI, while the second represent how confident they are that it belongs in their COI. First I present the percentage of participants who rank a given CSU at all. Figure 28 shows results from participants from San Luis Obispo County, and Figure 29 shows results from those from Santa Barbara County.

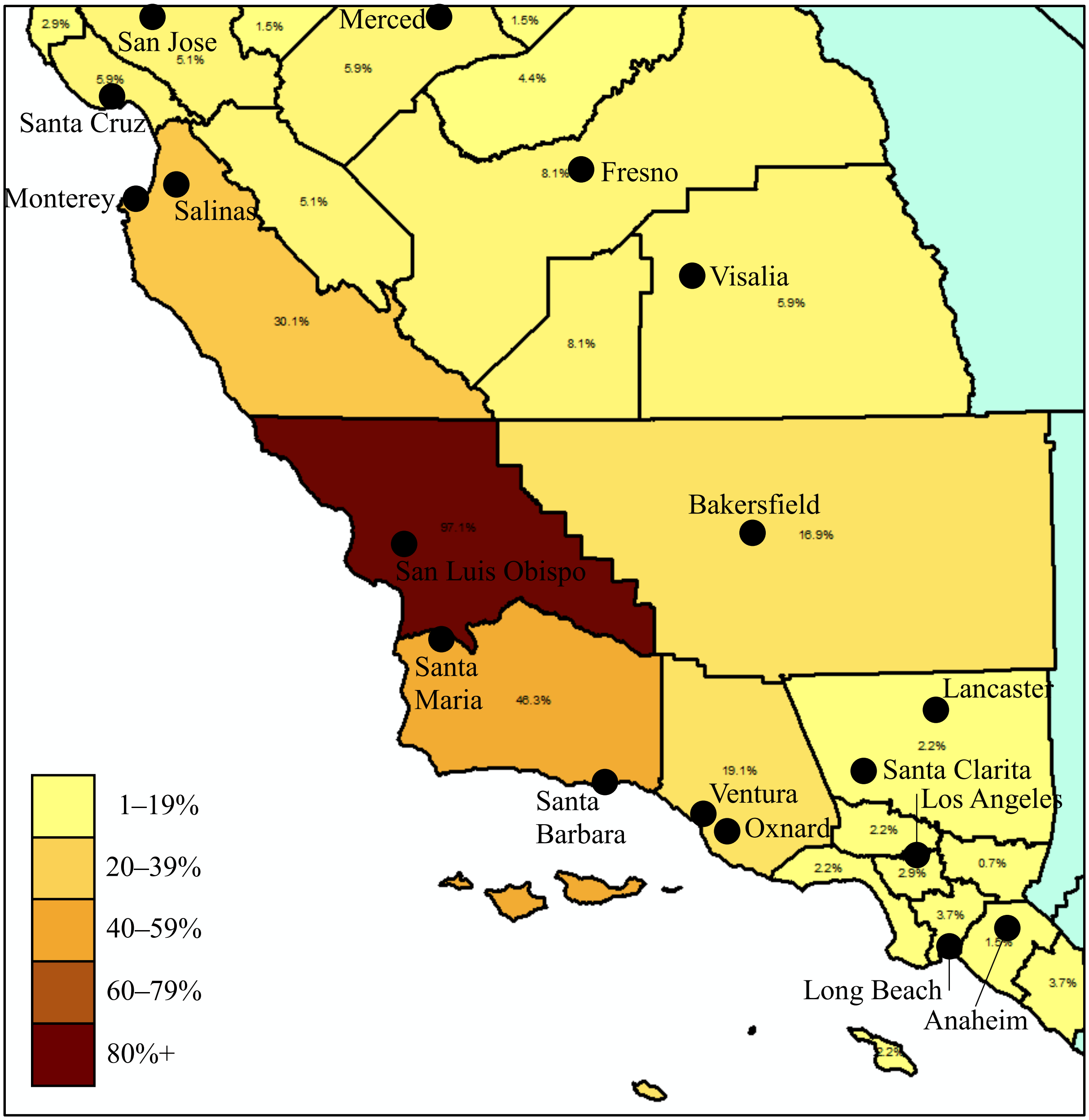

Figure 28. Map of CSUs with the percentage of participants from San Luis Obispo County who rank a given unit at all. The darker the shade of orange/brown, the greater the percentage.

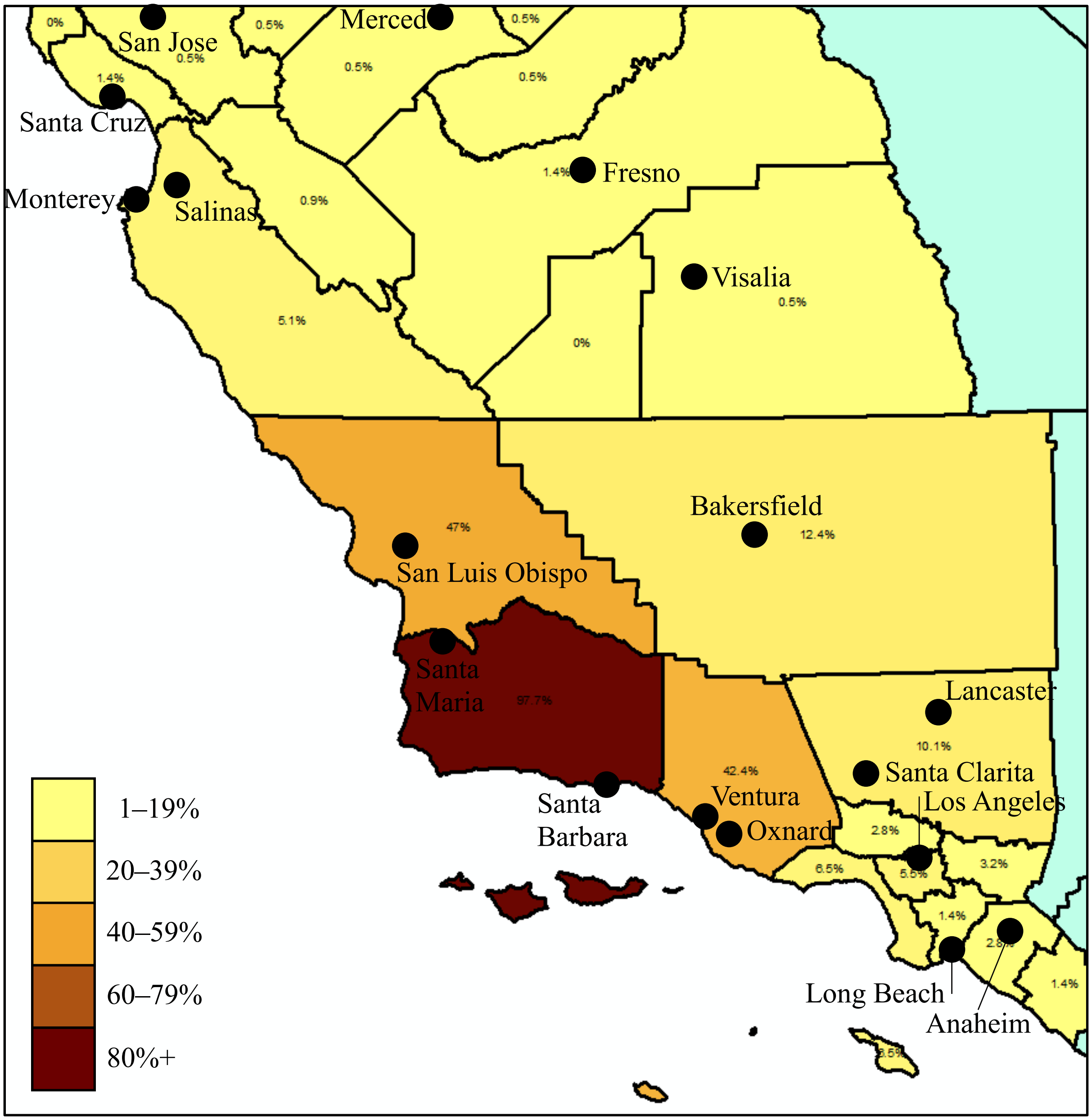

Figure 29. Map of CSUs with the percentage of participants from <u>Santa Barbara County</u> who rank a given unit at all. The darker the shade of orange/brown, the greater the percentage.

Turning first to the results for participants from San Luis Obispo County, that county dominates as it is ranked by 97.1% of them. Residents of that county rank neighboring counties to the north and south much less often, as 30.1% of them rank Monterey County and 46.3% rank Santa Barbara County. For participants from Santa Barbara County, that county dominates as it is ranked by 97.7% of them. Those residents rank neighboring counties much less often, as 47.0% of them rank San Luis Obispo County and 42.4% rank Ventura County. Even though Kern County in the Central Valley is just as adjacent to the study areas as the coastal counties of Monterey and Ventura are, it is ranked by only 16.9% of participants from San Luis Obispo County and 12.4% of those from Santa Barbara County.

Next I consider the average transposed score given to each CSU that is ranked by at least 5% of the residents of San Luis Obispo or Santa Barbara Counties, which are 15 altogether. When looking at results from participants from both counties, I find that a CSU's average transposed score correlates almost perfectly with the percentage of participants who rank it ($r[13] = .99$, $p < .001$). This holds when breaking the results down by participants from one county or the other, both for those from San Luis Obispo County ($r[13] = .99$, $p < .001$), and for those from Santa Barbara County ($r[13] = .99$, $p < .001$). Given these correlation values, there is no need to present the results for the average transposed scores for CSUs, except to report the correlation between those rankings given by residents of the two counties ($r[13] = .52$, $p = .05$).

Finally, I consider how many CSUs participants decide to rank on average, and what is the mean population and area of all of those CSUs combined (i.e. the total population and area of their CSU-defined COI). These results appear in Table 19.

Table 19. Means for total CSUs ranked, and the total population and area of those CSUs.

Participants from:	Total CSUs ranked	Total population	Total area (in sq. km.)
Both counties combined	2.7	1,639,473	19,321
San Luis Obispo County	3.0	1,684,602	22,730
Santa Barbara County	2.4	1,611,497	17,208

Participants on average tend to rank between two and three CSUs. Those in San Luis Obispo County tend to rank three, while those in Santa Barbara County rank about two and a half. The total population of the COI that participants define with the CSUs they rank hovers around 1.6 million, with the number higher for those from San Luis Obispo County because they tend to rank slightly more CSUs. For perspective, the population of San Luis Obispo, Santa Barbara, and Ventura Counties combined totals close to 1.6 million. The total area of the COI that participants define with their CSUs hovers around 20,000 square kilometers, again, with the number higher for San Luis Obispo County residents. For perspective, the area of San Luis Obispo, Santa Barbara, and Ventura Counties combined just exceeds 20,000 square kilometers.

b. Rankings given by residents of both counties for municipal-scale units

In this next section, I look at the results for rankings of municipal-scale units (MSUs). I consider the same two sets of results as before: the percentage of participants who rank a certain MSU at all, and the average transposed score that participants give to that MSU. First I present the percentage of participants who rank a given MSU at all. Figure 30 shows results from participants from San Luis Obispo County, and Figure 31 shows results from those from Santa Barbara County.

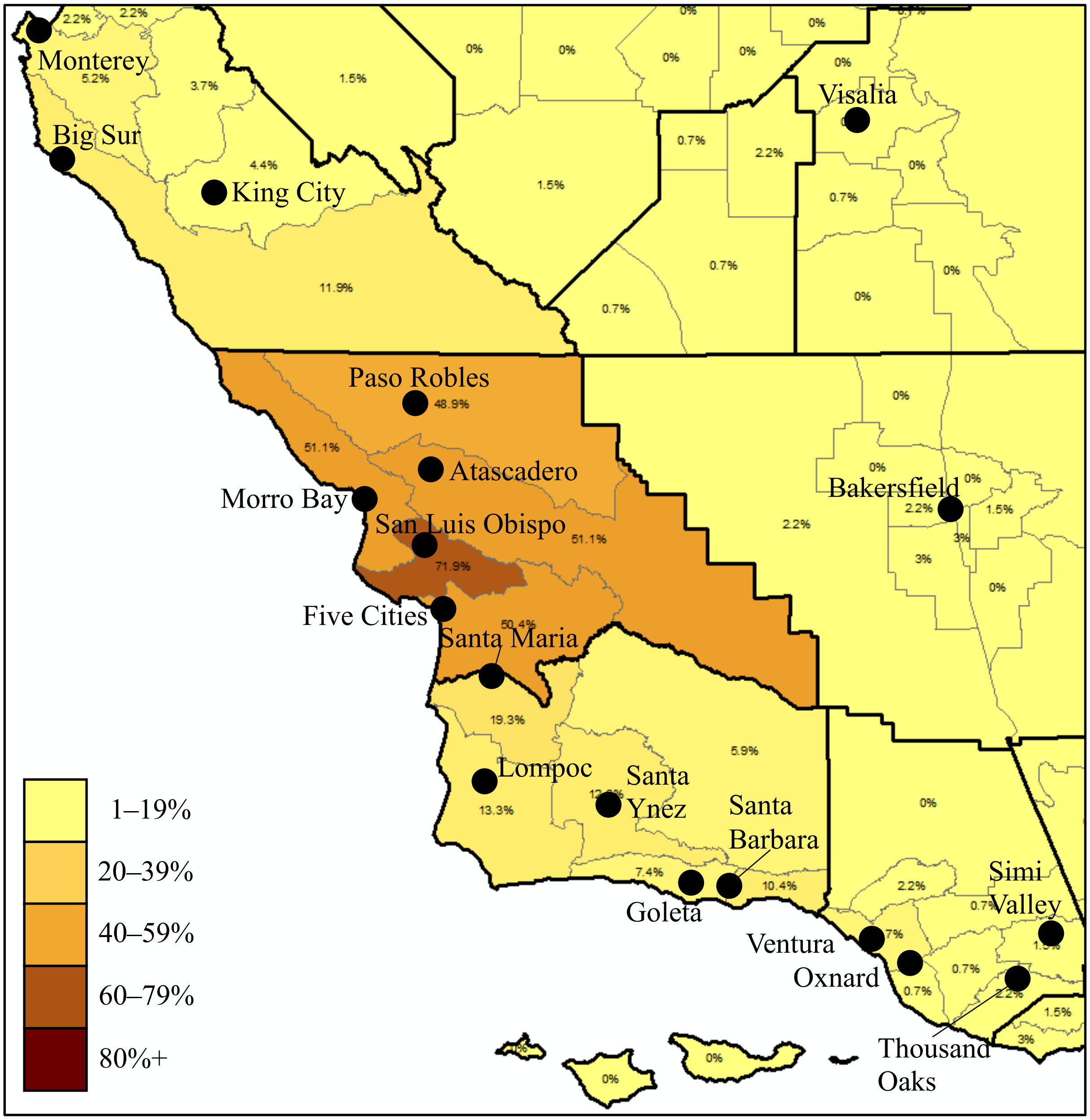

Figure 30. Map of MSUs with the percentage of participants from <u>San Luis Obispo County</u> who rank a given unit at all. The darker the shade of orange/brown, the greater the percentage.

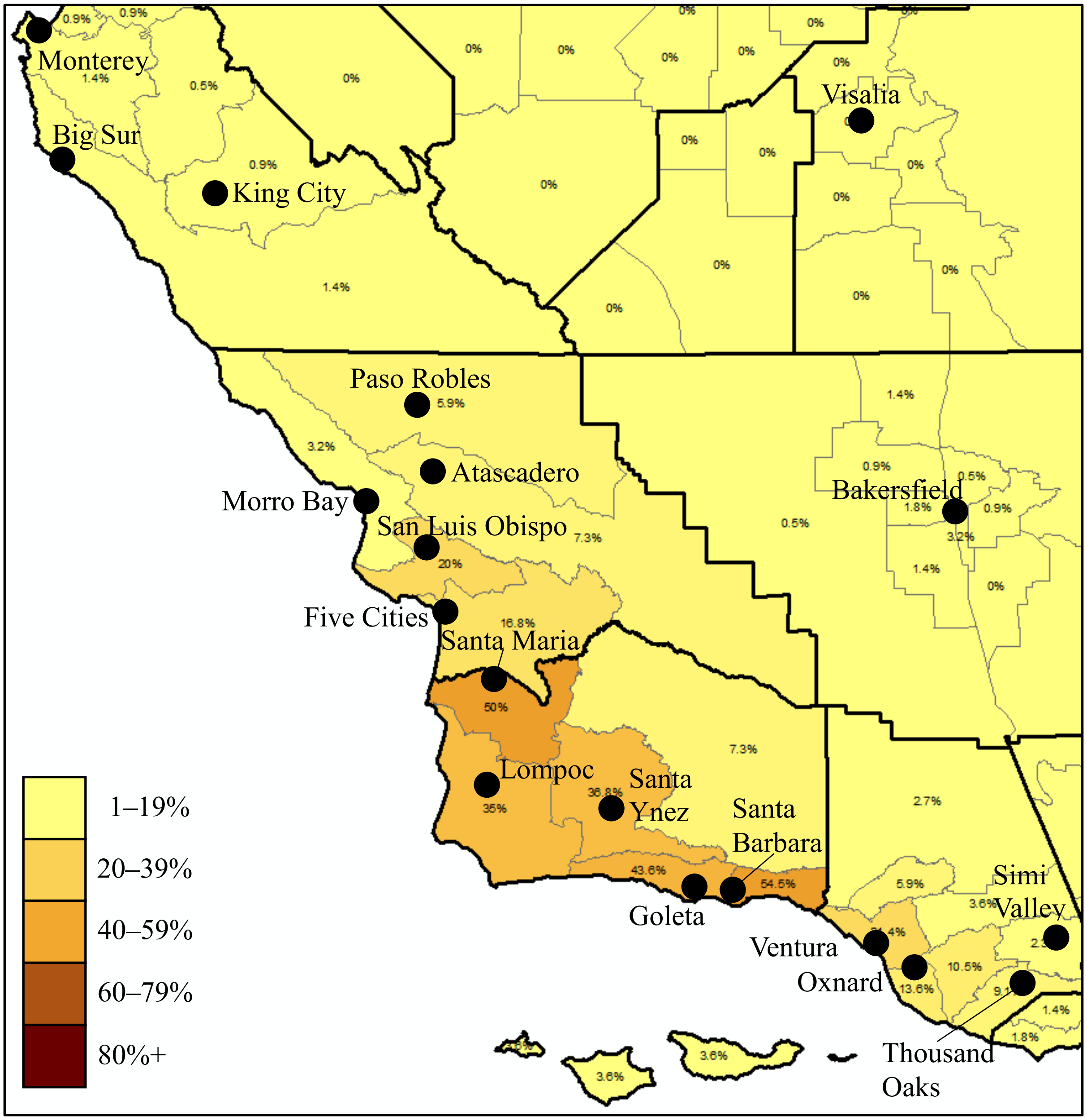

Figure 31. Map of MSUs with the percentage of participants from Santa Barbara County who rank a given unit at all. The darker the shade of orange/brown, the greater the percentage.

Participants from San Luis Obispo County rank the MSUs in that county much more often than MSUs in any other CSU. All five MSUs that make it up are ranked by close to if not more than half of those participants, averaging 54.7%. The San Luis Obispo area leads the way with 71.9%, much higher than any other MSU. The other four MSUs in the county range from 51.1% to 48.9%. MSUs in northern Santa Barbara County and coastal Monterey County are also ranked relatively frequently, by at least 10% of them, led by Santa Maria Valley with 19.3%. Those in Santa Barbara County as a whole average 9.8%, while those in Monterey County average 4.3%. Every other CSU's component MSUs average 2% or less.

Participants from Santa Barbara County likewise rank the MSUs in that county more often than MSUs in any other CSU. Five of the seven MSUs that make it up are ranked by more than a third of those participants, and all seven average 33.0%. The Santa Barbara area leads the way with 54.5%, followed closely by Santa Maria Valley with 50.0%. The three other MSUs in the county that have substantial populations—Goleta, Santa Ynez, and Lompoc Valleys—range from 43.6% to 35.0%. The two that do not barely register. MSUs in coastal Ventura County and southern San Luis Obispo County are also ranked relatively frequently, by at least 10% of them, led by the Ventura and San Luis Obispo areas with 21.4% and 20.0%, respectively. Those in Ventura County as a whole average 8.6%, while those in San Luis Obispo County average 10.6%. Every other CSU's component MSUs average less than 1.5%.

I can also compare the percentage of participants who rank a given MSU to its population to see if some MSUs are ranked more frequently than one would expect just based on their population. I propose that a notable exception would be one where the actual percentage of participants who rank it deviates from that predicted by population alone by 10% in either direction (see Table 20). Here I consider MSUs that are located in San Luis Obispo County and Santa Barbara County, which are 12 altogether. When examining results from participants from both counties, I find that an MSU's population correlates very strongly—but not exactly—with the percentage of participants who rank it ($r[10] = .83$, $p <$

.001). Since this correlation is not close to being perfect, I do see the value in presenting the results for the populations for MSUs. That way, I can investigate whether there are any meaningful exceptions to the general pattern of participants ranking more populous MSUs more frequently.

Table 20. Population of each MSU in San Luis Obispo and Santa Barbara Counties, compared to the percentage of participants from both counties who rank it (y = 2.13E-4x + 12.7, R^2 = .68).

