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Impact of Demographic Trends on Future Development Patterns and the Loss of Open Space in the California Mojave Desert

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Impact of Demographic Trends on Future Development Patterns and the Loss of Open Space in the California Mojave Desert

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Abstract

During the post-World War II era, the Mojave Desert Region of San Bernardino County, California, has experienced rapid levels of population growth. Over the past several decades, growth has accelerated, accompanied by significant shifts in ethnic composition, most notably from predominantly White non-Hispanic to Hispanic. This study explores the impacts of changing ethnicity on future development and the loss of open space by modeling ethnic propensities regarding family size and settlement preferences reflected by U.S. Census Bureau data. Demographic trends and land conversion data were obtained for seven Mojave Desert communities for the period between 1990 and 2001. Using a spatially explicit, logistic regression-based urban growth model, these data and trends were used to project community-specific future growth patterns from 2000 to 2020 under three future settlement scenarios: (1) an "historic" scenario reported in earlier research that uses a Mojave-wide average settlement density of 3.76 persons/ ha; (2) an "existing" scenario based on community-specific settlement densities as of 2001; and (3) a "demographic futures" scenario based on community-specific settlement densities that explicitly model the Region's changing ethnicity. Results found that under the demographic futures scenario, by 2020 roughly 53% of within-community open space would remain, under the existing scenario only 40% would remain, and under the historic scenario model the communities would have what amounts to a deficit of open space. Differences in the loss of open space across the scenarios demonstrate the importance of considering demographic trends that are reflective of the residential needs and preferences of projected future populations.

Keywords: Demographic futures, Land use change, Logistic regression, Open space, Sustainable development, Urban growth models

Introduction

The Mojave Desert Region (the Region) of San Bernardino County lies approximately 80 miles east of the city of Los Angeles, California (Fig. 1). The 4.4-million-ha Region and its dispersed communities traditionally have supported military training and testing operations, mining, ranching, transportation services, limited agriculture, and more recently, outdoor recreation-related activities. Like many areas within commuting distance of major U.S. metropolitan centers, the Region has experienced intense growth and development pressures due to rapidly increasing populations (Alig and others 2004; Carrion-Flores and Irwin 2004; Kocabas and Dragicevic 2007; Lilieholm and others 2010; Ma and others 2007; Radeloff and others 2010; Rouget and others 2003, 2006; Stein and others 2005; White and others 2009).

These pressures, which threaten to alter both community character and the ecologically fragile desert landscape, convert natural or undeveloped lands into developed uses in the form of residential development and associated growth in manufacturing, commercial, industrial, and retail sectors (Hunter and others 2003). In 1990, for example, 223,779 people lived in the Region (Gonzalez 2001), with 86% (192,682) residing in the seven Mojave Desert communities of Adelanto, Apple Valley, Barstow, Hesperia, Twentynine Palms, Victorville, and Yucca Valley (Southern California Association of Governments, SCAG 2004) (Fig. 2). By 2000, the total population of the seven communities had increased 31% (to 251,728); by 2010, the total population of the seven communities had increased another 49% (to 375,363) (SCAG 2011). The SCAG projects that the population of these seven communities will reach nearly 425,000 by 2020, which is an increase of 52% over 2000 levels (SCAG 2004).

To accommodate future growth, thoughtful planning is needed to ensure that the Region’s quality-of-life and natural systems are protected. Also important is the long-term viability of the Region’s five economically important military installations, including Edwards Air Force Base and the Naval Air Weapons Station China Lake (Mouat 2009; Parent 2008; Shearer 2009). With 78% of the land area in the Region largely protected from development through public ownership (Fig. 2), particular attention is needed to ensure that open space within existing communities is recognized and protected in order to maintain community character and enhance local quality-of-life.