Name of MSU	Population (ACS 2017)	Percentage who rank it	Predicted percentage	Residual
Santa Maria Valley	148,096	38.3%	44.2%	–5.9%
Santa Barbara / Montecito / Carp.	121,724	37.7%	38.6%	–0.9%
Goleta Valley / Isla Vista / Gaviota	89,989	29.9%	31.9%	–2.0%
Five Cities / Nipomo Area	79,839	29.6%	29.7%	–0.1%
San Luis Obispo Area	65,148	39.7%	26.6%	+13.2%
Lompoc Valley / Vandenberg	60,317	26.8%	25.5%	+1.2%
Paso Robles Area	51,273	22.3%	23.6%	–1.3%
Atascadero/Templeton Area	46,399	23.9%	22.6%	+1.4%
Morro Bay/Los Osos/Cambria Area	37,460	21.4%	20.7%	+0.8%
Santa Ynez/Los Alamos Valleys	21,923	27.6%	17.3%	+10.3%
Cuyama Valley / San Rafael Mtns.	941	6.8%	12.9%	–6.1%
Channel Islands	6	2.3%	12.7%	–10.4%

To discern the relationship between an MSU's population and the percentage who rank it, I plot the two and fit a linear function between them. The linear equation then predicts what the percentage who rank that MSU should be (y) based on its population (x). The residual is the deviation between the actual percentage who rank it and the predicted percentage. As Table 20 shows, most MSUs do not deviate much from their predicted percentages, but there are a few notable exceptions. The San Luis Obispo area is ranked much more often than its population would suggest, with a residual of more than +10%; this is also the case with Santa Ynez Valley. At the other end of the spectrum, the Channel

Islands are ranked much less often than even their meager population would suggest, with a residual exceeding –10%.

Next I consider the average transposed score given to each MSU that is ranked by at least 5% of the residents of San Luis Obispo or Santa Barbara Counties, which are 18 altogether. When looking at results from participants from both counties, I find that an MSU's average transposed score correlates almost perfectly with the percentage of participants who rank it ($r[16] > .99$, $p < .001$). This holds when breaking the results down by participants from one county or the other, both for those from San Luis Obispo County ($r[16] > .99$, $p < .001$), and for those from Santa Barbara County ($r[16] > .99$, $p < .001$). Given these correlation values, there is no need to present detailed results for the average transposed scores for MSUs.

That being said, I do think it is worthwhile to report the degree to which participants' rankings correlate depending on where they live, to see whether people from different MSUs rank similarly or not. If I find a large correlation between a pair of MSUs, that would indicate that residents of one MSU largely agree with those of the other regarding which MSUs they choose to rank, including their own. Since the percentage of participants who rank a given MSU at all and the average transposed score they give that MSU correlate so strikingly, I can choose to examine either one. I opt to look at the latter, mainly because it is easier to calculate an average ranking for the residents of each MSU than determine what percentage of those residents rank a certain MSU. I present these correlation values for the 10 MSUs whose residents I survey in the correlation matrix below. I also depict the strongest correlations I find by representing them as arrows of varying widths on the map that follows.

The wider the arrow between a pair of MSUs, the stronger the correlation is between their residents' rankings.

Table 21. Correlation matrix of the 10 MSUs where survey participants live, showing the correlation values for their average transposed scores.

	SMV	SB	GOL	FCN	SLO	LVV	PR	ATA	MB	SYV
Santa Maria Valley	—	–.06	–.15	.31	.18	.68	.01	.03	–.04	.53
Santa Barbara / Montecito		—	.82	–.27	–.14	.26	–.25	–.26	–.27	.43
Goleta Valley / Isla Vista			—	–.30	–.18	.16	–.26	–.30	–.27	.35
Five Cities / Nipomo Area				—	.81	–.03	.30	.54	.54	–.14
San Luis Obispo Area					—	–.10	.42	.67	.76	–.16
Lompoc Valley / Van.						—	–.16	–.24	–.21	.76
Paso Robles Area							—	.87	.41	–.21
Atascadero/ Temp. Area								—	.62	–.29
Morro Bay / Los Osos									—	–.24
Santa Ynez Valley										—

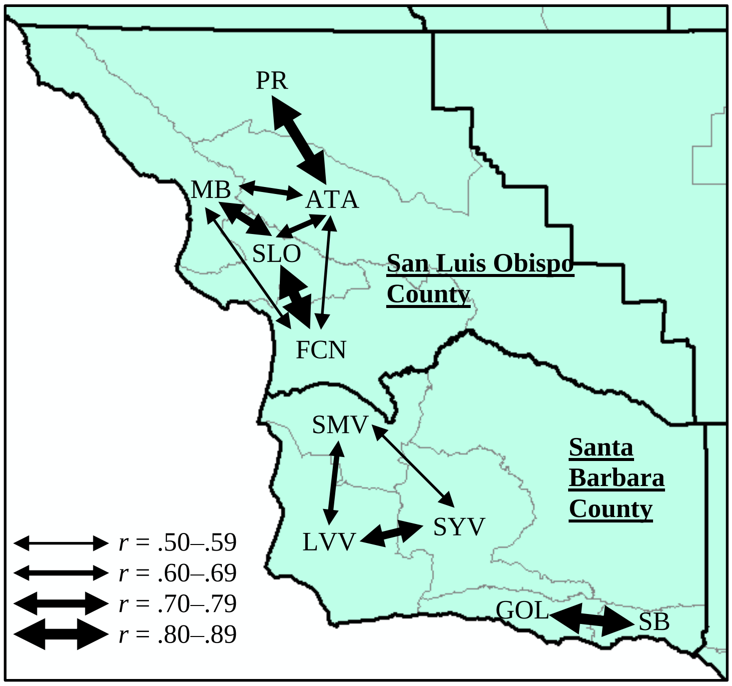

Figure 32. Map of the 10 MSUs where survey participants live, with correlations between them. It shows correlation values for their average transposed scores that are greater than 0.5.

The correlation matrix and accompanying map reveal that some pairs of MSUs correlate much more than others in regard to how their residents rank the same 18 most commonly ranked MSUs. Of the 45 possible pairings, 11 have correlation values that are greater than 0.5, which are the values displayed on the map. Three of these have values greater than 0.8, and so stand out in particular. Residents of the Paso Robles and Atascadero areas agree a great deal on how they rank their MSUs, as do residents of the Santa Barbara and Goleta areas and residents of the Five Cities and San Luis Obispo areas. No pairing of MSUs from different counties exceeds 0.5. Rather, three closed systems are present: one in San Luis Obispo County, another in North and Central Santa Barbara County combined, and a third in South Santa Barbara County.

Finally, I consider how many MSUs participants decide to rank on average, and what is the mean population and area of all of those CSUs combined (i.e. the total population and area of their MSU-defined COI). These results appear in Table 22.

Table 22. Means for total MSUs ranked, and the total population and area of those MSUs.

Participants from:	Total MSUs ranked	Total population	Total area (in sq. km.)
Both counties combined	4.9	483,328	4,656.1
San Luis Obispo County	5.7	499,394	7,259.3
Santa Barbara County	4.4	473,368	3,042.4

Participants on average tend to rank about five MSUs, as opposed to between two and three CSUs; this difference is significant ($t[439] = 7.11$, $p < .001$). Those in San Luis Obispo County tend to rank close to six, while those in Santa Barbara County rank about four and a half. The total population of the COI that participants define with the MSUs they rank approaches half a million, with the number higher for those from San Luis Obispo County because they tend to rank slightly more MSUs. For perspective, the population of Santa Barbara County is about 450,000. The total area of the COI that participants define with their MSUs approaches 5,000 square kilometers, again, with the number higher for San Luis Obispo County residents. For perspective, the area of Santa Barbara County is about 7,000 square kilometers.

c. Rankings given by San Luis Obispo County residents for town-scale units

In this next section, I now look at the results for rankings of town-scale units (TSUs). Because participants only had the opportunity to rank TSUs within their own county of residence, I must break these results down by county. This section presents the rankings for TSUs in San Luis Obispo County, given by participants living in that county. I consider the same two sets of results as before: the percentage of participants who rank a certain TSU at all, and the average transposed score that participants give to that TSU. First I present the percentage of participants who rank a given TSU at all. Figure 33 shows results from participants from North San Luis Obispo County, Figure 34 shows those from Central San Luis Obispo County, and Figure 35 shows those from South San Luis Obispo County.

Instead of breaking down the county into the five MSUs that compose it and reporting results for TSU rankings from participants who live in each of those five, I report my results from three larger parts: North County, Central County, and South County. This seems better because I did not sample enough participants from some of those MSUs to allow for much statistical power. For example, I cannot say with enough certainty that the population of the Morro Bay area feels a certain way about their TSU-defined COI because I only sampled 19 people from that MSU. Therefore, I amalgamate four MSUs into two larger parts.

The Atascadero and Paso Robles areas join to become what I define as North San Luis Obispo County, home to 48 participants. I merge those two MSUs because they share the Salinas River Valley, mountains separate them from the rest of the county, and the correlation between their residents' MSU rankings is a very strong 0.87. The Morro Bay and San Luis Obispo areas join to become what I define as Central San Luis Obispo County, home to 50 participants. I merge those two MSUs because they share Los Osos Valley and the Nine Sisters chain of volcanoes, and the MSU rankings of residents of the Morro Bay area correlate the most with those of residents of the San Luis Obispo area. The Five Cities area remains as is to become South San Luis Obispo County, because it already has a fairly large number of 41 participants.

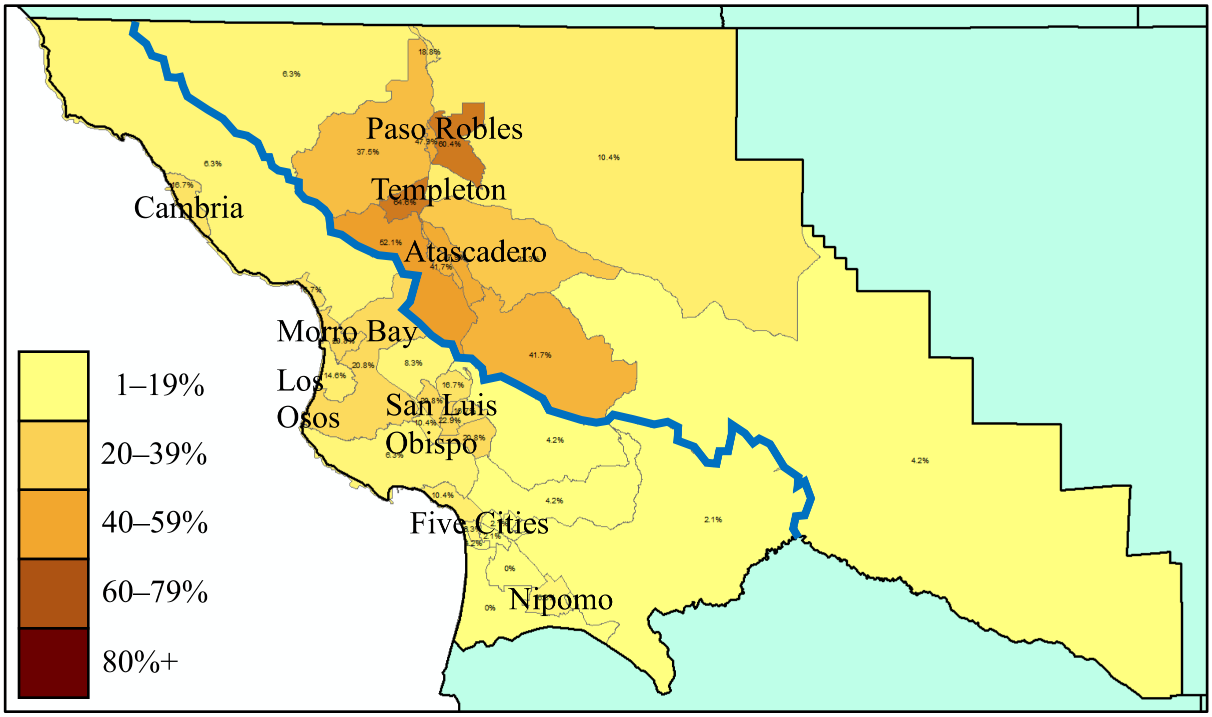

Figure 33. Map of TSUs with the percentage of participants from North San Luis Obispo County (within the blue line) who rank a given unit at all.

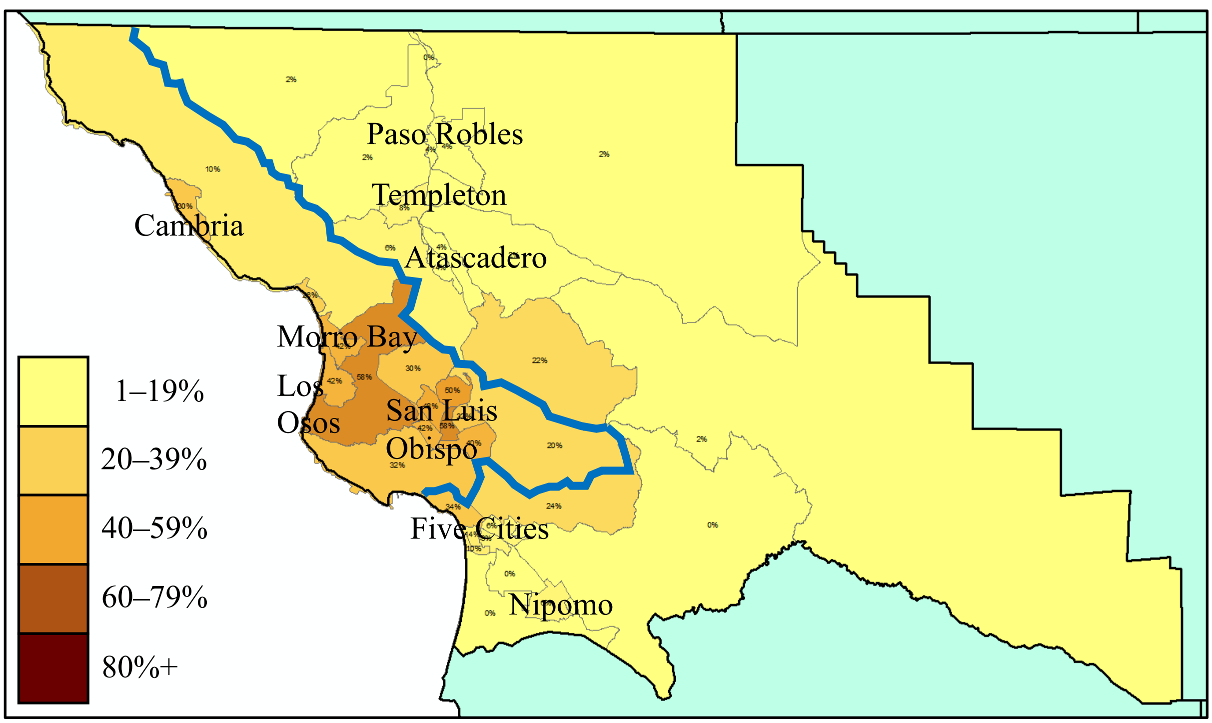

Figure 34. Map of TSUs with the percentage of participants from Central San Luis Obispo County (within the blue line) who rank a given unit at all.

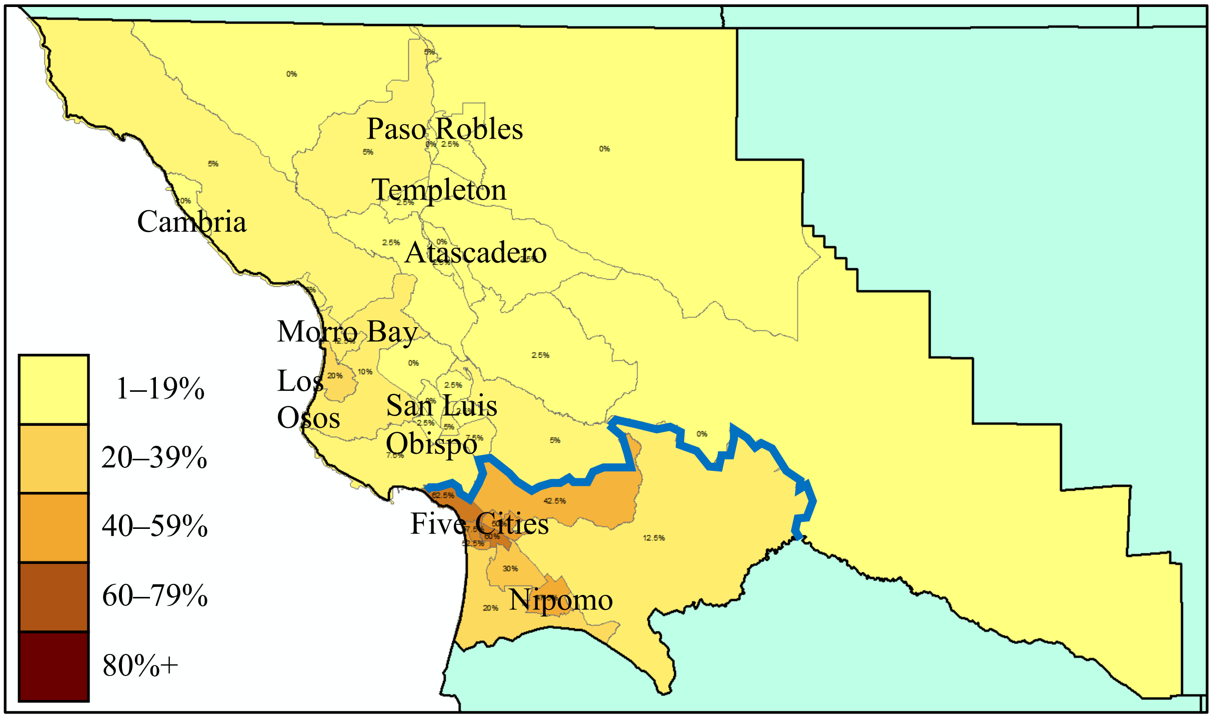

Figure 35. Map of TSUs with the percentage of participants from South San Luis Obispo County (within the blue line) who rank a given unit at all.

Participants from North San Luis Obispo County rank the TSUs in that part of the county more often than TSUs in any other part. Eight of the thirteen TSUs that make it up are ranked by more than a third, and all thirteen are ranked by 35.7% on average. Templeton leads the way with 64.6%, followed closely by East Paso Robles with 60.4%. The TSUs ranked the next-most often are Central Paso Robles and East Atascadero, each with 47.9%. Three TSUs in San Luis Obispo and two in the Morro Bay area are also ranked relatively frequently, by at least 20% of them, led by Central San Luis Obispo with 22.9%. Those in Central County as a whole average 14.9%, while those in South County average 3.8%.

Participants from Central San Luis Obispo County likewise rank the TSUs in that part of the county more often than TSUs in any other part. Eight of the fifteen TSUs that make it up are ranked by more than a third of those participants, and all fifteen are ranked by 37.3%

on average. Central San Luis Obispo and Los Osos Valley tie for the lead with 58.0%. The TSUs ranked the next-most often are Cal Poly and North San Luis Obispo, with 50.0% and 48.0%. Two TSUs in the Five Cities and one in the Atascadero area are also ranked relatively frequently, by at least 20% of them, led by Pismo Beach with 34.0%. Those in South County as a whole average 10.2%, while those in North County average 4.8%.

Participants from South San Luis Obispo County rank the TSUs in that part of the county much more often than TSUs in any other part. Seven of the ten TSUs that make it up are ranked by more than a third of those participants, and all ten are ranked by 43.5% on average. Pismo Beach leads the way with 62.5%, followed closely by West Arroyo Grande with 60.0%, and Grover Beach with 57.5%. The TSUs ranked the next-most often are Oceano and Central Arroyo Grande, with 52.5% and 50.0%. Los Osos is also ranked relatively frequently with 20.0%. TSUs in Central County as a whole average 5.7%, while those in North County average 1.9%.

I can also compare the percentage of San Luis Obispo County residents who rank a given TSU to its population to see if some of the county's 38 TSUs are ranked higher or lower than one would expect just based on their population. Again, I propose that a notable exception would be one where the actual percentage of participants who rank it deviates from that predicted by population alone by ±10% (see Table 23). When examining results from participants from all parts of the county, I find that a TSU's population correlates somewhat strongly with the percentage of participants who rank it ($r[36] = .43$, $p < .01$). Since this correlation is not close to being perfect, I do see the value in presenting the results for the populations for TSUs. I can then investigate whether there are any meaningful exceptions to the general pattern of participants ranking more populous TSUs more frequently.

Table 23. Population of each TSU in San Luis Obispo County, compared to the percentage of participants from all parts of the county who rank it (y = 6.63E-4x + 12.8, R^2 = .19).

Name of TSU	Population (ACS 2017)	Percentage who rank it	Predicted percentage	Residual
East Paso Robles	23,411	23.2%	28.3%	–5.1%
East Atascadero / Downtown	19,579	18.1%	25.8%	–7.7%
Nipomo	16,117	18.1%	23.5%	–5.4%
Los Osos / Baywood Park	15,124	26.1%	22.8%	+3.2%
Grover Beach	13,524	23.9%	21.8%	+2.1%
Central San Luis Obispo / Downtown	13,054	30.4%	21.5%	+9.0%
Cal Poly / Grand	12,581	24.6%	21.2%	+3.5%
West Arroyo Grande / Fair Oaks	11,827	21.0%	20.7%	+0.4%
Morro Bay	10,676	26.1%	19.9%	+6.2%
North San Luis Obispo / Foothill	10,138	24.6%	19.5%	+5.1%
West San Luis Obispo / Madonna	9,293	19.6%	19.0%	+0.6%
Rural Northeast County / Shandon	8,974	4.3%	18.8%	–14.4%
Pismo/Shell Beach	8,019	34.1%	18.1%	+15.9%
West Atascadero	7,818	16.7%	18.0%	–1.3%
Callender / Halcyon / Los Berros	7,745	8.7%	17.9%	–9.2%
East San Luis Obispo / Johnson	7,421	18.1%	17.7%	+0.4%
Central Arroyo Grande / Village	7,372	17.4%	17.7%	–0.3%
Templeton	7,271	26.1%	17.6%	+8.5%
Oceano	7,238	20.3%	17.6%	+2.7%
Central Paso Robles / Downtown	7,122	18.1%	17.5%	+0.6%
Cambria	5,934	16.7%	16.7%	–0.1%
West Atascadero Outskirts	5,721	21.0%	16.6%	+4.4%
West Paso Robles Outskirts	4,706	15.2%	15.9%	–0.7%
Cuesta College / Camp S.L.O.	4,545	13.8%	15.8%	–2.1%
Lake Nacimiento / Camp Roberts	4,425	2.9%	15.7%	–12.8%
Far South San Luis Obispo Outskirts	3,898	15.9%	15.4%	+0.5%
South San Luis Obispo / Tank Farm	3,661	23.9%	15.2%	+8.7%
East Arroyo Grande Outskirts	3,530	22.5%	15.1%	+7.3%
Santa Margarita Area	3,039	23.2%	14.8%	+8.4%
West Nipomo Outskirts	2,876	5.8%	14.7%	–8.9%
Cayucos	2,847	16.7%	14.7%	+2.0%
San Miguel	2,635	8.0%	14.6%	–6.6%
Creston Area	2,233	12.3%	14.3%	–2.0%
East Nipomo Outskirts	1,591	4.3%	13.9%	–9.5%
Rural North Coast / San Simeon	1,459	7.2%	13.8%	–6.5%
Los Osos Valley / Montaña de Oro	1,420	31.2%	13.7%	+17.4%
Pozo / California Valley	738	2.2%	13.3%	–11.1%
Lopez Lake/Canyon/Mountain	557	10.1%	13.2%	–3.0%

To discern the relationship between a TSU's population and the percentage who rank it, I plot the two and fit a linear function between them, as I do with MSUs. As Table 23 shows, most TSUs do not deviate much from their predicted percentages, but there are a few notable exceptions. Los Osos Valley is ranked much more often than its meager population would suggest, with a residual of more than +15%; this is also the case with Pismo Beach. At the other end of the spectrum, three TSUs are ranked much less often than their populations would suggest, with residuals exceeding –10%. The rural northeast has the largest negative residual with just under –15%, followed closely by the Lake Nacimiento and Pozo areas.

Next I consider the average transposed score given to each TSU that is located in San Luis Obispo County, which are 38 altogether. When looking at results from participants from all parts of the county, I find that a TSU's average transposed score correlates extremely strongly with the percentage of participants who rank it ($r[36] = .95$, $p < .001$). This holds when breaking the results down by participants from North County ($r[36] = .98$, $p < .001$), those from Central County ($r[36] = .95$, $p < .001$), and those from South County ($r[36] > .99$, $p < .001$). Given these correlations, I see no need to present the results for the average transposed scores for TSUs.

As I do with MSUs, I also report the degree to which participants' average transposed scores for TSUs correlate depending on where they live. That way I can investigate whether participants from one TSU largely agree with those from another TSU regarding which TSUs they choose to rank, including their own. Since in some TSUs I survey very few participants, I lump together the rankings given by residents of these TSUs with those of residents of adjacent TSUs. I do so for TSUs with fewer than four participants; I use this as the threshold because many of the TSUs in the Five Cities have this amount of participants, and it is too arbitrary to decide which should be combined with which. Most TSUs retain their original form through this process, but others combine to form larger entities. This process whittles down the number of units whose correlations I analyze from the 34 original TSUs with surveyed residents to 22 “updated” TSUs, each with at least four residents who participate in this study. I present the strongest correlation values I find for these areas in Table 24; there are too many to present every value in a full correlation matrix. I also depict these strongest correlations by representing them as arrows of varying widths on the map that follows.

Table 24. All correlation values greater than 0.5 for the average transposed scores given by survey participants living in the 22 “updated” TSUs in San Luis Obispo County.

More populous “updated” TSU	Less populous “updated” TSU	Value
Los Osos/Baywood Park + L.O. Valley	Morro Bay + Cayucos	.889
East Atascadero + Sta. Marg. + Creston	West Atascadero + W. Atas. Outskirts	.877
Cal Poly / Grand	North San Luis Obispo / Foothill	.828
North San Luis Obispo / Foothill	East San Luis Obispo / Johnson	.795
North San Luis Obispo / Foothill	West San Luis Obispo / Madonna	.759
West San Luis Obispo / Madonna	East San Luis Obispo / Johnson	.745
Central San Luis Obispo / Downtown	North San Luis Obispo / Foothill	.743
Grover Beach	West Arroyo Grande / Fair Oaks	.733
Central San Luis Obispo / Downtown	Cal Poly / Grand	.725
Ctrl. Arroyo Grande + East A.G. Outs.	Pismo/Shell Beach	.722
South S.L.O. + Far South S.L.O. Outs.	East San Luis Obispo / Johnson	.717
East Paso Robles	Ctrl. P.R. + W. P.R. Outs. + San Miguel	.715
West San Luis Obispo / Madonna	South S.L.O. + Far South S.L.O. Outs.	.707
Central San Luis Obispo / Downtown	East San Luis Obispo / Johnson	.696
East Paso Robles	Rural Northeast County / Shandon	.694
Cal Poly / Grand	East San Luis Obispo / Johnson	.682
Morro Bay + Cayucos	Cambria + Rural North Coast	.679
East Atascadero + Sta. Marg. + Creston	Rural Northeast County / Shandon	.646
Cal Poly / Grand	West San Luis Obispo / Madonna	.643
Central San Luis Obispo / Downtown	South S.L.O. + Far South S.L.O. Outs.	.641
Grover Beach	Oceano	.640
West Arroyo Grande / Fair Oaks	Oceano	.637
West Arroyo Grande / Fair Oaks	Pismo/Shell Beach	.636
East Atascadero + Sta. Marg. + Creston	Templeton	.630
Cal Poly / Grand	South S.L.O. + Far South S.L.O. Outs.	.626
Los Osos/Baywood Park + L.O. Valley	Cambria + Rural North Coast	.618

Table 24, cont. All correlation values greater than 0.5 for the average transposed scores given by survey participants living in the 22 "updated" TSUs in San Luis Obispo County.

More populous "updated" TSU	Less populous "updated" TSU	Value
Nipomo + E. Nip. Outs. + W. Nip. Outs.	Callender / Halcyon Mesa / Los Berros	.603
Grover Beach	Pismo/Shell Beach	.602
West Arroyo Grande / Fair Oaks	Ctrl. Arroyo Grande + E. A.G. Outs.	.592
East Paso Robles	Templeton	.579
West Atascadero + W. Atascadero Outs.	Rural Northeast County / Shandon	.568
West Atascadero + W. Atascadero Outs.	Templeton	.564
North San Luis Obispo / Foothill	South S.L.O. + Far South S.L.O. Outs.	.559
West Arroyo Grande / Fair Oaks	Callender / Halcyon Mesa / Los Berros	.554
Rural Northeast County / Shandon	Templeton	.539
Callender / Halcyon Mesa / Los Berros	Oceano	.527
Pismo/Shell Beach	Callender / Halcyon Mesa / Los Berros	.526
Pismo/Shell Beach	Oceano	.506
Ctrl. P.R. + W. P.R. Outs. + San Miguel	Rural Northeast County / Shandon	.502

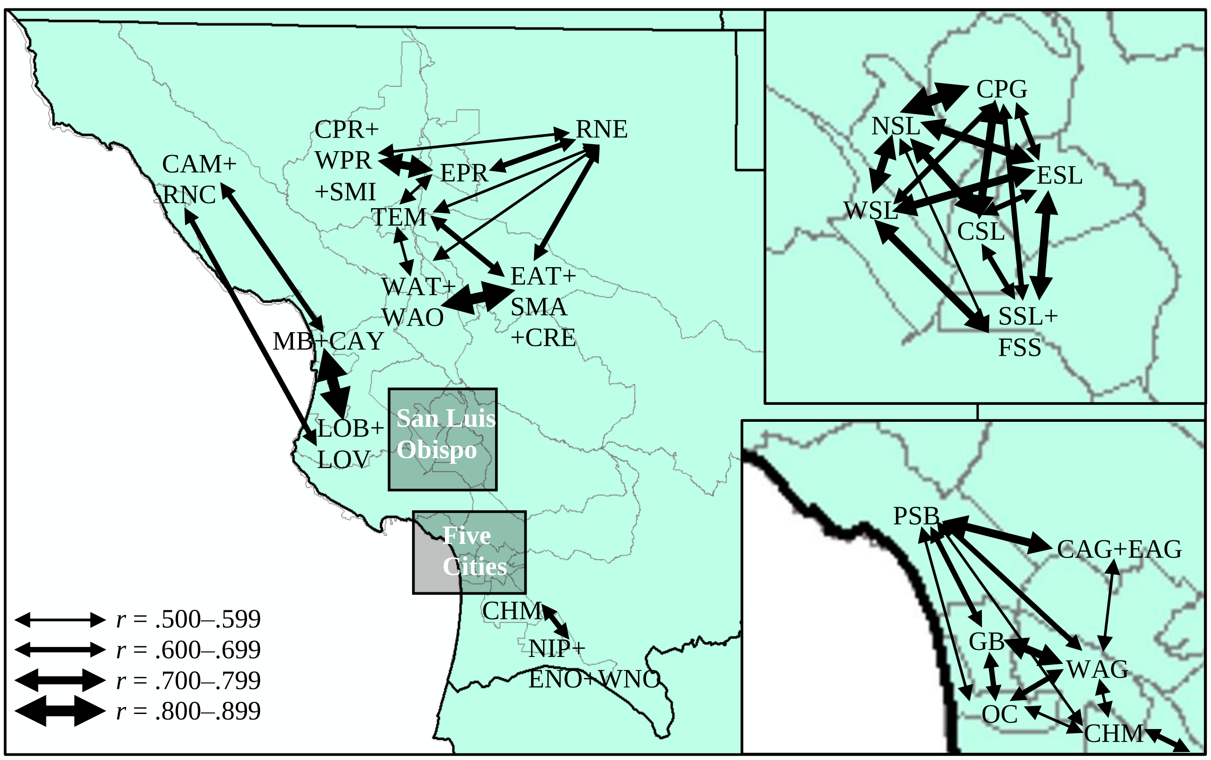

Figure 36. Map of the 22 "updated" TSUs in San Luis Obispo County where survey participants live, with correlations between them. It shows correlation values for their average transposed scores that are greater than 0.5. San Luis Obispo and the Five Cities are shown in insets at the top right and bottom right, respectively, for greater clarity. CHM appears twice on the map.

The correlation table and accompanying map reveal that some pairs of "updated" TSUs correlate much more than others in regard to how their residents rank the same 38 TSUs. Of the 231 possible pairings, 39 have correlation values that are greater than 0.5, which are the values displayed on the table and map. Three of these values stand out as being greater than 0.8. Residents of the Los Osos and Morro Bay areas agree a great deal on how they rank their TSUs, as do residents of the East Atascadero and West Atascadero areas and residents of Cal Poly / Grand and North San Luis Obispo. No pairing of "updated" TSUs from different parts of the county exceeds 0.5. Rather, four closed systems are present: one in North County, two in Central County (a Morro Bay area one and a San Luis Obispo one), and one in South County. Each system features ten or more such pairings, except for the Morro Bay area, which only has three.

Finally, I consider how many TSUs San Luis Obispo County residents decide to rank on average, and what is the mean population and area of all of those TSUs combined (i.e. the total population and area of their TSU-defined COI). These results appear in Table 25.

Table 25. Means for total TSUs units ranked in San Luis Obispo County, and the total population and area of those TSUs.

Participants from:	Total TSUs ranked	Total population	Total area (in sq. km.)
All parts of the county	7.2	58,816	795.3
North County	8.2	68,303	1,122.3
Central County	7.7	59,599	823.4
South County	5.3	46,756	378.4

Participants on average tend to rank about seven TSUs, as opposed to about six MSUs; this difference is not significant ($t[274] = 1.74$, $p = .08$). Those in North County and Central County tend to rank close to eight, while those in South County rank about five. The total population of the COI that participants define with the TSUs they rank averages close to

60,000. For perspective, the population of the San Luis Obispo area is about 65,000. This number is lower for those from South County because they tend to rank fewer TSUs. The total area of the COI that participants define with their TSUs approaches 800 square kilometers. For perspective, the area of the Five Cities area, that is, South County itself, is about 1,200 square kilometers. Again, this number is lower for South County residents.

d. Rankings given by Santa Barbara County residents for town-scale units

In this final subsection, I present the rankings for TSUs in Santa Barbara County, given by participants living in that county. As before, I first consider the percentage of participants who rank a given TSU at all. Figure 37 shows results from participants from North Santa Barbara County, Figure 38 shows those from Central Santa Barbara County, and Figure 39 shows those from South Santa Barbara County.

Instead of breaking down the county into the seven MSUs that compose it and reporting results for TSU rankings from participants who live in each of those seven, I report my results from three larger parts: North County, Central County, and South County. I do this for the same reason I do it for San Luis Obispo County, because the number of participants sampled in some of these MSUs is small or even zero. For example, I cannot say with enough certainty that the population of Santa Ynez Valley feels a certain way about their COI because I only sampled 11 people from that MSU. Therefore, I amalgamate the seven MSUs into three larger parts.

Cuyama Valley and Santa Maria Valley join to become what I define as North Santa Barbara County, home to 76 participants (all of whom come from Santa Maria Valley, as the other MSU is barely populated). I merge those two MSUs because they share the Highway 166 corridor, and mountains separate them from the rest of the county. Lompoc Valley and

Santa Ynez Valley join to become what I define as Central Santa Barbara County, home to 37 participants. I merge those two MSUs because they share the Highway 246 corridor, mountains separate them from both North County and South County, and the correlation between their residents' MSU rankings is stronger than that between them and any other MSU. Finally, the Channel Islands, Goleta area, and Santa Barbara area join to become South Santa Barbara County, home to 108 participants (none of whom come from the uninhabited Channel Islands). The correlation between their residents' MSU rankings is stronger than that between any other pairing of MSUs in Santa Barbara County, at a robust 0.82.

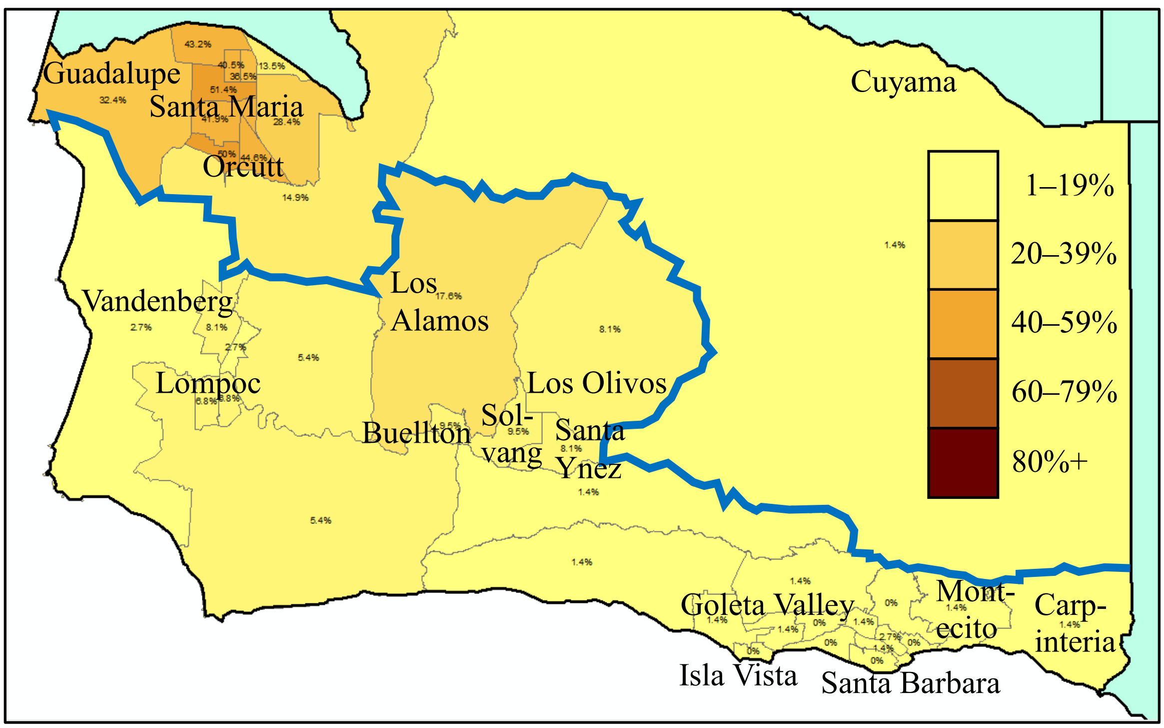

Figure 37. Map of TSUs with the percentage of participants from North Santa Barbara County (within the blue line) who rank a given unit at all (Channel Islands not shown).

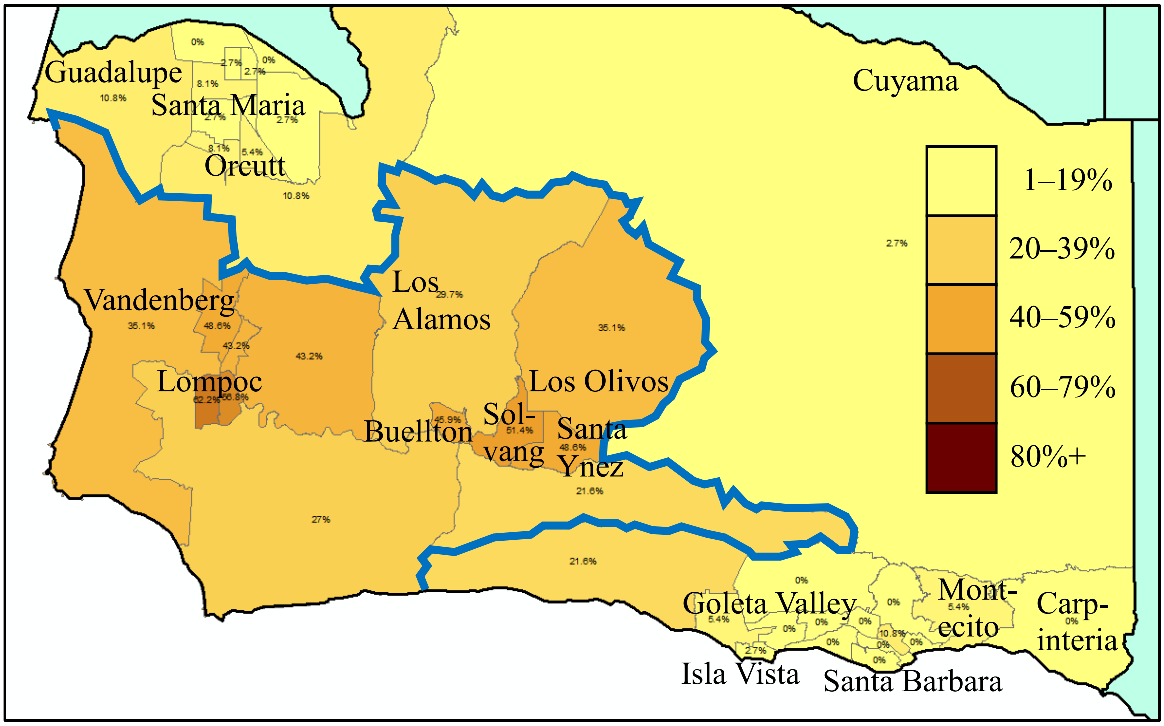

Figure 38. Map of TSUs with the percentage of participants from <u>Central</u> Santa Barbara County (within the blue line) who rank a given unit at all (Channel Islands not shown).