Earlier research by Gonzalez (2001) developed a spatially explicit, logistic regression-based urban growth model (UGM) to estimate the probability of future development for undeveloped lands in the Region based on development between 1970 and 1990 (Fig. 1). The model was then used to evaluate the effects of alternative future development scenarios on landscape-level biodiversity between 2000 and 2030 based on a range of assumptions regarding human population growth, settlement densities, and alternative land use policies (Hunter and others 2003). The approach developed by Gonzalez (2001) and Hunter and others (2003) assumed that, aside from population levels, the Region’s ethnic composition would remain unaltered over the planning horizon and would not influence settlement densities or patterns. Yet planners in the Region and elsewhere increasingly recognize that as socio-demographic variables such as ethnic composition vary, so too will preferences for various types of residential housing and living conditions (Myers 2001). This realization highlights the importance of modeling “demographic futures” in which land change projections move beyond simple population and settlement density scenarios to consider projected trends in ethnicity and/or age demographics (Myers and Pitkin 2001; Myers and others 2005). The concept of developing demographic futures is particularly germane for the California Mojave Desert Region. For example, between 2000 and 2040, the demographic composition of California’s population is expected to shift from a plurality of White non-Hispanic residents, to Hispanic residents (California Department of Finance 2002). This ethnic shift is likely to exert growing influence on the form and function of future development, especially with regard to the creation and maintenance of compact urban areas.

Myers (2001) identified three characteristics of the Hispanic population that suggest a propensity for more compact urban dwelling. Across all income levels examined, for example, one-third fewer units housed Hispanic residents as opposed to the same number of non-Hispanics due to larger family size of Hispanic households (Myers 2001). In addition, Hispanics were almost twice as likely as non-Hispanics to use public transportation, bicycles, or walking as a method of transportation to places of employment (Myers 2001). Although at higher income levels this behavior decreased, Hispanics were still more likely to use compact commuting methods than non-Hispanics of equal income. Finally, Hispanics were also more likely to live in multi-family housing (Myers 2001).

San Bernardino County is one of the fastest-growing metropolitan areas in the nation, and development increasingly threatens to alter irreversibly the Region’s natural and human systems. In response, the County has incorporated open space strategies into its General Plan (San Bernardino County 2007). The General Plan notes that the County contains an abundant amount of open space, but recognizes that most large open spaces are public lands located beyond established municipalities. While these lands are largely precluded from future development, they provide little in the way of access for large numbers of citizens (Anderson and Berglund 2003). More at-risk are open spaces located within existing communities. These areas are readily accessible to residents yet increasingly valued for development (Nowak and others 2010; Platt 2004).

Hunter and others (2003) considered private lands in the entire Mojave Desert area of California—some 1.5 million ha scattered among 7.4 million ha—in their alternative futures analysis. The coarse-scale approach was suitable for their objective of assessing impacts of growth on landscape-level biodiversity, and the resulting viability of the Region’s major military installations as private habitat was altered and installations faced increasing calls to manage for species protection (Hunter and others 2003). Here, we focus on community-level development by using Gonzalez’s (2001) model to explore the effects of a shift from a predominantly White non-Hispanic population to one that is predominantly Hispanic. By focusing on how changing demographic trends are likely to affect future settlement patterns and the loss of open space within our focus communities, we hope to arrive at a more detailed description of the loss of within-community open space, and provide insight into subtle differences in growth between communities.

Background

Demographic Trends in the U.S.

In the U.S., the Hispanic population increased from 22.4 million in 1990, to 35.3 million in 2000—an increase of 58%. Since 2000, the Hispanic population has increased by over 40% to a projected 50 million. Hispanics currently comprise approximately one of every six Americans (U.S. Census Bureau 2011). For comparison, between 1990 and 2000 the total U.S. population as a whole grew by just 13% (248.7 million to 281.4 million), while between 2000 and 2010 it grew by just 9% to roughly 306 million (U.S. Census Bureau 2011).