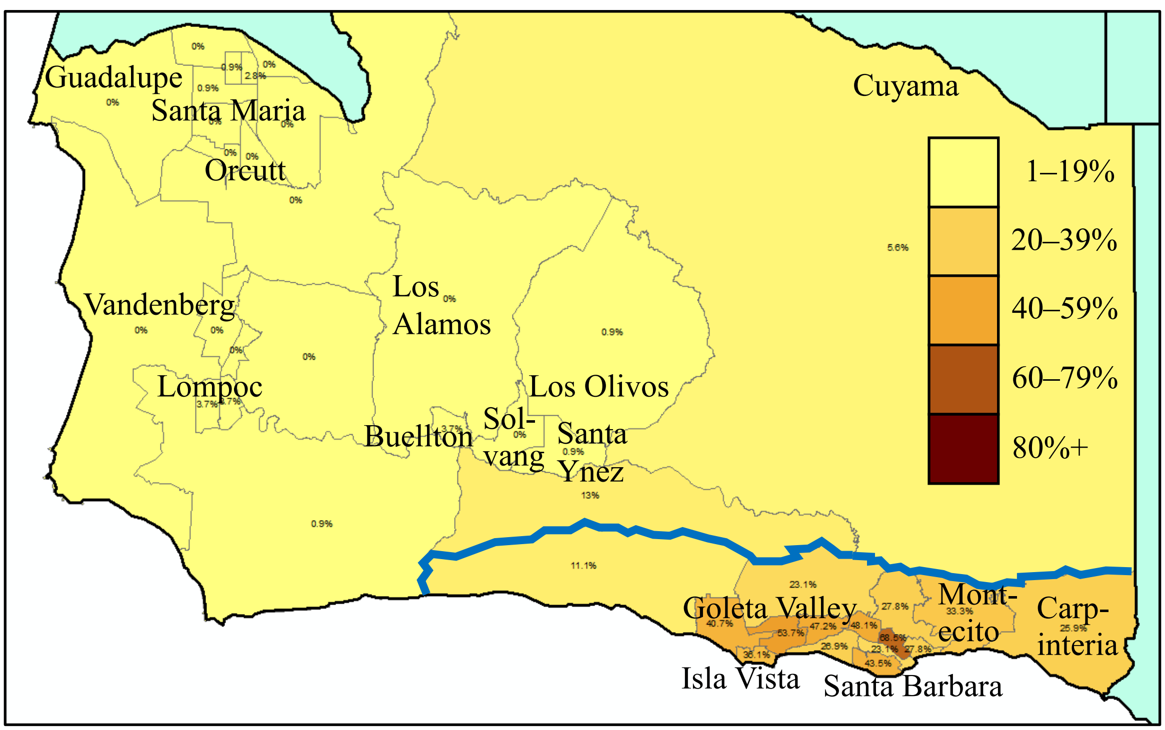

Figure 39. Map of TSUs with the percentage of participants from <u>South</u> Santa Barbara County (within the blue line) who rank a given unit at all (Channel Islands not shown).

Participants from North Santa Barbara County expectedly rank the TSUs in that part of the county more often than TSUs in any other part. Seven of the twelve TSUs that make it up are ranked by more than a third of those participants, and all twelve are ranked by 33.2% on average. South Santa Maria leads the way with 51.4%, followed closely by West Orcutt with 50.0%. The TSUs ranked the next-most often are East Orcutt and North Santa Maria, with 44.6% and 43.2%. One TSU in Santa Ynez Valley—Los Alamos—is also ranked relatively frequently, with 17.6%. TSUs in Central County as a whole average 7.1%, while those in South County average 0.8%.

Participants from Central Santa Barbara County rank the TSUs in that part of the county much more often than TSUs in any other part. Ten of the thirteen TSUs that make it up are ranked by more than a third of those participants, and all thirteen are ranked by 42.2% on average. West Lompoc leads the way with 62.2%, followed closely by East Lompoc with 56.8%. The TSUs ranked the next-most often are Solvang, with 51.4%, and Santa Ynez and Vandenberg Village, tied with 48.6%. One TSU in the Goleta area is also ranked relatively frequently, that being the Gaviota Coast with 21.6%. TSUs in South County as a whole average 2.9%, while those in North County average 4.7%.

Those from South Santa Barbara County likewise rank the TSUs in that part of the county much more often than TSUs in any other part. Eight of the sixteen TSUs that make it up are ranked by more than a third of those participants, and all sixteen are ranked by 33.7% on average. Downtown Santa Barbara has a large lead over any other TSU with 68.5%; the next-closest is Central Goleta Valley with 54.6%. The TSUs ranked the next-most often are Upper State and East Goleta Valley, with 48.1% and 47.2%. One TSU outside South

County—the Santa Ynez Mountains—is also ranked relatively frequently, with 13.0%. TSUs in Central County as a whole average 2.1%, while those in North County average 0.8%.

I can also compare the percentage of Santa Barbara County residents who rank a given TSU to its population to see if some of the county's 41 TSUs are ranked higher or lower than one would expect just based on their population, focusing on those with residuals close to or exceeding ±10% (see Table 26). When examining results from participants from all parts of the county, I find that a TSU's population correlates somewhat strongly with the percentage of participants who rank it ($r[39] = .55$, $p < .001$). Since this correlation is not close to being perfect, I do see the value in presenting the results for the populations for TSUs. That way, I can investigate whether there are any meaningful exceptions to the general pattern of participants ranking more populous TSUs more frequently.

Table 26. Population of each TSU in Santa Barbara County, compared to the percentage of participants from all parts of the county who rank it ($y = 4.45\text{E-}4x + 9.0$, $R^2 = .31$).

Name of TSU	Population (ACS 2017)	Percentage who rank it	Predicted percentage	Residual
West Central Santa Maria	27,846	14.6%	21.4%	–6.7%
Isla Vista / UCSB	27,708	18.3%	21.3%	–3.0%
West Lompoc	22,575	14.6%	19.0%	–4.4%
East Orcutt / Bradley	22,381	16.0%	18.9%	–2.9%
Westside / Bel Air / Hidden Valley	21,481	11.9%	18.5%	–6.7%
E. Goleta Valley / Noleta / Turnpike	20,769	23.3%	18.2%	+5.1%
North Santa Maria	19,912	14.6%	17.8%	–3.2%
East Central Santa Maria	18,100	14.2%	17.0%	–2.9%
East Lompoc	17,950	13.7%	17.0%	–3.3%
Carpinteria / Summerland / Toro Cyn.	17,932	13.2%	16.9%	–3.7%
Downtown Santa Barbara / Oak Park	17,595	36.5%	16.8%	+19.7%
South Santa Maria	17,392	19.2%	16.7%	+2.5%
W. Goleta Valley / Ellwood / Storke	17,034	21.5%	16.5%	+4.9%
Far South Santa Maria / Airport	14,714	14.6%	15.5%	–0.9%
Upper State / Hope / San Roque	14,686	24.2%	15.5%	+8.7%
Riviera / Mission Canyon	14,625	13.7%	15.5%	–1.8%
Eastside / Laguna	13,724	13.7%	15.1%	–1.4%

Table 26, cont. Population of each TSU in Santa Barbara County, compared to the percentage of participants from all parts of the county who rank it (y = 4.45E-4x + 9.0, R^2 = .31).

Name of TSU	Population (ACS 2017)	Percentage who rank it	Predicted percentage	Residual
Central Goleta Valley / Old Town	13,275	27.4%	14.9%	+12.5%
Santa Barbara Mesa / Campanil	12,221	21.5%	14.4%	+7.1%
East Santa Maria / Pioneer Valley	11,550	4.6%	14.1%	–9.5%
Montecito	9,460	17.8%	13.2%	+4.6%
Guadalupe / West Santa Maria Valley	7,581	12.8%	12.3%	+0.4%
Vandenberg Village	7,541	11.0%	12.3%	–1.4%
Cathedral Oaks/San Marcos Foothills	7,464	11.4%	12.3%	–0.9%
Solvang Area	7,369	11.9%	12.2%	–0.4%
Vandenberg Air Force Base	6,450	6.8%	11.8%	–5.0%
West Orcutt / Old Town	5,871	18.3%	11.6%	+6.7%
Buellton	5,139	12.8%	11.3%	+1.5%
Mission Hills	4,535	8.2%	11.0%	–2.8%
Santa Ynez Area	3,767	11.4%	10.6%	+0.8%
Hope Ranch	3,240	13.2%	10.4%	+2.8%
Los Olivos Area	2,595	9.1%	10.1%	–1.0%
Los Alamos Area	2,175	11.0%	9.9%	+1.0%
Sisquoc/Garey Area / Orcutt Hills	1,613	6.8%	9.7%	–2.8%
East Santa Maria Valley	1,136	10.0%	9.5%	+0.6%
Cuyama Valley / San Rafael Mtns.	941	3.7%	9.4%	–5.7%
Santa Ynez Mtns. / Lake Cachuma	878	10.5%	9.4%	+1.1%
West Lompoc Valley / Lompoc Hills	730	6.8%	9.3%	–2.4%
East Lompoc Valley / Purisima Hills	536	9.1%	9.2%	–0.1%
Gaviota / Refugio / El Capitan	499	9.6%	9.2%	+0.4%
Channel Islands	6	1.4%	9.0%	–7.6%

To discern the relationship between a TSU's population and the percentage who rank it, I plot the two and fit a linear function between them, as I do with TSUs in San Luis Obispo County. As Table 26 shows, most TSUs do not deviate much from their predicted percentages, but there are a couple exceptions on the positive side. Downtown Santa Barbara is ranked much more often than its population would suggest, with a residual of almost +20%. Central Goleta Valley is also ranked very frequently relative to its population, as it has a residual of about +13%, and Upper State comes close to +10% with a residual of

+8.7%. While there are no TSUs with negative residuals exceeding –10%, East Santa Maria comes close with a residual of –9.5%, with the Channel Islands not far behind at –7.6%.

Next I consider the average transposed score given to each TSU that is located in Santa Barbara County, which are 41 altogether. When looking at results from participants from all parts of the county, I find that a TSU's average transposed score correlates extremely strongly with the percentage of participants who rank it ($r[39] = .97$, $p < .001$). This holds when breaking the results down by participants from one part of the county or the other, for those from North County ($r[39] = .99$, $p < .001$), for those from Central County ($r[39] = .97$, $p < .001$), and those from South County ($r[39] =.99$, $p < .001$). Given these correlation values, I see no need to present the results for the average transposed scores for TSUs in Santa Barbara County.

That being said, I do think it is worthwhile to report the degree to which participants' rankings correlate depending on where they live, as I do for TSUs in San Luis Obispo County. That way I can investigate whether participants from one TSU largely agree with those from another TSU regarding which TSUs they choose to rank, including their own. Since in some TSUs I survey very few participants, I lump together the rankings given by residents of these TSUs with those of residents of adjacent TSUs. I do so for TSUs with fewer than four participants, the same threshold I use for TSUs in San Luis Obispo County. Most TSUs retain their original form through this process, but others combine to form larger entities. This process whittles down the number of units whose correlations I analyze from the 34 original TSUs with surveyed residents to 26 "updated" TSUs, each with at least four residents who participate in this study. I present the strongest correlation values I find for these 26 "updated" TSUs in Table 27; there are too many to present every value in a full correlation matrix. I also depict these strongest correlations by representing them as arrows of varying widths on the map that follows.

Table 27. All correlation values greater than 0.5 for the average transposed scores given by survey participants living in the 26 “updated” TSUs in Santa Barbara County.

More populous “updated” TSU	Less populous “updated” TSU	Value
Solvang Area + Santa Ynez Area	Buellton + Los Olivos + Los Alamos	.886
West Lompoc	East Lompoc	.861
East Lompoc	Vandenberg Village + Mission Hills	.816
Downtown Santa Barbara / Oak Park	Santa Barbara Mesa / Campanil	.811
West Central Santa Maria	North Santa Maria	.807
Westside / Bel Air / Hidden Valley	Santa Barbara Mesa / Campanil	.794
West Goleta Valley / Ellwood / Storke	Central Goleta Valley / Old Town	.777
West Lompoc	Vandenberg Village + Mission Hills	.769
E. Goleta Valley / Noleta + Hope Ranch	Cathedral Oaks/San Marcos Foothills	.764
Upper State / Hope / San Roque	Riviera / Eucalyptus Hill / Mission Cyn.	.756
Downtown Santa Barbara / Oak Park	Upper State / Hope / San Roque	.756
Isla Vista / UCSB	Central Goleta Valley / Old Town	.751
West Central Santa Maria	East Central Santa Maria	.748
Westside / Bel Air / Hidden Valley	Downtown Santa Barbara / Oak Park	.746
Downtown Santa Barbara / Oak Park	Riviera / Eucalyptus Hill / Mission Cyn.	.732
North Santa Maria	East Central Santa Maria	.732
Downtown Santa Barbara / Oak Park	Eastside / Laguna	.726
East Orcutt + West Orcutt / Old Town	Far South Santa Maria / Airport	.666
Upper State / Hope / San Roque	Santa Barbara Mesa / Campanil	.658
East Central Santa Maria	Guadalupe / West Santa Maria Valley	.655
E. Goleta Valley / Noleta + Hope Ranch	West Goleta Valley / Ellwood / Storke	.654
Riviera / Eucalyptus Hill / Mission Cyn.	Santa Barbara Mesa / Campanil	.644
West Central Santa Maria	Guadalupe / West Santa Maria Valley	.641
E. Goleta Valley / Noleta + Hope Ranch	Santa Barbara Mesa / Campanil	.634
Carpinteria / Summerland / Toro Cyn.	Montecito	.631
Isla Vista / UCSB	West Goleta Valley / Ellwood / Storke	.631
Far South Santa Maria / Airport	Guadalupe / West Santa Maria Valley	.615
Eastside / Laguna	Santa Barbara Mesa / Campanil	.612
E. Goleta Valley / Noleta + Hope Ranch	Downtown Santa Barbara / Oak Park	.607
Central Goleta Valley / Old Town	Cathedral Oaks/San Marcos Foothills	.602
Isla Vista / UCSB	Downtown Santa Barbara / Oak Park	.600
Carpinteria / Summerland / Toro Cyn.	Riviera / Eucalyptus Hill / Mission Cyn.	.600
E. Goleta Valley / Noleta + Hope Ranch	Central Goleta Valley / Old Town	.592
West Goleta Valley / Ellwood / Storke	Cathedral Oaks/San Marcos Foothills	.583
Carpinteria / Summerland / Toro Cyn.	Downtown Santa Barbara / Oak Park	.571
Westside / Bel Air / Hidden Valley	Riviera / Eucalyptus Hill / Mission Cyn.	.548

Table 27, cont. All correlation values greater than 0.5 for the average transposed scores given by survey participants living in the 26 "updated" TSUs in Santa Barbara County.

More populous "updated" TSU	Less populous "updated" TSU	Value
Carpinteria / Summerland / Toro Cyn.	Santa Barbara Mesa / Campanil	.544
Westside / Bel Air / Hidden Valley	Eastside / Laguna	.535
East Orcutt + West Orcutt / Old Town	E.S.M. + E.S.M. Valley + Sisquoc Area	.533
E. Goleta Valley / Noleta + Hope Ranch	Upper State / Hope / San Roque	.529
Westside / Bel Air / Hidden Valley	Upper State / Hope / San Roque	.528
North Santa Maria	Guadalupe / West Santa Maria Valley	.523
Westside / Bel Air / Hidden Valley	Carpinteria / Summerland / Toro Cyn.	.521
Far South Santa Maria / Airport	E.S.M. + E.S.M. Valley + Sisquoc Area	.520

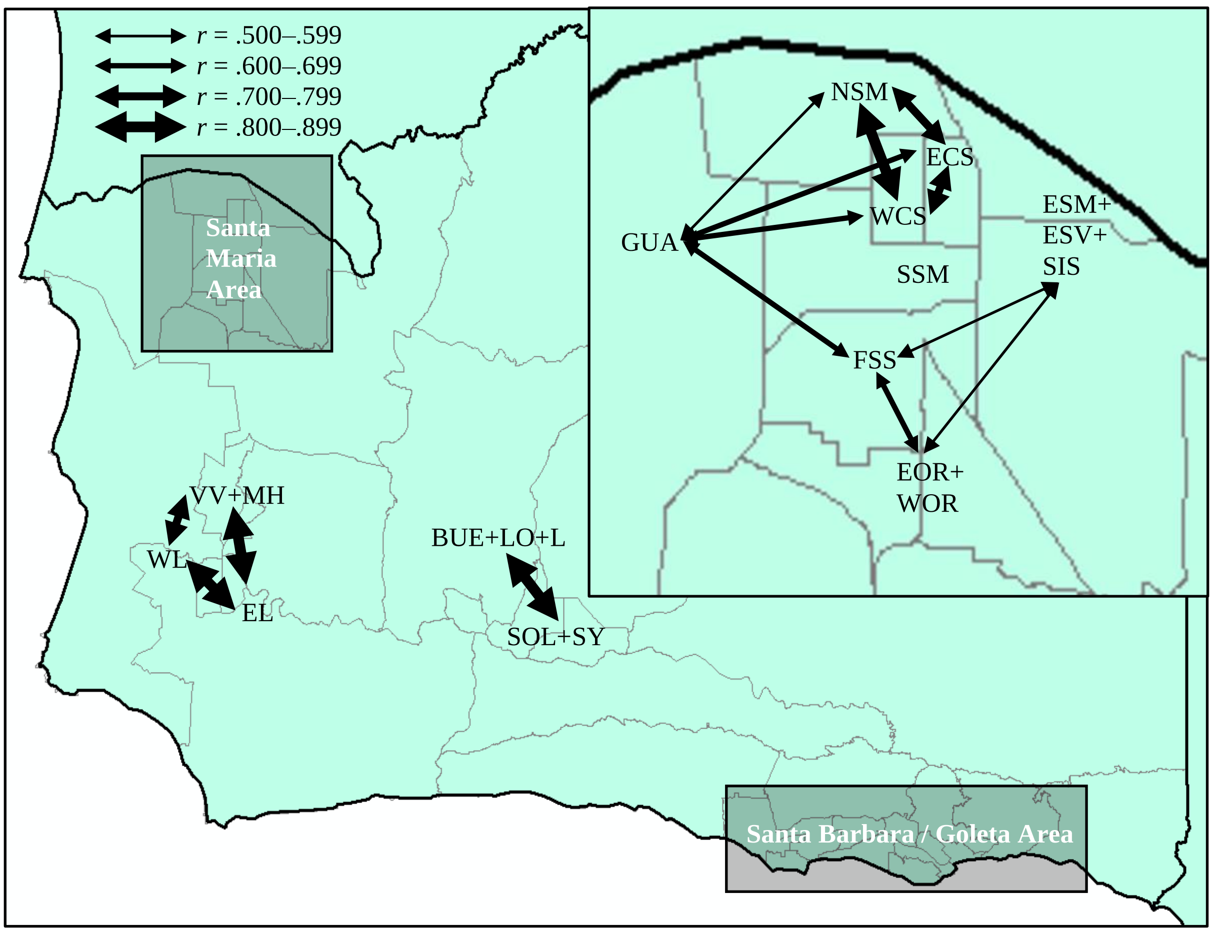

Figure 40. Map of the 26 "updated" TSUs in Santa Barbara County where survey participants live, with correlations between them. It shows correlation values for their average transposed scores that are greater than 0.5. The Santa Barbara / Goleta and Santa Maria areas are shown in insets at the bottom and top right, respectively, for greater clarity.

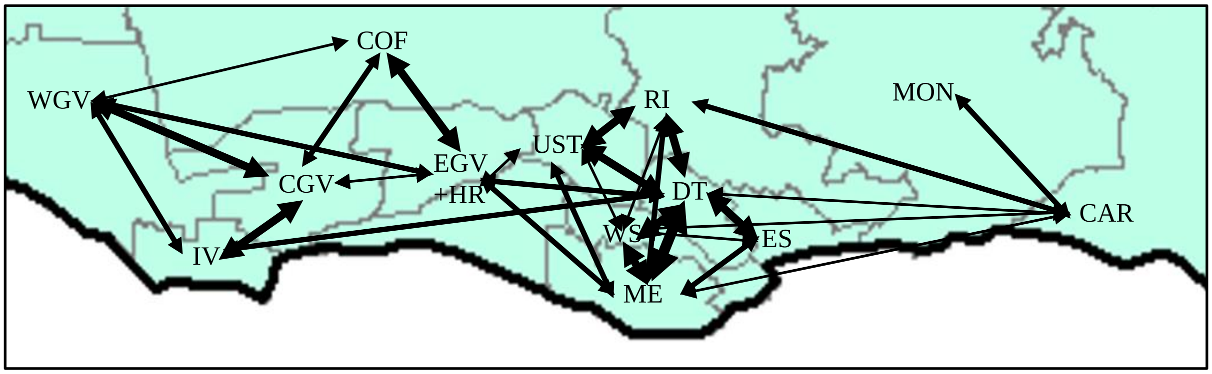

Figure 40, cont. Map of the 26 “updated” TSUs in Santa Barbara County where survey participants live, with correlations between them. It shows correlation values for their average transposed scores that are greater than 0.5. The Santa Barbara / Goleta and Santa Maria areas are shown in insets at the bottom and top right, respectively, for greater clarity.

The correlation table and accompanying map reveal that some pairs of “updated” TSUs correlate much more than others in regard to how their residents rank the same 41 TSUs. Of the 325 possible pairings, 44 have correlation values that are greater than 0.5, which are the values displayed on the table and map. Five of these have values stand out as being greater than 0.8. Residents of the Solvang and Buellton areas agree a great deal on how they rank their TSUs, as do residents of West Lompoc and East Lompoc, those of East Lompoc and the Vandenberg area, those of Downtown Santa Barbara and the Santa Barbara Mesa, and those of West Central Santa Maria and North Santa Maria. No pairing of “updated” TSUs from different parts of the county exceeds 0.5. Rather, four closed systems are present: one in North County, two in Central County (one in Lompoc Valley and one in Santa Ynez Valley), and one in South County. The systems in North County and South County feature ten or more such pairings, but the ones in Central County feature only three or two.

Finally, I consider how many TSUs Santa Barbara County residents decide to rank on average, and what is the mean population and area of all of those TSUs combined (i.e. the total population and area of their TSU-defined COI). These results appear in Table 28.

Table 28. Means for total TSUs ranked in Santa Barbara County, and the total population and area of those TSUs.

Participants from:	Total TSUs ranked	Total population	Total area (in sq. km.)
All parts of the county	5.6	72,443	474.4
North County	5.0	65,176	384.2
Central County	6.5	52,249	929.2
South County	5.8	84,475	382.0

Participants on average tend to rank about between five and six TSUs, as opposed to between four and five MSUs; this difference is significant ($t[440] = 3.54$, $p < .001$). Those in Central County tend to rank between six and seven, while those in North and South County rank about five and six, respectively. The total population of the COI that participants define with the TSUs they rank exceeds 70,000. For perspective, the population of the Lompoc area is about 60,000. This number is lower for those from Central County, despite the fact that they tend to rank more TSUs. The total area of the COI that participants define with their TSUs approaches 500 square kilometers. In contrast, the area of Santa Maria Valley is more than 700 square kilometers. This time the number is much higher for Central County residents.

2. Spatial similarity between cognitive COIs and electoral districts

a. Between the CSU-defined COI and the congressional district

I first assess the spatial similarity between a CSU-defined COI and the congressional district with which that COI overlaps the most. I survey participants from the two CSUs of San Luis Obispo and Santa Barbara Counties. The correlation between the two is greater than 0.5 at 0.52, so they together form a COI at this scale level, with a total population of 723,115.

California's 24th Congressional District includes the entirety of San Luis Obispo and Santa Barbara Counties, but only a small portion of Ventura County's population, so for my purposes the district comprises just those two CSUs. Thus in this case, the two groups of units are the same, and the spatial similarity between the two is perfect as the two regions are identical in shape and extent. Such perfect similarity, while facilitated by this method, is not guaranteed by it. For instance, the two counties could have been placed in different congressional districts, which would have resulted in low spatial similarity.

b. Between MSU-defined COIs and the state assembly districts

When I move to MSUs, the number of units from which I survey participants increases from 2 to 10, so it is not a simple manner of considering just a single pair of units, but rather 45! Using the method of identifying "closed system" networks of correlations as COIs, I identify three MSU-defined COIs that I can compare with the corresponding electoral districts at the state assembly level. Those COIs are San Luis Obispo County, North and Central Santa Barbara County, and South Santa Barbara County. Figure 41 illustrates how these three COIs compare to the two state assembly districts within the two counties. The COI for San Luis Obispo County overlaps with just one of these districts, while the other two overlap with both of them. Table 29 shows how I determine the spatial similarity between pairs of regions based on the population overlap. I compare each COI with the district that it overlaps the most in terms of population.

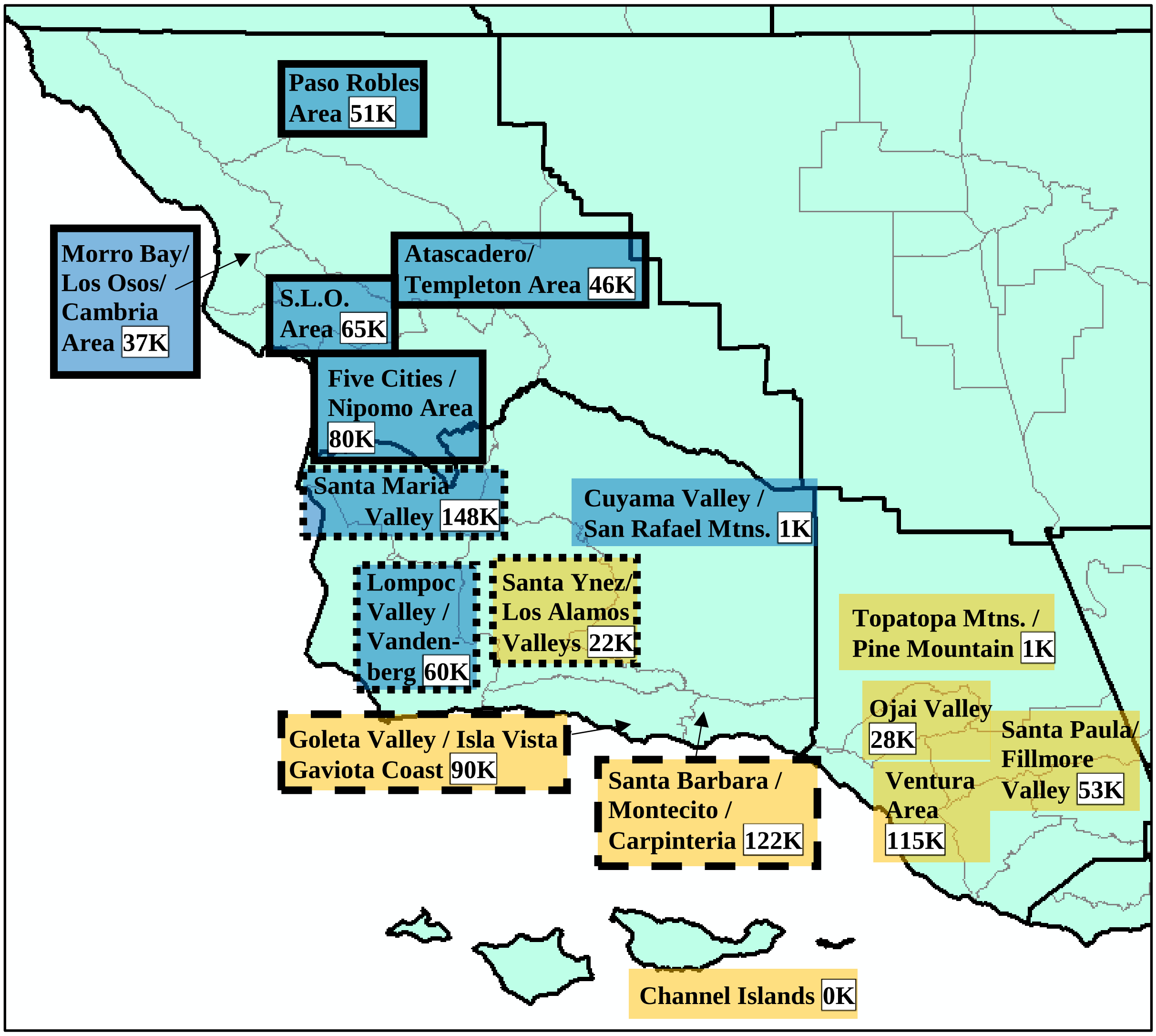

Figure 41. Map of MSUs that are part of either one of the three MSU-defined COIs, or one of the two state assembly districts in the area. Each MSU is indicated by a colored label that includes its population (ACS 2017). The COIs are differentiated by the style of the label outline. The COI for San Luis Obispo County is symbolized by a solid outline, that for North and Central Santa Barbara County is by a dotted outline, and that for South Santa Barbara County by a dashed outline. The districts are differentiated by the label color. The 35th District is symbolized by blue, and the 37th District by yellow.

Table 29. Spatial similarity between MSU-defined COIs and state assembly districts, in terms of population (ACS 2017).

COI	District	Population of COI (C)	Population of district (D)	Population of overlap (O)	Spatial similarity: $2\times O/(C+D)$
San Luis Obispo County	35^{th}	280,119	489,473	280,119	0.728
North & Central Santa Barbara County	35^{th}	230,336	489,473	208,413	0.579
South Santa Barbara County	37^{th}	211,713	431,038	211,713	0.659

The spatial similarity between the pairs of regions ranges from less than 0.6 to greater than 0.7. The COI for North and Central Santa Barbara County coincides the least with its corresponding state assembly district, as most of that district's population overlaps with another COI, namely San Luis Obispo County. That COI coincides the most, because it is fully contained by the 35^{th} State Assembly District and no part of the COI is another district. South Santa Barbara County falls in between, as it is fully contained by the 37^{th} State Assembly District, but most of that district's population is found outside that COI.

c. Between TSU-defined COIs and BOS districts in San Luis Obispo County

Now I turn to TSUs, first focusing on those in San Luis Obispo County. Using the same method of identifying COIs as with MSUs, I identify four TSU-defined COIs that I can compare with the corresponding electoral districts at the county board of supervisors level. Those COIs are North San Luis Obispo County, the Morro Bay / Los Osos area, San Luis Obispo, and South San Luis Obispo County. Figure 42 illustrates how these four COIs compare to the five board of supervisors districts. The COI for North San Luis Obispo County is so large in population that I compare it to two districts combined; I compare the other three to just one. Table 30 shows how I determine spatial similarity by population, comparing each COI with the district that it overlaps the most in terms of population.

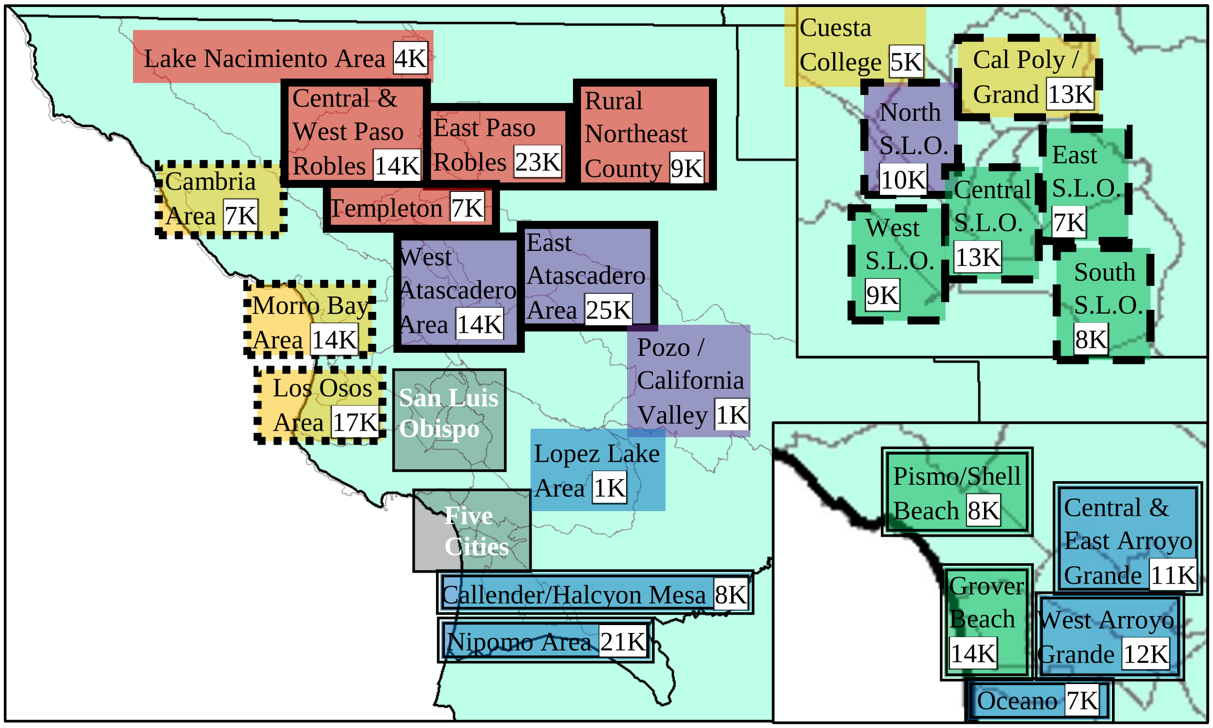

Figure 42. Map of "updated" TSUs in San Luis Obispo County and their membership in a TSU-defined COI or a board of supervisors district. Each "updated" TSU is indicated by a colored label that includes its population (ACS 2017). The COIs are differentiated by the style of the label outline. The COI for North San Luis Obispo County is symbolized by a solid outline, that for the Morro Bay / Los Osos area is by a dotted outline, that for San Luis Obispo by a dashed outline, and that for South San Luis Obispo County by a double outline. The districts are differentiated by the label color. The 1st District is symbolized by red, the 2nd District by yellow, the 3rd District by green, the 4th District by blue, and the 5th District by purple.

Table 30. Spatial similarity between TSU-defined COIs and board of supervisors districts in San Luis Obispo County, in terms of population (ACS 2017).

COI	District	Population of COI (*C*)	Population of district (*D*)	Population of overlap (*O*)	Spatial similarity: $2 \times O/(C+D)$
North San Luis Obispo County	1st & 5th	92,509	107,810	92,509	0.924
Morro Bay / Los Osos area	2nd	37,460	54,586	37,460	0.814
San Luis Obispo	3rd	60,046	58,870	37,327	0.628
South San Luis Obispo County	4th	79,839	58,853	58,296	0.841

The spatial similarity between the pairs of regions ranges from greater than 0.6 to greater than 0.9. The COI for San Luis Obispo coincides the least with its corresponding board of supervisors district, as much of that district's population overlaps with another COI, namely South San Luis Obispo County. The COI for North San Luis Obispo County coincides the most with the two districts combined, because it almost fully contained by them both. The Morro Bay / Los Osos area and South San Luis Obispo County fall in between. The former is fully contained by its district, but that district overlaps with much of San Luis Obispo. The latter fully contains the 4th District, but much of it is also covered by the 3rd.

d. Between TSU-defined COIs and BOS districts in Santa Barbara County

Finally, I turn to TSUs in Santa Barbara County. Using the same method of identifying COIs as before, I identify four TSU-defined COIs that I can compare with the corresponding electoral districts at the county board of supervisors level. Those COIs are Santa Maria Valley, Lompoc Valley, Santa Ynez Valley, and South Santa Barbara County. Figure 43 illustrates how these four COIs compare to the five board of supervisors districts. The COI for South Santa Barbara County is so large in population that I compare it to two districts combined; I compare the other three to just one. Table 31 shows how, as before, I determine spatial similarity by population, comparing each COI with the district that it overlaps the most in terms of population.

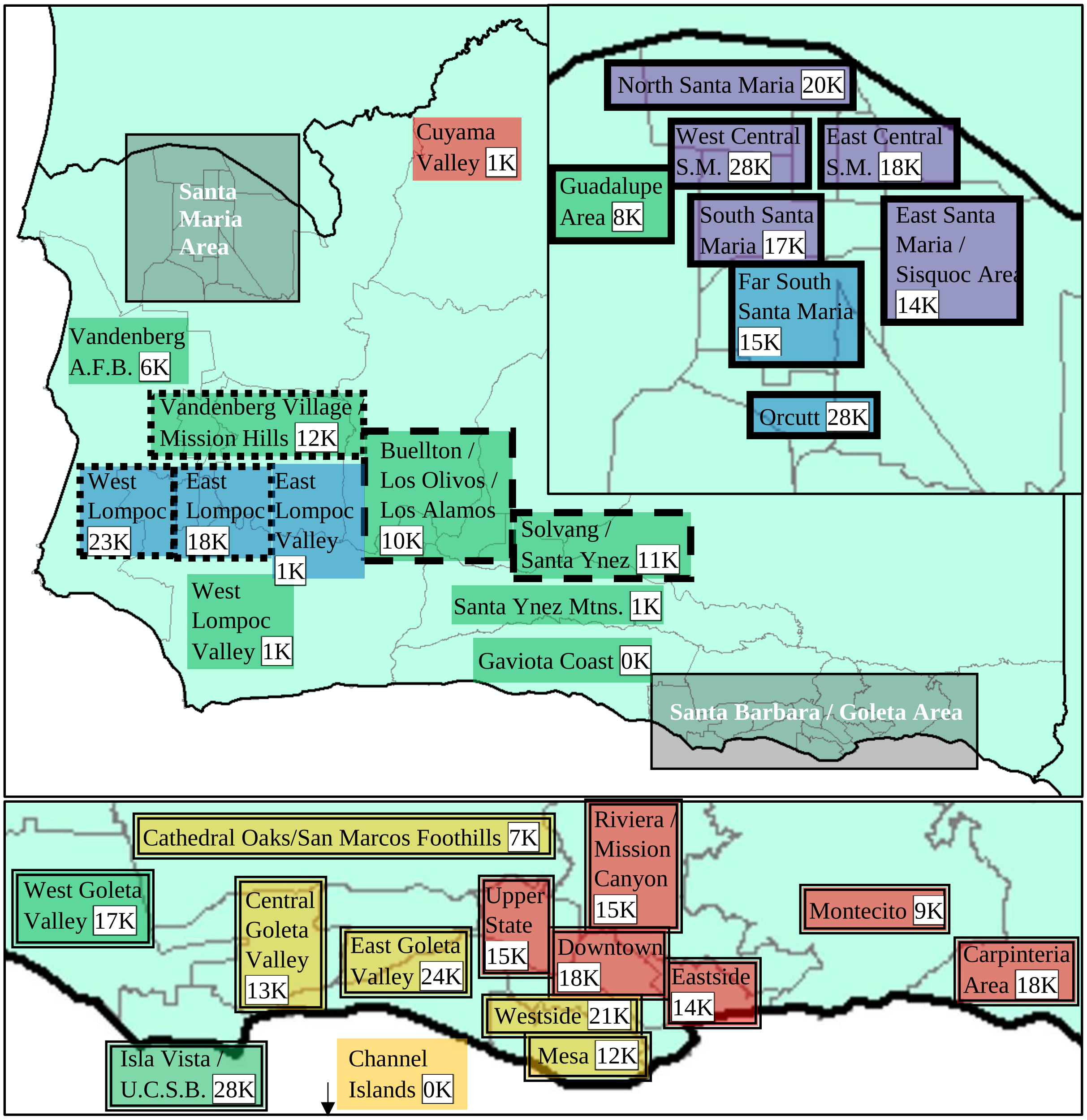

Figure 43. Map of "updated" TSUs in Santa Barbara County and their membership in a TSU-defined COI or a board of supervisors district. Each "updated" TSU is indicated by a colored label that includes its population (ACS 2017). The COIs are differentiated by the style of the label outline. The COI for Santa Maria Valley is symbolized by a solid outline, that for Lompoc Valley is by a dotted outline, that for Santa Ynez Valley by a dashed outline, and that for South Santa Barbara County by a double outline. The districts are differentiated by the label color. The 1st District is symbolized by red, the 2nd District by yellow, the 3rd District by green, the 4th District by blue, and the 5th District by purple.

Table 31. Spatial similarity between TSU-defined COIs and board of supervisors districts in Santa Barbara County, in terms of population (ACS 2017).

COI	District	Population of COI (C)	Population of district (D)	Population of overlap (O)	Spatial similarity: $2\times O/(C+D)$
Santa Maria Valley	5th	148,096	96,413	96,413	0.789
Lompoc Valley	4th	52,601	85,163	41,061	0.596
Santa Ynez Valley	3rd	21,045	94,001	21,045	0.366
South Santa Barbara Co.	1st & 2nd	211,214	167,419	166,472	0.879

The spatial similarity between the pairs of regions ranges from less than 0.4 to less than 0.9. The COI for Santa Ynez Valley coincides the least with its corresponding board of supervisors district, as much of that district's population overlaps with another COI, namely South Santa Barbara County. The COI for South Santa Barbara County coincides the most with the two districts combined, because it is almost fully contained by them both. Lompoc Valley and Santa Maria Valley fall in between. The former is fully contained by its district, but that district overlaps with much of Santa Maria Valley. The latter fully contains the 5th District, but much of it is covered by the 4th District as well.

3. Degree of identification with different scales of COI

Each participant rates how much they identify with each spatial scale of COI that they define, on a rating scale from "Very much" to "Not at all." Having assigned a numeric value to each level of the rating scale, as described above, I can compute a mean degree of identification for each spatial scale of COI. Those means turn out to be identical across the three different scales: 4.3 for each scale of COI. This indicates that participants rate each scale of COI equally highly, between "Very much" and "Quite a bit," though closer to the latter. As one would expect, there is no significant difference between the three scales ($F[2, 1054] = 0.16$, $p = .86$).

4. Names given by participants for their COIs

Having explained the coding system for the names given for COIs, I can now detail how frequently each standardized name appears across the three scale levels. I present this data by giving a table for the 32 standardized names, then for the 10 categories (these numbers do not count the category for those who choose not to give a name).

Table 32. Frequencies in raw numbers and percent of participants who give a standardized name for all scales of communities of interest (totals add up to more than 360 and 100% due to multiple names being given by some participants).