In the U.S., Hispanic and White non-Hispanic populations are geographically heterogeneous, with 45% of Hispanics residing in Western states, compared with just 20% of White non-Hispanic populations. Differences also exist between Hispanics and White non-Hispanics with regard to urban vs. non-urban living, with 46% of Hispanics living in a central city area compared to just 21% of White non-Hispanics (Therrien and Ramirez 2001). Only 9% of Hispanics lived in non-metropolitan areas, as opposed to 23% for White non-Hispanics. Hispanics are more likely to work in service occupations (19%) than White non-Hispanics (12%), and are nearly twice as likely—22% compared to 12%—to work as laborers or machinery operators (Therrien and Ramirez 2001). Hispanics are also more likely to live in poverty than White non-Hispanics, with lower levels of education and higher levels of unemployment (Therrien and Ramirez 2001).

Demographic Trends in California

During the twentieth Century, California's population grew from two million to 35 million people—an increase of more than 1,750% (Public Policy Institute of California 2002a). Today, California is the most populous state in the U.S., with one-in-eight Americans residing there. California is largely an urban state, and during the 1990s most population growth occurred in urban areas (Mackun and Wilson 2000). For example, between 1990 and 2000, 82% of population growth occurred in California's 456 urban areas that existed as of 1990. Twelve percent occurred in areas incorporated after 1990, and just 6% occurred in unincorporated regions (Public Policy Institute of California 2002b).

Given such high levels of population growth, the state has seen significant shifts in the composition of its population. For example, in 1970 just 1.8 million Californians were foreign-born, while by 2000 that number had reached 8.9 million (Public Policy Institute of California 2002a). Approximately 56% of all California immigrants (international and domestic combined) are from Latin America, including Mexico and El Salvador, while 33% of total immigration is from Asia, including the Philippines and Vietnam (Public Policy Institute of California 2002a). International immigrants to California are typically younger than the state's population at large. In 2000, half of the international immigrants to California were between 22 and 44 years of age, as compared to less than 30% of native-born Californians. Nearly 80% of the state's population growth during the 1990s was due to increases in the Hispanic population (Myers 2001; Myers and Pitkin 2001; Pitkin 2001).

While immigration and migration have long been drivers of growth for the state, domestic migration gains reversed in the early 1990s during a severe recession, resulting in a net loss of roughly 2 million people (Johnson 2000). Those leaving were disproportionately White non-Hispanics, e.g., 71% of outmigrants were White non-Hispanic, although they comprised just 50% of the state's total.

Projections by the California Department of Finance forecast the state's population to increase rapidly over the next 30 years, growing from approximately 34 million in 2000, to 45 million by 2020, and 59 million by 2040 (Table 1). Projections forecast that: (1) the state's absolute growth level will be high, but growth rates will be lower than in the past; (2) natural increase will provide more growth than net migration; (3) domestic migration will be less than in the past, while international migration will continue to be strong; and (4) the state's growth rates will exceed rates for the rest of the U.S.

Given such increases, it is not surprising to expect uneven growth across ethnic groups, giving rise to an increase in the state's ethnic diversity (Sandoval and others 2002). For example, the total number of White non-Hispanics in California is expected to stay relatively constant at approximately 18 million, but the proportion of White non-Hispanics in the total population is projected to shift from 47% in 2000 to 31% by 2040.

In absolute numbers, the Hispanic population will nearly triple between 2000 and 2040, from roughly 11 million to over 28 million (California Department of Finance 2002). Hispanics will comprise a plurality of the population by 2040, accounting for nearly 48% of persons in the state (Table 1). Other ethnicities will increase in number but continue to comprise approximately 20% of the total. In general, the number of younger and less-affluent households in California will increase and, over time, the state's White non-Hispanic population will grow comparatively older and more wealthy (Goldman 2001).