Standardized name	CSU number	CSU percent	MSU number	MSU percent	TSU number	TSU percent
California	10	2.8%	10	2.8%	1	0.3%
Northern California	16	4.4%	10	2.8%	0	0.0%
Central California	45	12.5%	29	8.1%	5	1.4%
Southern California	37	10.3%	23	6.4%	0	0.0%
Central Coast	101	28.1%	93	25.8%	35	9.7%
Coastal California	12	3.3%	5	1.4%	0	0.0%
West Coast	3	0.8%	1	0.3%	1	0.3%
South Coast	7	1.9%	5	1.4%	3	0.8%
Tri-County	3	0.8%	0	0.0%	0	0.0%
San Luis Obispo County	23	6.4%	28	7.8%	9	2.5%
Santa Barbara County	37	10.3%	19	5.3%	13	3.6%
North S.L.O. County	2	0.6%	6	1.7%	14	3.9%
South S.L.O. County	0	0.0%	2	0.6%	6	1.7%
North S.B. County	1	0.3%	4	1.1%	3	0.8%
South S.B. County	1	0.3%	2	0.6%	4	1.1%
San Luis Obispo Only	4	1.1%	10	2.8%	25	6.9%
Five Cities	0	0.0%	3	0.8%	15	4.2%
Nipomo	0	0.0%	0	0.0%	3	0.8%
Pismo Beach	0	0.0%	0	0.0%	3	0.8%
Atascadero	0	0.0%	0	0.0%	4	1.1%
Paso Robles	1	0.3%	5	1.4%	8	2.2%
Santa Barbara Only	24	6.7%	33	9.2%	59	16.4%
Goleta	0	0.0%	5	1.4%	13	3.6%
Santa Maria	1	0.3%	14	3.9%	46	12.8%
Lompoc	3	0.8%	7	1.9%	14	3.9%
Santa Ynez Valley	0	0.0%	1	0.3%	8	2.2%
S.L.O. Neighborhood	0	0.0%	0	0.0%	6	1.7%
Santa Barbara Neighborhood	1	0.3%	1	0.3%	13	3.6%
Santa Maria Neighborhood	0	0.0%	0	0.0%	18	5.0%

Table 32, cont. Frequencies in raw numbers and percent of participants who give a standardized name for all scales of communities of interest (totals add up to more than 360 and 100% due to multiple names being given by some participants).

Beyond	17	4.7%	22	6.1%	0	0.0%
Personal	3	0.8%	4	1.1%	7	1.9%
Other	6	1.7%	16	4.4%	32	8.9%
Did not answer	13	3.6%	13	3.6%	7	1.9%
Total	371	103.1%	371	103.1%	375	104.2%

Table 33. Frequencies in raw numbers and percent of participants who gave a categorized name for all scales of communities of interest (totals add up to exactly 360 and 100% due to mutually exclusive categorization); "A" represents "Appropriate" and "I" represents "Inappropriate," explained below.

Category	CSU number	CSU percent	MSU number	MSU percent	TSU number	TSU percent
State	[I]10	[I]2.8%	[I]10	[I]2.8%	[I]1	[I]0.3%
Sub-State	[A]94	[A]26.1%	[I]61	[I]16.9%	[I]5	[I]1.4%
Coast	[A]123	[A]34.2%	[A]110	[A]30.6%	[I]38	[I]10.6%
Multi-County	[A]5	[A]1.4%	[A]5	[A]1.4%	[I]0	[I]0.0%
One County	[A]63	[A]17.5%	[A]43	[A]11.9%	[I]22	[I]6.1%
Sub-County	[I]35	[I]9.7%	[A]93	[A]25.8%	[A]239	[A]66.4%
Sub-City	[I]1	[I]0.3%	[I]2	[I]0.6%	[A]40	[A]11.1%
Beyond	13	3.6%	19	5.3%	0	0.0%
Personal	2	0.6%	4	1.1%	6	1.7%
Other	1	0.3%	0	0.0%	2	0.6%
Did not answer	13	3.6%	13	3.6%	7	1.9%
Total	360	100.0%	360	100.0%	360	100.0%

Turning to Table 32 first, by far the most common standardized name given by participants for their CSU-composed COI is "Central Coast," with almost three-tenths of them giving some form of that name. The next-most-common responses for that COI are "Central California," "Southern California," "Santa Barbara County," "Santa Barbara Only," and "San Luis Obispo County," respectively. However, these responses are much less common than "Central Coast." For their MSU-defined COI, participants again name it "Central Coast" much more than any other name, but this time just over a quarter of them give this name. No other name is given by more than 10% of participants, with "Santa

Barbara Only," "Central California," "San Luis Obispo County," "Southern California," "Beyond," and "Santa Barbara County" being the next-most-common. Finally, with their COI made up of TSUs, participants become much more eclectic with their naming, with only "Santa Barbara Only," "Santa Maria," and "Central Coast" named by more than or close to 10%. In addition, several participants give an "Other" name for this scale of COI.

Turning now to Table 33, the most common categories for participants' COI made up of CSUs are "Coast," with more than a third of the responses, "Sub-State," with more than a quarter, "One County," with more than a sixth, and "Sub-County," with almost a tenth. All other categories fall far behind. For their MSU-defined COI, the "Coast" and "Sub-County" categories prevail, with more than three-tenths and one quarter of the responses, respectively. The next-most-common are "Sub-State" and "One County." For their TSU-composed COI, the "Sub-County" category dominates all others, with almost two-thirds of all responses. The only other categories that break 10% are "Sub-City" and "Coast." Two patterns stand out the most in this table. The first is the steady decline in the "Coast," "Sub-State," and "One County" categories as one goes from larger to smaller scale. The other is the contrary rise in the "Sub-County" and, to a lesser extent, "Sub-City" categories going in the same direction. The differences between the CSUs and TSUs are marked.

To put these numbers into more perspective, I lump the seven categories besides "Beyond," "Personal," and "Other" into two "mega-categories," which I label "Appropriate" and "Inappropriate." For CSUs, "Inappropriate" includes the "State" category because the size of the state as a whole is much larger than the extent of the survey map, as well as the "Sub-County" and "Sub-City" categories because the county is usually the smallest CSU that participants can rank. The other four categories therefore land in "Appropriate." For MSUs, “Inappropriate” still includes “State” but now also “Sub-State,” because participants would have to rank every single one of the MSUs on the map to reach that size, which is an unlikely and unreasonable expectation. At the lower end, “Sub-County” is now considered “Appropriate” since one can reasonably rank just one to three MSUs within a single county, but “Sub-City” remains “Inappropriate” because that is too fine a resolution for most of the MSUs on the map. Finally for TSUs, most categories count as “Inappropriate,” with the only “Appropriate” categories being “Sub-County” and “Sub-City.” “One County” becomes “Inappropriate” for the same reason that “Sub-State” is so for MSUs, because participants would have to rank every single one of the TSUs on the map to reach the size of the county.

With this further categorization in mind, I will now consider the “mega-categories” for each scale of COI. For CSUs, “Appropriate” totals 79.2% while “Inappropriate” garners 12.8%, a difference of 66.4%. For MSUs, “Appropriate” receives 69.7% while “Inappropriate” sums to 20.3%, a difference of 49.4%. For TSUs, “Appropriate” earns 77.5% while “Inappropriate” musters 18.3%, a difference of 59.2%. These numbers show that participants give a name considered “Inappropriate” the most often for their MSU-composed COI, relative to how often they give a name considered “Appropriate.” It is vice versa for their CSU-defined COI, with that made up of TSUs close behind. To investigate whether there is a significant difference in “appropriateness” between the three scales, I conduct McNemar tests on the three possible pairings of scales. The number of participants who give an “appropriate” name with CSUs but an “inappropriate” one for MSUs—61—is significantly different from the number who give an “inappropriate” name with CSUs but an “appropriate” one for MSUs—34 ($\chi^2[1] = 7.12$, $p < .01$). However, there is no significant difference in "appropriateness" for the pairing of MSUs and TSUs ($\chi^2[1] = 0.48$, $p = .49$), nor for the pairing of CSUs and TSUs ($\chi^2[1] = 3.15$, $p = .08$).

One further note about naming concerns the fact that many participants give the same name for their CSU-defined COI as their MSU-defined one. More than half of those participants who do give a name for both COIs opt to repeat names for these two scales that share the same map and sheet face: 178 repeat names, while 176 give different names. In fact, many participants repeat all the information they give in the white box, including name, degree of identification, and number of years having resided in that COI. Less than half of them—166—replicate all this information, while 190 show some variation. Such rote repetition may have implications for the "appropriateness" of the names given by participants, especially for their CSU-defined COI, as that is the COI the name of which is most often a repeat.

5. Qualitative properties of COIs defined by participants' unit rankings

a. Topology of COIs

In addition to degree of identification and given names, I can glean data on the qualitative ways in which participants rank their units to define their different scales of COI regions. First I consider the issue of topology. Participants vary in how they construct their COIs by ranking different units. Some rank their units so that they link up into a contiguous COI, while others rank units that are quite far away from each other with no linkage between them. In other cases, participants rank units that are contiguous with each other as well as units that are noncontiguous. Table 34 shows how often a particular form of topology appears in participants' rankings for a given scale of COI.

Table 34. Frequencies in raw numbers and percent of participants who have a form of topology for all scales of communities of interest.

Category	CSU number	CSU percent	MSU number	MSU percent	TSU number	TSU percent
COI both contiguous and non-contiguous	45	12.5%	108	30.0%	149	41.4%
COI completely contiguous	190	52.8%	172	47.8%	169	46.9%
COI completely non-contiguous	23	6.4%	37	10.3%	23	6.4%
COI solely one unit	95	26.4%	38	10.6%	16	4.4%
No COI defined or topology unclear	7	1.9%	5	1.4%	3	0.8%
Total	360	100.0%	360	100.0%	360	100.0%

As the table evidences, some forms of topology are much more common than others. With CSUs, most participants construct a COI that is at least partially contiguous, almost two-thirds. In fact, more than half define a COI that is completely contiguous, with no nonadjacent units. A large number, more than a quarter, just rank one unit by itself. With MSUs, again, most participants construct a COI that is at least partially contiguous, but an even larger proportion of more than three-quarters. Here, a little less than half define a COI that is completely contiguous. However, at this scale, a good chunk of more than two-fifths of participants define a COI that is at least partially non-contiguous. With TSUs, a yet larger share of almost nine-tenths of participants construct a COI that is at least partially contiguous. Again, less than half define a COI that is completely contiguous, and a similar number define a COI that is at least partially non-contiguous. Two main patterns stand out from this table. First, the proportions of most forms of topology besides complete contiguity and solely one-unit increase going from a larger scale to a smaller one. Second, the proportions of those two aforementioned forms of topology decrease going in the same direction, though the decline in solely one unit is more pronounced.

Another way to look at this topology data is to consider the linkage between just the top two ranked units in each participant's COI. I can investigate whether those units are connected to each other in a contiguous COI, either directly by being neighbors or indirectly by having a common neighbor between them that is ranked third or lower. Such an analysis would ignore those COIs where just one unit is ranked. To investigate whether there is a significant difference in connectedness between the three scales, I conduct McNemar tests on the three possible pairings of scales, but find no significant difference with any of them. The pairing of CSUs and TSUs comes fairly close to being significantly different ($\chi^2[1] = 3.21$, $p = .07$), with the number of participants with connected top two CSUs but unconnected top two TSUs—43—greater than the number of those with unconnected top two CSUs but connected top two TSUs—27. The pairing of CSUs and MSUs ($\chi^2[1] = 2.16$, $p = .14$), as well as MSUs and TSUs ($\chi^2[1] = 1.38$, $p = .24$), do not come close to being significantly different.

I also consider whether somebody only ranks one unit, a very basic aspect of topology that might inform about the effects of scale. To investigate whether there is a significant difference between the three scales in tendency to rank just one unit, I conduct McNemar tests on the three possible pairings of scales, and this time find significant differences with all of them. The pairing of CSUs and TSUs yields a huge chi-square statistic ($\chi^2[1] = 65.01$, $p < .001$), with the number of participants who rank just one CSU but multiple TSUs—88—far greater than the number of those who rank multiple CSUs but just one TSU—8. The pairing of CSUs and MSUs also yields a very large chi-square statistic ($\chi^2[1] = 40.73$, $p < .001$), again with more participants ranking just one CSU but multiple MSUs than vice versa. Finally, the pairing of MSUs and TSUs yields the smallest chi-square statistic of the three but one that is still considerable ($\chi^2[1] = 11.61$, $p < .001$), with the same pattern of greater tendency to rank just one unit at the larger scale but multiple units at the smaller scale, rather than vice versa.

b. Expansion of COIs

Next I consider the issue of COI expansion. This refers to the fact that participants' rankings for one level of units may expand upon their rankings for a lower, or smaller-scale, level of units. To illustrate with an actual example, one participant in Isla Vista / UCSB ranks San Luis Obispo County as one of her CSUs, even though she does not rank any MSUs within that county. So she expands upon what she has access to in the regional map for her MSU rankings. This counts as an expansion of her CSU-defined COI region. To illustrate the other type of expansion, another participant in Isla Vista / UCSB ranks Goleta Valley / Isla Vista / Gaviota Coast and Santa Barbara / Montecito / Carpinteria as her only MSUs, but does not rank any TSUs within the latter MSU. So she expands upon what she has access to in the county map for her TSU rankings. This counts as an expansion of her MSU-defined COI region. A McNemar test reveals that the number of participants who expand their CSU-defined COI but not their MSU-defined COI—57—is not significantly different from the number of those who do the opposite—78 ($\chi^2[1] = 2.96$, $p = .09$). Table 35 shows the number who expand their regions.

Table 35. Frequencies in raw numbers and percent of participants who expand their COI.

Category	Yes number	Yes percent	No number	No percent	N/A number	N/A percent	Total number	Total percent
Expand CSUs	160	44.4%	196	54.4%	4	1.1%	360	100.0%
Expand MSUs	181	50.3%	177	49.2%	2	0.6%	360	100.0%
Expand both	103	28.6%	255	70.8%	2	0.6%	360	100.0%
Expand either	238	66.1%	118	32.8%	4	1.1%	360	100.0%

c. The effect of insets on COIs

Next I examine the issue of insets on the survey maps. As described in the methods section on materials, for the sake of clarity and legibility, I had to create insets for certain areas with dense populations on both the regional and county maps. This presents the question of whether this design has an effect on how participants rank their units, especially, whether they confine their rankings inside or outside the inset. Perhaps the regions that participants define with their rankings would be different if no such inset were present. Here I focus on the insets for the county map, which are more likely to have an impact than the insets on the regional map that are farther away. That is because almost three-fifths of participants live in the areas covered by the county map insets, namely the San Luis Obispo, Santa Maria, and Santa Barbara areas.

Results show that an overwhelming number of 279 participants, or 77.5%, only rank TSUs that are either all inside or all outside a map inset, not across both. I label this the "Cis-Inset" group. The "Cis-Inset" proportion rises to 80.5% for those who live in an inset area, and falls to 73.3% for those who do not. This difference is not significant, however ($t[355] = 1.68$, $p = .09$). 78 participants, or 21.7%, do in fact rank TSUs that are both inside and outside a map inset. I label this the "Trans-Inset" group. The "Trans-Inset" proportion falls to 18.6% for those who live in an inset area, and rises to 26.0% for those who do not, but this difference is not significant (see last *t*-test). These results show that the most common practice among participants is for those living in an area that has an inset to confine one's rankings within that inset, and for those living in an area outside an inset to ignore that inset when completing one's rankings.

d. COIs with tied unit rankings

Lastly, I look at the issue of tied rankings. Despite the fact that survey instructions encourage participants to rank their units 1, 2, 3, and so on, many insist on giving tied rankings, often to the extent of giving de facto ratings. For example, a participant may rank a couple units first, another few units second, and several more third. Results show that an overwhelming number of 290 participants, or 80.6%, follow the intent of the survey instructions by not giving tied rankings. However, 67 participants, or 18.6%, do in fact give tied rankings. Of those 67, 18 have tied CSUs, 38 have tied MSUs, and 50 have tied TSUs. To investigate whether there is a significant difference between the three scales in tendency to give tied rankings, I conduct McNemar tests on the three possible pairings of scales, and find significant differences with two of them. The pairing of CSUs and TSUs yields the largest chi-square statistic ($\chi^2[1] = 21.84$, $p < .001$), with the number of participants who give tied rankings for CSUs but not for TSUs—6—much less than the number of those who give tied rankings for TSUs but not for CSUs—38. The pairing of CSUs and MSUs yields a smaller but still substantial chi-square statistic ($\chi^2[1] = 11.28$, $p < .001$), again with fewer participants who give tied rankings for CSUs but not for MSUs than vice versa. The pairing of MSUs and TSUs does not yield a significant difference ($\chi^2[1] = 3.36$, $p = .07$); though it follows the same pattern as the other two pairings, the effect is not nearly as great.

I not only consider *whether* participants give tied rankings, but also *how many* units have a ranking that is a repeat of one already given to another unit. Given that so many participants do not give any tied rankings, the average number of units with a repeated ranking will come close to 0. The number of CSUs with a repeated ranking averages to 0.1, the number of MSUs averages to 0.6, and the number of TSUs averages to 0.9. I find that there is a significant difference between the three scales ($F[2, 1073] = 5.90$, $p < .01$). Comparing between pairs of scales reveals where this difference lies. The means for CSUs and MSUs are significantly different from one another ($t[366] = –2.47$, $p = .01$), as are those for CSUs and TSUs ($t[370] = –4.06$, $p < .001$). However, those for MSUs and TSUs are not significantly different ($t[711] = –0.94$, $p = .35$). This data therefore reveals a greater tendency for participants to give tied rankings when dealing with MSUs and TSUs than when dealing with CSUs, both in deciding *whether* to give tied rankings and *how many* units to give a repeat ranking.

D. Discussion

This second study, like the first, seeks to determine the extent of the cognitive COIs that survey respondents depict at three different scales. But unlike the first, this study asks them to do so at all three scales, rather than assigning them to just one. It also investigates whether people identify with one scale of region more than others, and assesses variation within each region by asking people to rank administrative regions according to level of confidence. Finally, this study investigates how people's cognitive COIs coincide with the existing electoral districts. I find that people depict COIs with very different extents at the different scales, but identify about equally with each scale of COI. Meanwhile, the way in which they rank certain areas mirrors the frequency in which they rank those areas at all. That is, areas that are ranked more often are also ranked highly. Lastly, I identify multiple COIs at different scales by isolating those areas whose residents have similar rankings. I find that those COIs coincide with electoral districts at the same scale rather well, but that spatial similarity varies both within and across scales.

1. Rankings given by participants for units to define their COI

Participants rank some CSUs more than others, and as one might expect, almost every participant includes their own county of residence in their CSU-defined COI. Residents of Santa Barbara County seem to feel almost as much affinity toward Ventura County as they do San Luis Obispo County, as they rank it almost just as often. A fair amount of residents of San Luis Obispo County include Monterey County, but less often than those of Santa Barbara County include Ventura County. Even though Kern County is just as proximate to the two counties in the study area as Monterey and Ventura Counties, participants rank it much less often. They clearly perceive Kern County differently than the counties considered part of the Central Coast, recognizing that its inland geography and agricultural outlook make it less like their own COI.

Participants do not tend to rank very many CSUs, just about two or three. This makes sense because these units are larger and so there are not as many of them to rank. Most participants just rank their own county and one or two others that are adjacent. It is no accident that the total population and area of the average COI that participants define with CSUs approximates that of San Luis Obispo, Santa Barbara, and Ventura Counties combined. That is because they are the three CSUs that are most frequently ranked by participants. So the average participant's CSU-defined COI tends to consist of Santa Barbara County (where most participants live), San Luis Obispo County (where the remaining participants live), and Ventura County (which is right next to the first county). This tri-county area thus represents the rough extent of people's CSU-defined COI.

Rankings of MSUs allow for finer resolutions of COI perceptions. San Luis Obispo County residents have a tendency to rank every MSU in their own county, but seldom rank

MSUs elsewhere, so they clearly limit their MSU-defined COI to the county itself. Santa Barbara County residents, in contrast, tend to leave out two barely populated MSUs within their own county, preferring instead to include MSUs outside the county like the Ventura and San Luis Obispo areas. So participants from Santa Barbara County appear to have a more expansive conception of their MSU-defined COI than those from San Luis Obispo County. I suspect this is because Santa Barbara County's two main urban areas—the Santa Barbara and Santa Maria areas—are closer to neighboring counties than other urban areas in their own county. Therefore, the many participants who live in either one of those areas have a good deal of interaction with areas outside their own county. This interaction is thus reflected in the COI they define with their MSUs.

There is a strong positive correlation between the frequency in which an MSU is ranked and its population. This suggests that people tend to rank more populated MSUs frequently because more of them live in one of these units and therefore rank it first or only. There are a few notable exceptions to that general pattern, however. For example, the San Luis Obispo area is over-ranked relative to its population. People rank the San Luis Obispo area more often not just because many of them live in this area, but because those who live elsewhere also tend to rank it a good amount. They seem to feel a special affinity toward the San Luis Obispo area, which exceeds that felt toward more populous MSUs. San Luis Obispo's more central location in its county, status as the county seat, and historic importance as the site of the mission and major university all probably to various extents explain this special attraction. Santa Ynez Valley is also over-ranked. It appears to benefit from its central location in its own county, as people both to the north and the south include it in their COI, despite its small population. The Channel Islands are actually under-ranked relative to their population, probably due to their isolated, remote location. Population therefore is not a perfect predictor; other factors come into play.

By examining the similarities in the way in which residents of different MSUs rank all of their MSUs, I can determine which MSUs are more closely related. This is because residents who have similar views about which MSUs belong in their COI are more likely to belong to the same COI, as they share a common cognitive conception. This relates to the cognitive thread for defining a COI, the idea that a COI is "cognizable" by its inhabitants (Grofman 1993). If people have a common understanding of the extent of a COI, that COI is a meaningful entity with which they identify (Morrill 1990). At this scale, three COIs manifest themselves through these shared conceptions: one for San Luis Obispo County, one for North and Central Santa Barbara County, and one for South Santa Barbara County.

One question that arises is why three COIs emerge, rather than just two, one for each county. Each county has the same number of populated MSUs—five, so that cannot explain why Santa Barbara County is split into two while San Luis Obispo County is not. While South Santa Barbara County is indeed physically isolated from the rest of the county by the Santa Ynez Mountains, so also is North San Luis Obispo County separated from the rest of that county by the Santa Lucia Range. So why does the former constitute its own COI while the latter does not? One plausible explanation is that South Santa Barbara County is especially distinct from the other parts of that county in terms of culture, economics, and politics, as I touch on below. Another is that the forenamed has so large of a population that people recognize it as its own separate COI. Note that the three COIs have roughly equal total populations, between 200,000 and 300,000. Perhaps this reflects a tendency among participants to agree on a COI of a certain population size, not too large but not too small either. There is thus greater connection among the MSUs of San Luis Obispo County than there is among those of Santa Barbara County because the latter is too populous for all of its residents to agree on the existence of one single COI. Even with no population figures displayed on their survey map, participants seem to recognize and agree upon an appropriate size for a COI at this scale.

On average, participants tend to rank a few more MSUs than they do CSUs. This makes sense because these units are smaller and so there are more of them to rank. Most participants rank their own MSU and a few others that are adjacent. Residents of San Luis Obispo County tend to rank about the same number of MSUs—maybe slightly more—as those of Santa Barbara County, about five. However, the total area of the average COI defined by San Luis Obispo County residents is much larger because the average MSU in that county is larger. But regardless of where they are from, participants tend to define a COI with about half a million people. This is to be expected because most participants live in Santa Barbara County, and if they on average rank about five MSUs, that would total to close to half a million if they tend to rank the five populated MSUs within Santa Barbara County.

Rankings of TSUs allow for even finer resolutions of COI perceptions than those for MSUs. In San Luis Obispo County, participants from North County appear to have a more expansive conception of their TSU-defined COI than those from Central County or South County. I suspect this is because those from the more rural North County must often travel to Central County for certain goods and services available only there, like the main hospital, university, courthouse, and airport, not to mention commuting. They are thus more inclined to include TSUs in Central County in their COI due to their interaction with it, while those in Central County have no such need. This tendency is not found among those from South

County, though. I surmise that these residents do not rely on Central County to the degree that those from North County do. The Santa Maria area to the south offers many of the things that the San Luis Obispo area does, and it is just as close. North County residents, in contrast, have no other major service center anywhere near as close as San Luis Obispo. This would therefore explain why South County residents' TSU-defined COI seems more limited in scope than one might expect.

In Santa Barbara County, participants from North County and Central County appear to have a more expansive conception of their TSU-defined COI than those from South County. I suspect this is the case for those from the more rural Central County because they must often travel to North County or South County for certain goods and services available only there, like the main hospitals, colleges, courthouses, and airports, not to mention commuting. This leaves the question of why residents of North County include TSUs in Central County more often than those from South County do. I surmise that they have some affinity toward Central County that is not matched by those from South County, likely because North County and Central County share a lot in common economically and culturally. While North County is not nearly as rural as Central County, it is still much more rural than South County, as crop fields surround the cities of that part of the county. The two parts thus share common agricultural interests and concerns.

These shared economic and cultural interests can also translate to a feeling of political isolation. Many in North County and South County share a common feeling of neglect from the political power center of South County, where the county seat of Santa Barbara is located. The interests of the generally more liberal and environmentalist residents of South County often clash with those of the generally more conservative and petroleum-friendly residents of North and Central County. In fact, in 2006, some residents from those two parts of the county launched a ballot initiative in an attempt to split off from South County and form their own new county called "Mission County." While county residents resoundingly rejected that proposal in the referendum, the fact that such a proposal went as far as it did demonstrates this common feeling of separateness or neglect shared by many in North and Central County (Mission County 2005). That would explain why North and Central County residents are more likely to include parts of the other in their TSU-defined COI, while those in South County have a more limited conception of their COI. It would also explain why they share a COI at the MSU level.

There is somewhat of a positive relationship between the frequency in which a TSU is ranked and its population, but there are a several notable exceptions to that general pattern. In San Luis Obispo County, Los Osos Valley and Pismo Beach are over-ranked relative to their populations. The former appears to benefit from lying between the two main population clusters in Central County, with participants from both Morro Bay and Los Osos to the north and San Luis Obispo to the south including it in their COI, despite its small population. Pismo Beach seems to be over-ranked for a similar reason as Los Osos Valley, though to a lesser extent. It draws rankings from both San Luis Obispo to the north and the rest of the Five Cities to the south. Three TSUs in rural North County are under-ranked relative to their populations. All these areas are relatively remote and isolated from the rest of the county, and one of these (the Lake Nacimiento area) was not sampled because it had restricted access.

In Santa Barbara County, Downtown Santa Barbara and Central Goleta Valley are over-ranked relative to their populations. The former appears to benefit from its central location in Santa Barbara, surrounded on all sides by several other TSUs. It also surely draws rankings from those living in other TSUs who nonetheless work and shop Downtown. Central Goleta Valley seems to be over-ranked for a similar reason as Downtown Santa Barbara, though to a lesser extent. It also occupies a central position, but for Goleta Valley, and serves as a central business district for that community. No TSU is substantially under-ranked relative to its population. Two themes are apparent from examining the relationship between rankings and population. One is that TSUs with central locations and/or attractive amenities that would draw people in tend to be over-ranked relative to their populations. The other is that those with remote locations and less accessibility tend to be under-ranked.

By examining the similarities in the way in which residents of different TSUs rank any of the TSUs in a given county, I can determine which TSUs are more closely related. In San Luis Obispo County, four TSU-defined COIs emerge: North County, the Morro Bay / Los Osos area, San Luis Obispo, and South County. Four appear in Santa Barbara County as well: Santa Maria Valley, Lompoc Valley, Santa Ynez Valley, and South County. These COIs seem to cohere fairly well with the MSUs that make up the two counties, with the exceptions that the Paso Robles and Atascadero areas combine into one, as do the Santa Barbara and Goleta areas. In both cases, this appears to be because the two MSUs are not as separated from each other as the other ones are, as they are joined by an almost continuous string of settlements along the Salinas River in the former case and the shore of the Santa Barbara Channel in the latter. Thus it seems that COIs at this scale take the size of a municipal area, unless their populations are close together.

On average, participants tend to rank about the same number of TSUs as they do MSUs. Even though these units are smaller and there are more of them to rank within the county, participants do not feel the need to rank very many. Most rank their own TSU and several others that are adjacent, but rarely more than six or seven total. I believe this is because most people do not wish to spend a lot of time ranking dozens of TSUs, and so they stop once they are ready to move on to the next part of the survey. Residents of South San Luis Obispo County tend to rank fewer TSUs—about five—than those of the northern and central parts of that county—about eight. Again, this may have to do with an affinity toward the nearby Santa Maria area that cannot be expressed because it is in a different county and so does not appear on the map for TSUs. If the Santa Maria area were to appear, then those residents may well rank TSUs there and thus rank more TSUs overall. Meanwhile, residents of South Santa Barbara County tend to define a COI that is greater in population than that defined by those in the northern part of that county, though the two groups of participants rank about the same number of TSUs. However, South County has 60,000 more people than North County does, so residents of the former are more likely to rank a more populous TSU than residents of the latter, and so the COI that they define with those TSUs is more likely to have a greater population.

Finally, the fact that a unit's average ranking correlates almost perfectly with the amount of times it is ranked at all—no matter the scale—demonstrates something important. It shows that areas that are ranked more often are also ranked highly. What makes this relationship so strong? The fact of the matter is that units that are frequently ranked are ranked so often for a reason. It is generally because they have a lot of people who live there, and those people tend to rank the unit in which they live. Not only that, but those people naturally tend to rank their unit of residence first. So it makes sense that there exists a strong relationship between the two across the three scales. The places that people most agree belong in their COI are also the places where people most confidently express that they do indeed belong therein.

2. Spatial similarity between cognitive COIs and electoral districts

By assessing which units' residents agree the most about their unit rankings, I can identify COIs at each scale to compare with the existing electoral districts. The degree to which these two sets of regions coincide varies with scale. I find perfect spatial similarity at the largest scale. Granted, this may just be because I only survey residents of those two counties. But the fact that San Luis Obispo County residents rank Santa Barbara County second more often than any other, and vice versa, indicates that those two CSUs belong in the same COI. Therefore, the California redistricting commission managed to create a congressional district that best reflects the COI that these residents define. The state assembly districts that the commission created are less optimal from the perspective of North and Central Santa Barbara County residents, as it split the MSU-defined COI based there between the 35th and 37th Districts while keeping the COI based in San Luis Obispo County intact within the former.

The lack of spatial similarity between this pair of regions demonstrates the inherent challenge in redistricting of deciding where to begin the process and which group of people's opinions to privilege. In this case, the commission privileged the COI of San Luis Obispo County, but it is unclear whether they did so entirely intentionally. This is because the nature of the redistricting process is such that decisions made elsewhere in the state have a reverberating effect throughout. Once one district's boundaries are defined, that will limit the boundaries of the district that is created adjacent to the first, and in turn the one created adjacent to the second, and so on until the last district's boundaries are automatically defined.

The COI in North and Central Santa Barbara County may then be a victim of falling later in that sequence, after a district was drawn for San Luis Obispo County.

This redistricting challenge lessens when dealing with county board of supervisors districts, as the process takes place within the confines of just a particular county and only has to result in five districts. Even so, the county authorities must decide where to begin the process, and so must inevitably privilege one area of the county over the others. A COI-centric approach privileges those areas with the strongest similarities in how they rank their units, thus prioritizing cognitive connections over other considerations like compactness and “practical contiguity” (explained below). This seems better than arbitrarily selecting one area in which to create the first district. The degree to which these TSU-defined COIs coincide with the board of supervisors districts will depend on the extent to which those county authorities adopted a COI-centric approach when they created those five districts.

In San Luis Obispo County, San Luis Obispo is divided among three of the existing districts and the Five Cities between two of them; in Santa Barbara County, Santa Barbara and Goleta Valley are split between two. A COI-centric approach would keep these entities whole because participants recognize them as COIs, as measured by how much they agree about which TSUs belong in their COI. Such an approach would, however, exacerbate the urban-rural dichotomy, perhaps something that each county’s board of supervisors sought to avoid when creating its actual districts. The board might contend that each of its members should have to cater to both urban and rural interests, and that otherwise a member would be too narrowly focused on one set of issues. Districts that span the urban-rural divide might also generally have more competitive elections. But it is hard to argue that some urban residents in particular do not suffer from being divided between two or even three supervisors, each of whom must give much if not most of their attention to the interests of other parts of the county.

Another drawback of a COI-centric approach is that some of the districts that might result from it may suffer from a lack of “practical contiguity” (Maryland 2015, pp. 26–27). If the authorities in San Luis Obispo County were to take this approach and prioritize not splitting San Luis Obispo and the Five Cities, they would have to draw a district linking Atascadero to Nipomo in order to follow the equal population criterion. Such a district may be technically contiguous via a mountainous wilderness, but there is no way to travel on roads between the two areas without having to pass through a San Luis Obispo-based district. Thus one might question whether that district follows the spirit of the contiguity criterion. But does such a criterion even matter at this scale? When these areas are so close together that they consume the same news media and observe the same weather patterns, how important is it really that one is able to drive from one end of the district to the other without passing through another district? I would argue that striving to keep COIs like San Luis Obispo and the Five Cities together is a worthier goal.

One final drawback to consider concerns the relationship between smaller COIs that must be linked to form equipopulous districts. A COI-centric approach would prioritize keeping these smaller COIs intact, striving to not separate the TSUs that compose them because of the strong similarities they share in their rankings. But if one of these smaller COIs is not populous enough to form a district on its own, it must join with another smaller COI. Often these smaller COIs have little in common with one another in regard to how their residents rank their TSUs, but they must nonetheless join in order to form a district. One might wonder whether it would be better to prioritize making the final district as internally similar as possible, so that the COIs that make it up are not very different from each other, even if they are themselves not kept completely intact. Others might contend that it is more important that immediate neighbors be kept together, in recognition of the "first law" of geography that closer things are more related to each other. All these questions are worth considering when stakeholders prepare for redistricting.

3. Degree of identification with different scales of COI

Participants clearly do not express much difference in degree of identification with different scales of COI. They rather rate each scale the same. This initially suggests that the participants identify equally with all scales of COI, and do not feel any greater affinity toward one scale over the other. Of course, this does not mean that they *actually* feel this way, only that they self-report as such. Many participants may choose to fill out a "straight ticket" because they consider it quicker and easier to carry their rating for the first scale over to the other two, not willing to stop and ponder how their degree of identification might differ with each scale. On the other hand, they may treat degree of identification as a proxy for degree of residence, leading them to rate "Very much" across the board because they consider themselves to be full, 100% residents of each scale of COI. This lone self-report measure then can only inform so much. That is why I include another measure in the survey, asking participants to give a name for each scale of COI, in the hope that that might serve as some kind of proxy for degree of identification.

4. Names given by participants for their COIs

In contrast to degree of identification, participants do show variation with the names they give for their different scales of COI. This shows that most participants are not content to do a "straight ticket" when naming a COI, but recognize that different scales of COI require different names. Such variation in naming allows me to assess whether a given scale receives a greater frequency of “inappropriate” names. In this context an “appropriate” name is one that reasonably fits the scale of the COI in question; an “inappropriate” name does not. The relative proportion of “inappropriate” names given tends to be higher with participants’ MSU-defined COI, which suggests that they are least able to describe a COI at that scale in a meaningful way. Given that half of participants repeat the name for their MSU-defined COI (which they are asked for first) as that for their CSU-defined COI, this means that often the name they give is actually more “appropriate” for the repeat than the original. This makes sense, because almost all of the “inappropriate” names given for the MSU-defined COI are deemed so because they are for areas that are bigger, such as for the state or sub-state, and so more befitting a CSU-defined COI.

This greater tendency for “inappropriateness” with MSUs perhaps implies that, even though participants rate it the same as the other scales of COI when it comes to degree of identification, that scale level is actually more nebulous to them. That might explain why they are more prone to give a name that better fits a larger area than that encompassed by the MSUs they rank. They seem more familiar with a name befitting a CSU-defined COI than the MSU-defined COI that they are actually asked to name first. This may indicate that they identify more with, and have closer affinity to, the larger scale of COI than the medium scale. So even though participants do not explicitly rate the three scales of COI differently, they name them in a manner that suggests that they do have different levels of place attachment toward each. I propose that they have less attachment to the scale they can least name appropriately, which is the MSU scale.

5. Qualitative properties of COIs defined by participants' unit rankings

I can tease out some interesting findings from the qualitative data I collect about participants' rankings. First, the COIs that participants define with CSUs are more likely to be made up of either just one unit or multiple units that are completely contiguous, as opposed to the COIs that they define with TSUs. This makes intuitive sense because the CSUs themselves are larger in both population and area, and so participants tend to rank fewer of them or even just one. Furthermore, CSUs are more likely to be right next to each other when they take up more space and there are fewer of them on the map to begin with. TSUs are smaller in area and population, and so participants tend to rank more of them and rarely just one. Moreover, they are less likely to be right next to each other when they take up less space and there are more of them.

Second, many participants consciously expand the spatial extent of their COI as they go through the survey. Conscious expansion involves ranking units that do not contain smaller scale units ranked previously. The high proportion of participants who consciously expand either their CSU- or MSU-defined COI shows that many adopt a broader conception of their COI when asked to rank larger scale units. Many participants seem to feel that they should add to the spatial scope of a larger scale COI rather than just rank units that contain smaller scale units already ranked, so that their conception goes further beyond the area of their own town or municipality. Granted, less than three-tenths of participants expand both their CSU- and MSU-defined COI, so most do not consistently expand their COI with each higher scale. But the fact that two-thirds of participants do so at one scale or the other demonstrates something important. It shows that, for most participants, this survey is not a thoughtless exercise of just ranking whichever CSU and MSU one's home is located in.

Rather, it is a means by which they thoughtfully consider how each scale of COI is meaningfully distinct.

Third, for many participants, the insets on the map seem to have an effect on how they rank their TSUs. Only about one fifth of participants rank TSUs both inside and outside an inset, with the rest limiting their rankings to either inside or outside. This provokes the question of how many of those restricting their rankings do so out of genuine desire or because they neglect to notice either the inset or anything outside the inset. Those who live in areas covered by insets, which are the densest and most urban parts of this congressional district, may not feel the need to rank TSUs outside their inset because they rarely have need to frequent those areas. Thus their exclusion of non-inset areas may well reflect genuine desire; plus, it is more difficult to miss the non-inset areas because they take up the majority of the map space. On the other hand, those who live in areas not covered by insets, which are generally less dense and urban, would probably be more inclined to frequent areas that are covered by insets in order to procure goods and services available only there, or commute there. Thus their exclusion of inset areas may owe more to neglect, especially since the insets take up less space on the map. In sum, I surmise that the exclusion of TSUs is more likely to be genuine for those living inside an inset area.

Finally, while the vast majority of participants do not give tied rankings, many insist on doing so. Either they cannot make up their minds about which of two or more units they are more confident is in their COI, or they are treating the task as assigning ratings of confidence. The survey instructions intend for participants to adhere to a pure ranking system in which they give a unique ranking to each unit they rank, and discourage them from treating the survey as a rating exercise. Those who give the same ranking to multiple units must therefore confirm to the survey administrator that they are in fact giving tied rankings. Reminding them that these are *rankings* hopefully encourages them to repeat a ranking only once or twice, rather than give the same number repeatedly, as in a rating system.

IV. General Discussion

A. Summary of main findings

My dissertation investigates whether people conceive of different scales of COI when they are exposed to different map types, and also how these conceptions depend on where they live. Such conceptions would then, by definition, point to the existence of different scales of cognitive COIs. The first study does so by splitting subjects into urban and rural groups, manipulating scale by changing the extent and generalization of the map given to them (three different scales of "state," "regional," and "local"), and varying whether the boundaries of administrative regions are present on that map. I find significant differences between the urban and rural groups in the location and extent of the COI regions that subjects draw. This indicates that COI conceptions are indeed dependent on one's urban/rural context, either the area's urbanness itself or some related factor. I also find such differences between groups of subjects exposed to different map types, indicating that the map induces people to externalize their COIs in different ways. Crucially, this entails their depicting COIs at different scales, but not conforming them to the administrative region of the county.

The second study investigates those central questions by exposing all subjects to the same map types: two map extents with three levels of administrative regions present (which I call "county-scale units," "municipal-scale units," and "town-scale units"). Thus each subject is asked to represent their COI three different times, but using different levels of administrative regions each time, and viewing a different map extent for the first time than the second and third times. I find significant differences between the different levels in the location and extent of the COI that they define by their rankings, indicating that the map extent and/or the level of administrative regions present induces people to externalize their

COIs in different ways. This includes depicting COIs at different scales, and not just because of the size of the regions themselves. Subjects often define their COI by ranking regions that do not contain smaller regions that they already ranked, which means that they are consciously expanding their COI.

While these two studies chiefly aim to tease out different scales of cognitive COIs, each study has supplemental goals as well. Both consider how subjects express internal variation within their COI. The first study does so by asking subjects to draw freehand regions representing different levels of confidence, while the second does so by asking them to rank predefined areal units according to level of confidence. In both studies I tend to find that a COI ranges from a "core" of high confidence to a "periphery" of lower confidence. Both studies also examine how the COIs conceived by subjects compare to existing electoral districts. In the first study, COIs drawn at the "state scale" and "regional scale" compare the best, while those drawn at the "local scale" compare the worst. In the second study, COIs defined by "county-scale units" compare the best, with mixed but mostly good results for both "municipal-scale" and "town-scale units." However, the key point is that one can measure where the existing districts reflect cognitive COIs well and where they do not.

The second study uniquely considers how degree of identification might depend on scale, and also how much population has to do with which units people rank. It finds that subjects rate their degree of identification with each scale of COI equally, but they name each scale differently, which may serve as a better measure for degree of identification than the self-report rating itself. It also finds that the population of a unit is highly correlated with how often it is ranked, but other factors like centrality and commercial attractions also play a role. Finally, both studies look at the qualitative properties of the COIs that subjects depict by either drawing regions or ranking units. The key qualitative finding in the first study is that people tend to draw ovaline regions, and thus have a more vague idea about the extent of their COI. The key such finding in the second study is that people often consciously expand their COI at larger scales by ranking units that go beyond what they ranked at smaller scales.

When taken together, both studies paint a complementary picture of the nature and scale of cognitive COIs. The first study shows that, when looking between subjects, different map scales act as stimulants to reveal the existence of different scales of COIs. The second study shows that, when looking within subjects, different map scales act as stimulants to reveal the existence of different scales of COIs. So both studies communicate the same message, just in different ways. The first has the benefit of demonstrating that different people can conceive of roughly the same scale of COI when they receive the same type of map and live in the same urban/rural context, thus revealing the existence of a distinct, commonly-agreed-upon COI at each of the three scales. The second has the benefit of demonstrating that the same person can conceive of different scales of COI, and identify with each one. Moreover, it illustrates how that person can expand their conception of their COI not just because the survey design forces them to, but due to a genuine, conscious compulsion. Clearly then, COIs do exist as cognitive regions at multiple scales, and people recognize that they can belong to all of them. This does not necessarily mean that they identify with each of them equally; there may be less affinity toward the COI at the medium scale, if one measures by the appropriateness of the names they give. But multiple scales of COI do indeed exist.