Demographic Trends in the Study Region

Like California as a whole, San Bernardino County has increased in population, from 1.7 million people in 2000, to over 2 million in 2010 (U.S. Census Bureau 2011). The county is expected to reach 4.2 million residents by 2040 (Table 1). Legal immigration to the county in the 1990s remained fairly constant. From 1990 to 1998, 42,708 persons immigrated to the county from outside the U.S., ranging from a low of 3,858 immigrants in 1990 to a high of 5,681 immigrants in 1993 (California Department of Finance 2002). In 2000, approximately 44% of the county's population was classified as White non-Hispanic and 39% was Hispanic.

As a subset of the county, our seven focus communities within San Bernardino County's Mojave Desert Region grew by 59,046 persons between 1990 and 2000, a 31% increase (Table 2). Between 2000 and 2010 these communities added an additional 123,635 persons, representing a 49% increase (Table 2).

When compared to the demographic composition of both the county itself as well as the state of California, the fine-scale data provided in the 2000 Census show that our focus communities had a higher percentage of White non-Hispanic persons and a lower percentage of Hispanic persons. For example, of the 251,728 residents in our seven communities in 2000, approximately 28% were Hispanic and 58% were White non-Hispanic. Table 3 lists the change in ethnic demographics for each of the seven communities. Overall, between 1990 and 2000, White non-Hispanics dropped from 72% of the population to 58%. Hispanics grew from 18% of the population to 28%. Hispanics accounted for 59% of the population growth between 1990 and 2000—i.e., 34,889 of the 59,046 new residents were Hispanic.

Development and the Loss of Open Space

High rates of human population growth have the potential to alter irreversibly the function of human and natural systems in the Mojave Desert Region. Most at risk are open spaces lost to development through changing land cover and land use.

Open space can be defined in many ways. Fausold and Lilieholm (1999) defined open space as “undeveloped land that retains most of its natural characteristics,” a definition that includes forest lands, most lands used for agriculture and grazing, and some parks and other recreational areas. In a study of suburbanization and wilderness parks in Orange County, California, Rhodenbaugh (1998) expanded the concept of open space to include developed local and neighborhood parks. The U.S. Environmental Protection Agency (EPA 2001), in its highly influential model ordinance language for municipal open space guidelines, moves beyond these definitions to define open space as that part of a development site “permanently set aside for public or private use and [that] will not be developed.” In this research, we define open space as private lands within or adjacent to established communities that are not currently used for residential, commercial, industrial, or other such developed uses. In contrast, developed lands are defined as “urban” in our analysis. In this research we do not consider the vast areas of public lands that are located outside of our seven focus communities because they were largely the subject of work by Hunter and others (2003).

Open space provides a wide range of public and private benefits which may accrue regardless of whether such lands are located inside or outside of established developed areas (Escobedo and others 2008; Platt 2004). Values range from scenic and recreational opportunities to flood control, aquifer recharge, carbon storage, species habitat, and the provision of marketed goods and services such as food, fuel, and fiber (Collins and Larry 2007). Although difficult to quantify, a growing number of empirical studies have examined the monetary value of open space (see Fausold and Lilieholm (1999) and McConnell and Walls (2005) for reviews of the economic benefits of open space).

Open spaces can be irreversibly lost due to direct conversion of undeveloped lands to developed uses.

Open space function can be compromised by fragmented development that reduces or eliminates the amenities and ecological services associated with open lands. Each year, millions of hectares of open space in the U.S. are lost to urban, peri-urban and suburban development—often referred to as “sprawl” and characterized as low-density dispersed development (Bruegmann 2005). Alig and others (2004) project that developed area in the U.S. will increase from 5.2% in 1997 to 9.2% by 2025.