B. Shortcomings and potential threats to validity

That all being said, these studies are not without their flaws and limitations. Probably the biggest threat to the validity of my dissertation as a whole is the way I try to elicit cognitive COIs at different scales merely by showing map images of different scales. To be sure, I still view this method as the simplest and most effective way to evoke these conceptions. An alternative method could have presented subjects with the same map, but asked them to depict a COI that would be relevant for districts at different levels of government. However, most subjects are not familiar with what these different districts look like, and showing the districts on the map would probably condition them to draw their COIs to accord with them. Giving subjects different map scales guides them into depicting different scales of COI that exist in their minds, without having to reference any districts. Nevertheless, the method that I use here is not without its drawbacks. Chiefly, it is difficult to discern whether the results obtained are mainly due to just a graphical effect or a genuine conception of a scale of COI. Perhaps the scale of the map image is priming subjects into drawing a certain scale of COI, rather than drawing out something internal that is already there. While that may indeed be the case for some subjects, I take the phenomenon of conscious expansion that I observe in the second study as evidence that the survey tasks are, for most people, getting at something genuine. That is clearly not just a graphical effect. But this issue is nonetheless a major concern I have about this research.

On top of that one great concern, there are others that are common to both studies. One of these is the definition for a COI given to subjects. One could argue which definition should be given, if even any at all, given that the concept is so vague to begin with. But some definition is necessary; otherwise, there is not enough information for subjects to complete the task. The definition they are given does have a good conceptual and theoretical basis, as it derives from previous research done by Phillips and Montello (2017). Nevertheless, several alternative definitions exist, and may have prompted slightly different responses from subjects had they been used instead. That possibility is certainly something to consider. Another concern common to both studies is the spatial similarity index used. The question is whether or when it is appropriate to calculate that index using the population of the two regions in question and the overlap between them, rather than the spatial area of those three pieces of the earth's surface, as was originally intended for that index. I address this issue in the discussion section for the first study, but suffice it to say that I see merit in both approaches and it really depends on context. I argue that one should generally use area because a region is defined by more than just its population, such as natural resources. However, in certain circumstances it may be better to use population, particularly when one needs to make an "apples-to-apples" comparison between a COI and a proposed district that has to have a certain population, as I do in the second study. In both studies I contend that I compute spatial similarity in a manner that compares regions optimally, which is the purpose of the index.

Some shortcomings pertain to just the first study. One such flaw arose in the data collection phase, when a research assistant did not properly administer the survey instructions in a certain Census tract, mistakenly telling subjects that they were required to draw three regions. This error is not a serious threat to the study's validity, as it actually adds information rather than subtracts, but it prevents comparison with data gathered from the other Census tracts where subjects faced no such requirement. I therefore cannot use data from that Census tract that involves more than subjects' "definitely" regions, thus diminishing my sample size in certain contexts. While this, again, is not a fatal flaw, it demonstrates the importance of carefully training research assistants. An even more minor flaw demonstrates the importance of carefully writing survey instructions, as some subjects may have interpreted them to require drawing noncontiguous regions, as I explain in the study's discussion section. While these shortcomings are not serious threats to the study's validity, another one may be. That is the fact that the maps that show the boundaries of administrative regions only show those for counties. Perhaps if they had shown boundaries for cities or even districts themselves, then some subjects may have drawn region boundaries that adhered to them. So while I find no effect of county lines on the regions drawn by subjects, it is premature to say that this applies for all administrative boundaries.

The second study also has a number of limitations specific to it. Several of those involve the way I collected the data. For one, I was not able to survey every subarea of the study area; some of these were inaccessible due to being gated communities or within a military base (although a good argument could be made against surveying residents of the latter, who are mostly translocated from beyond the study area). Therefore, I could not obtain a fully representative sample of the entire study area. Furthermore, while I was able to survey the rural parts of the study area, I utilized a different sampling procedure there that minimized the amount of time and effort I had to spend in those parts. By doing so, I further sacrificed the idea of having a fully representative sample, as people living in the sparsest parts of the rural areas had no opportunity to be surveyed. The final issue with data collection concerns the low response rate I obtained. While the rate for those who answered the door was almost 80% for the first study, it was just over 40% for the second. I can only speculate on why such a disparity exists, with my main guess being that college students with more free time on their hands constitute the greater share of the sample in the first study. Whatever the reason might be, it is concerning that I received such a large rejection rate with the second study. Might that pose a threat to the representativeness of my sample and thus the validity of the data I collect? It is certainly possible, especially if a disproportionate number of a certain age group, ethnicity, or sex reject my solicitation. I see no evidence of that, however, as the average age and proportion of Hispanics closely track with the figures given by the Census (once one considers that I do not survey children, so my figures should be somewhat older and slightly less of the more youthful Hispanic population). Therefore, the low response rate is not as concerning as it may seem.

Additional threats to the second study's validity may come from the design of the survey map. As previously explained, the survey map sacrifices uniformity for legibility by blowing up certain parts into insets. I believe that this is a sacrifice worth making, as it would have been a greater threat to validity for subjects to be confused about which name applied to which place and whether they were even able to read the name correctly. But the insets may have led some subjects to disregard certain places they might have otherwise ranked. I explicitly consider this possibility in my analysis of qualitative properties, but find no conclusive evidence of a major effect. Another issue with the map is the choice of areal units to feature at each scale level. Counties are a natural choice for the largest scale, but the units used at the medium and smaller scales are more arbitrary. Most of those used at the medium scale are county subdivisions as defined by the Census, but other possibilities include school districts, supervisorial districts, or cities proper. Most of those used at the smaller scale are groups of census tracts, but other possibilities include school attendance zones, zip codes, or single census tracts. I contend that the units that I define do the best job of comprehensively covering the study area while being the right size for each scale. But one wonders whether those other possibilities could have yielded substantially different results than those I obtain. I do not suppose so, but there is no way of knowing without supplementing this study with one using different versions of those areal units.

I believe that the second study also suffers from the design of the survey instructions. Those instructions ask subjects to *rank* the predefined areal units according to how confident they are that a given unit is within their COI. However, the instructions could have instead asked them to *rate* each of those units according to some numerical scale. This exercise would provide more information about subjects' COI conceptions, as it would represent data on the interval scale and not just the ordinal. So why then do I forgo the rating task in favor of ranking? The problem with the former is that subjects often give the same rating to multiple units, which means that it can be difficult to determine a "cutoff" point when defining a COI of a certain population for each individual subject. If I want each individual COI to approximate the population of an electoral district, I need to know which units' populations to total up, but that would not be possible if a dozen units have the same rating. Ordinal rankings provide an exact sequence to follow when totaling, allowing me to tailor each subject's rankings so that they define a COI with the right population. However, my analysis finds that these tailored rankings do not yield data much different from those resulting from the unaltered rankings. Therefore, in retrospect, I regret not having required subjects to rate the units, because the main reason I eschew rating is to facilitate an analysis that does not add any value to the study as a whole. Had I used ratings, I would not have needed to transform the rankings into scores. Moreover, results for unit ratings may have been substantially different from those for the percentage of subjects that include a given unit at all, unlike what I find with unit rankings. I view this misguided decision as the second-most serious threat to the validity of my dissertation.

One final flaw I find in the second study concerns the way in which its instructions ask subjects to indicate how much they identify with a given scale of COI. For one, the term “identify” may not be the best choice to communicate what I am trying to measure. Shamai (1991) found this term confusing and preferred words like “belonging” and “attachment or affection” as different levels of measurement for “sense of place feelings.” The wide variety of related but distinct terminology makes one wonder whether the instructions are optimally worded. Perhaps subjects would have benefited from seeing all these synonymous terms together rather than just one, or a clear definition for “sense of place” or “place attachment.” As it is, the survey yields identical ratings for degree of identification for each scale of map, raising doubts as to whether subjects truly understand what they are being asked to report. The study discussion section speculates on how they may be misinterpreting these instructions, and why the names they give to each scale of COI may actually be a better measure of degree identification than the actual rating task itself. I could have avoided obtaining identical ratings by forcing subjects to rank how much they identify with a particular scale, and thus give a unique value for each scale. This may have prompted subjects to think more carefully about how much attachment they feel toward the different scales, since repeating the same answer would not have been possible. So it seems that I may have made a doubly wrong decision, asking subjects to rank units and rate how they identify with scales when I should have asked them to do the opposite. Still, the latter task is supplemented by the naming exercise, so it is not as serious of a shortcoming as the former.

C. Future research

Many of the flaws and shortcomings described above point toward avenues for future research. For one, a study might consider the effect of administrative regions on COI conception in a fuller way by exposing subjects to different types of such regions, not just counties. That way one can investigate whether subjects might be more prone to draw a COI that adheres to a certain type of administrative region as opposed to another. While I find no effect with county boundaries, perhaps such a study would show an effect with other types of boundaries. For two, a study might consider the effect of the areal units on COI conception by exposing subjects to different types of such units, such as school districts or zip codes. Such a study could maintain three different scales of units, but potentially show different results within a given scale when a different type of unit is shown at that scale. For example, at the smallest scale, would school attendance zones result in radically different COIs than would zip codes? For three, a future study could very well take the opposite approach that I do in my second study and ask subjects to rate units and rank scales rather than vice versa. So an individual subject would still be exposed to three scales of map, but that person would rate the units on each map scale on a five-point scale according to how confident he or she is that that unit belongs in his or her COI. Then, after having rated units at each of the three scale levels, the subject would rank the three scales from one to three based on the level of attachment of identification felt toward each of those scales. A study like this could provide information about a unit, not only whether subjects are generally more confident about it than they are another, but whether they are *a great degree* more confident as only discernable through interval data. On the other hand, the study could conceivably show that subjects consistently identify with one scale more than any other.

Moving beyond the ways in which my research could be improved upon, interesting theoretical questions await further exploration. One such question is the exact nature of the relationship between the COI and neighborhood. In particular, what scale of COI best corresponds to a particular neighborhood, and what degree of overlap exists between the two? To investigate this, one can conduct a study that asks residents of some area to define the boundaries of their neighborhood, as well as their COI at different map scales. One group of residents would describe the spatial extent of their neighborhood, while another group living in the same area would describe that of their COI at different scales. Such a study could then analyze which scale of COI, if any, the neighborhood definition best matches. One might then have a better idea how the concept of the neighborhood relates to that of the COI, and which scale of COI specifically.

One wonders whether the question of scale might be further explored through more advanced technologies. In particular, how might subjects define their COIs when using digital maps as opposed to static paper ones? Does scale matter as much when subjects can zoom and pan as they please on a digital device? To answer these questions, one can design an experiment where subjects are assigned to different conditions, namely, which scale of digital map they are first exposed to. If subjects depict COIs that reflect the scale of the initial map extent, even with the freedom to zoom and pan and make the COI as large or small as they please, then that will indicate that the initial map extent is still determinative. This will demonstrate that it does not matter whether the map shown to subjects is static or dynamic. Rather, what matters is which scale of map they are exposed to at the outset. Alternatively, one can inform subjects about the definition for a COI, let them zoom to what they believe to be the most appropriate scale to then draw their COI, and then ask them to what degree COIs exist at other scales, if they do at all.

I hoped to conduct one or both versions of this experiment myself as part of this dissertation, but ran into logistical and financial challenges in getting such a study up and running. Such a study requires considerable resources that I did not have at my disposal, particularly tablets with Internet access. With such resources on hand, one could survey door to door and present subjects with a dynamic digital map of their local area, set at a particular initial map extent. One could then measure the degree to which the subjects zoom and pan from that initial extent, and then have the subjects define their COI by drawing its boundaries with their finger on the map itself. Finally, one can compare the extent of the average COI defined by subjects with the initial map extent, to investigate whether there is a relationship between them. I suspect that the initial map extent is still important if not determinative for the size of the resulting COI, but this remains to be demonstrated through future research.

One can also envision a study that explores different scales of COIs in other ways than showing different maps to subjects. A survey could ask about COIs at different scales, but show subjects the same map image at all scales. For instance, a subject would receive a map of one large area, and then draw three different scales of COI, one that would be relevant for a congressional district, one for a state legislative district, and one for a city council district. Another subject would receive a map of a smaller area, and complete the same task. Then one could potentially determine how much of the results are attributable to just a graphical effect, and how much can be traced to a genuine distinction in scale. Such a study would also provide a stronger basis for exploring how cognitive COIs relate to neighborhoods. If, for example, the COI drawn for the city council district assumes roughly the same size and shape across all subjects, that COI could readily be compared to commonly held neighborhood definitions.

Lastly, one could design a study that explores the scale of a COI without giving subjects a map at all, nor any priming for scale. A survey could ask subjects to audibly describe their COI, giving them a definition for the concept with no reference to any scale. Subjects would list the areas that definitely lie within their COI, those that definitely fall outside of it, and any areas that may or may not be part of it. They might also describe any firm boundaries such as mountain ranges or coastlines. Such a description would then represent their default scale of COI. Once they give their description, the survey might then ask them if they identify with any other scales of COI beyond that default. Such a study would cater to those who are verbal processors as opposed to visual thinkers, but more importantly, avoid the pitfalls that come with priming, visual or otherwise. That great advantage must be weighed against the disadvantage that comes with such qualitative research, that is, the inability to precisely quantify the areas and/or populations of different regions. This all goes to show that there is a spectrum of possible survey methods to answer the question about the scale of a COI, and each of them has its own benefits as well as limitations. In sum, there are many opportunities for future research in this area, and this dissertation is just a starting point. Many other potentially rich studies await exploration.

D. Practical applications and implications

This research seeks to achieve a better understanding of the community of interest as a cognitive region, particularly how people conceive of several scales of such regions, one layering on top of the other. Beyond the goal of basic scientific research, this dissertation also has practical applications and implications that can contribute to and improve the redistricting process. The findings of this research can inform the decision makers and political actors who control the redistricting process so that they make better decisions about how to draw electoral districts that take into account the different scales of COI. Given that redistricting criteria tend to include respecting COIs, a better understanding of the nature and scale of those COIs will enable those in authority to follow that criterion all the better. They can therefore enhance and facilitate citizens' sense of representation by keeping not just one scale of COI but multiple scales intact within one electoral district. So how exactly does this dissertation promote such understanding?

First, this dissertation shows that political actors need to be aware that multiple scales of COI exist. This means that when they solicit the opinions of their citizens as to the location and extent of a COI, they should know that what emerges is not *the* COI that those citizens recognize. Rather, it is just one of a set of COIs of different scales layered upon each other. The scale of the map that is given to the citizens will determine which COI in the set they define. If they are given a map that covers the extent of a city, odds are that they will define a COI at the scale of a neighborhood. But this does not entail that that COI is the only one that is meaningful to them. If they are given a map that covers the whole state, they will probably define a COI of a completely different scale, likely much larger. Therefore, those in authority must be careful about which scale of map they choose to give to the citizens they are soliciting, as that choice will influence the results they obtain. The map scale may be too large and yield very broad COIs, or too small and result in very narrow ones. The best approach is to avoid the former, because COIs that are too small for the redistricting task at hand can be linked together to form a group that is not. If a COI is too large to use as a point of reference for an electoral district at a particular level of government, it may not always be clear how one should divide it. So those in charge of redistricting should err on the side of using a map with a smaller scale, but not so small that it is wildly out of proportion to the size of the district that they are creating. It can be a difficult balance to strike, but one that is critical in soliciting the right scale of COI.

Second, this research illustrates the pros and cons of different methods for defining a COI. Specifically, it shows a benefit and drawback of drawing a COI freehand versus defining it by ranking a certain number of units. The former method offers one main advantage. It allows subjects to define their COI exactly as they wish, as they can draw its boundaries wherever they please. They are not limited to the boundaries of predefined areas or wherever the Census happens to delineate regions. Rather, they have maximum flexibility in determining the location and extent of their COI, which can be done at different levels of confidence too. The main disadvantage of this approach is that it can be difficult to determine precise population statistics for such a COI, when such precision may be necessary to satisfy the legal requirement of equipopulous districts. Such statistics are only available for areal units predefined by the Census. Therefore, it is not always clear how many and what kind of people live within the boundaries of a region drawn freehand, or an overlapping of such regions. This information is necessary in order to know whether a COI is too populous to fit into a given district. One can avoid this drawback by ranking or rating a selection of areal units, so that the disadvantage of the former approach becomes the advantage of this latter one. However, the vice versa applies as well, as the flexibility of the former approach is lost when dealing with areal units that are predefined in advance by someone other than the actual subject. Decision makers must therefore weigh these pros and cons as they decide which method to use to solicit the conceptions of their citizens regarding the location and extent of their COI. If it is critical that they have knowledge of exact population statistics, then they should use the latter approach. If not, then they ought to use the method that gives subjects maximum flexibility.

Third, my dissertation shows different ways to identify a coherent COI by amalgamating the COIs of individual subjects together. The first study demonstrates one technique to do so, by measuring the degree of overlap between individual region drawings. The greater the overlap in a particular place, the more agreement there is among subjects that that place is part of their COI, and therefore the more likely it is that a commonly shared COI is indeed located there. The advantage of maximum flexibility from the freehand drawing method carries over into this technique, as one can have an exact idea of where the core of a particular COI lies, since subjects are not bound to adhere to the limits of a predefined areal units. The downside, however, is that one must decide exactly which group of subjects whose regions to amalgamate. One can examine the regions of all subjects in the survey, but this will likely result in few if any areas of relatively high overlap/agreement. On the contrary, one can examine the regions of only some subset of subjects, such as everyone who lives within a proposed electoral district. However, this arbitrarily excludes subjects living beyond the proposed borders who may show even higher levels of agreement were they to be included. This technique also suffers from the lack of population specificity.

Given these drawbacks, one might instead opt to use the technique demonstrated by the second study, which measures the correlation between different predefined areas in how they rank all the areas available to them. The greater the correlation between two particular areas, the more agreement there is between residents of those areas in how they rank areas, and the more likely it is that they share a common COI between them. If there are several areas with high correlations between them, the network that they form would constitute a COI in itself. This technique has the advantage of identifying a COI of a particular population. It also avoids the arbitrariness of deciding which group of subjects to examine, since one can look at how all residents of all areas relate to each other in how they rank or rate, and still discover clear patterns in the data. Two disadvantages of this technique stand out. One is the lack of flexibility that carries over from the ranking/rating method, as subjects are limited to a certain selection of areas the boundaries of which are predetermined. In addition, one must still make the arbitrary decision of how high of a correlation to consider when determining whether a strong link exists between a pair of areas. These two studies clearly lay out two different methods in identifying a commonly-agreed-upon COI. It is up to those in authority to decide which one fits their needs the best, though I would recommend the second technique. This is because it clearly identifies COIs via networks, allows for population specificity, and is minimally arbitrary.

Finally, my dissertation shows how one can use a spatial similarity index to compare a proposed electoral district to people's cognitive COI. When political actors are deciding how to carve up a jurisdiction into different districts, they need certain information in order to follow the criteria as they ought to. In order to satisfy the criterion of respecting COIs, they must have an idea of how a certain district they might create would cohere with a particular COI. This is possible by putting into practice the applications described above—first choosing the right map scale, then the right method for defining an individual's COI, then the right technique for identifying a COI common to many individuals—plus one more. Once one can identify a coherent COI that is meaningful to a large number of people using those first three applications, one can then use the spatial similarity index to compare that

COI to any number of proposed electoral districts. The district with the highest spatial similarity index relative to the COI would then satisfy the criterion the best. Whether one inputs area or population into the index will depend on preference or context, as discussed above. I imagine that in most circumstances population would be preferable, as what matters most is how many people/voters end up in the "right" district relative to their COI.

In light of all these potential applications of my research in redistricting, I recommend the following procedure to those who are in control of the redistricting process in a particular jurisdiction, whether the legislators themselves or an independent commission. First, they should invite members of the public to utilize an online mapping tool, which would expose them to a map centered on the Census unit where they live. That unit would be their tract if the redistricting jurisdiction is a county or large city, or their block group if it is a small city or town. The map should be zoomed in at the closest level in which the Census unit is fully visible, though people would be free to zoom out and pan from there as much as they please. Second, they should ask their citizens to rank or rate any number of tracts or block groups (including their own) according to how confident they feel that those areas belong in their COI, giving them an understandable definition for the concept such as that given in these studies. That would result in a collection of individual submissions, each depicting one citizen's conception of their COI, their cognitive region.

Third, those in authority should use those citizens' rankings or ratings to calculate correlations among different units, so that pairs or groups of units with high correlations between them are identified as COIs that should not be split apart if at all possible. What qualifies as a high correlation would depend on the context. In some areas there would be correlations greater than 0.5 between dozens of units, in which case only those greater than

0.75 should be prioritized; in other areas a correlation greater than 0.5 would stand out. Finally, they should compare each COI with any number of proposed districts to determine the degree to which it coincides with each alternative. If the COI is much less populous than the proposed district, they should just compute the part of the spatial similarity index that divides the population overlap by that of the COI, to ensure that the COI is kept mostly or entirely intact (an index of close to or exactly 1). If the COI is roughly the population of that of the proposed district, they should compute the full index to see how well the two regions coincide. Of course, those in authority must also balance COI concerns with other mandated criteria, and the district that best reflects a COI may not be the most optimal district when it comes to all criteria. Nevertheless, knowledge of the location and extent of a particular scale of COI, and how well that COI coincides with a proposed district, is essential for drawing a district that respects citizens' cognitive COI. When that goal is achieved, it ensures that those citizens are well represented as a result.

V. References

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