Rising development pressures and the loss of open space can adversely affect not only ecosystem services and quality-of-life (Brown 2001; Platt 2004), but may also generate increased demands for services and the need for higher tax rates (Burchell and others 2005; Persky and Wiewel 1996). Indeed, sprawling and unplanned development tends to shift public funding from the maintenance of existing infrastructure to the creation of new infrastructure located at the metropolitan fringe (Goldman 2001). This reallocation may result in under-used capacity of existing infrastructure, and increasing costs for water-delivery and sewer infrastructure, roads, schools and emergency services (Colorado Public Interest Research Foundation 2002; Coyne 2003). In California, Proposition 13, which constrains local government’s ability to generate property tax revenues from existing development, provides a perverse incentive for communities to develop open spaces in order to expand the tax base (Goldman 2001).

Rising awareness of the social, economic and biophysical costs of unplanned, low-density development has led to a spate of “Smart Growth” development guidelines to assist communities in their planning. Smart growth principles range from the establishment of urban growth boundaries and transit-oriented designs, to mixed-use zoning and the levying of impact fees for new developments that capture and internalize public-sector costs (Smart Growth Network 2009).

Urban Growth Models

The location and pace of development-induced land conversion is influenced by a wide range of factors, including population growth, household size and income, the location of employment centers, existing infrastructure, land values and availability, public policies, overall economic conditions, and a host of site-specific features including access, slope, aspect, and drainage (Alberti 2008; Alig and others 2004). Using such factors as inputs, a wide and expanding range of urban growth models (UGM) have been developed (Irwin 2010). These models are rapidly improving in their ability to generate alternative future growth scenarios that can: (1) engage a broad range of stakeholders in the exploration of various town and regional planning issues; (2) enhance public understanding of the costs and benefits of alternative development pathways, including distributional effects; (3) anticipate future needs with respect to infrastructure and public services; and (4) design public policies that leverage the benefits of new growth while protecting community values and natural systems function (Baker and others 2004; Hopkins and Zapata 2007; McCloskey and others 2011; Steinitz and others 2003).

A growing body of literature has reviewed and assessed the status of UGMs (see, e.g., Agarwal and others 2001; Irwin 2010; Klosterman and Pettit 2005; Parker and others 2003; Verburg and others 2004; Wu and Silva 2010). General approaches include: (1) large-scale urban planning models like METROPILUS (Putnam and Shih-Liang 2001), SPARTACUS (Lautso 2003), TRANUS (de la Barra 2001) and UrbanSim (Waddell 2005) that can assess the regional impacts of population growth and transportation policies; (2) rule-based models such as CUF (Landis 2001) and What if? (Klosterman and others 2003) that estimate the relative suitability of lands for development without attempting to simulate the socioeconomic processes that drive growth; (3) state-change models such as CUF II and CURBA (Landis 2001) that calibrate statistical models to derive spatially-explicit land conversion probabilities based on development footprints at different points in time; and (4) cellular automata models such as SLEUTH (Clarke and others 1997) and DUEM (Battie and Xie 2005), which represent urban areas as a set of gridcells, each assigned a state condition and operating under a set of transition rules that model landscape change via a step-process across time that considers neighboring cells and other emergent properties.

A sampling of the literature reveals the richness of UGM approaches and applications. Notable examples include UrbanSim (Waddell 2005), a disaggregated model that includes data from individual households, jobs, and location choices to "microsimulate" changes in real estate and employment markets. UrbanSim has been continually refined and applied in Eugene-Springfield, Oregon; Honolulu, Hawaii; and Salt Lake City, Utah (Waddell 2005). State-change models, the approach used here, are largely built on Landis' (2001) pioneering CURBA work in California. Subsequent applications have addressed planning issues in the Mojave Desert Region of California (Gonzalez 2001; Hunter and others 2003) and Utah's rapidly urbanizing Wasatch Front (Lilieholm and others 2005). Like all modeling approaches, state-change models have advantages and disadvantages. Agarwal and others (2001) found that state-change models such as CURBA provided an increased understanding of the factors driving historic development, allowing for the projection of future growth patterns based on past influences under easily-derived futures scenarios. Spatial interaction was another benefit, where changes in one gridcell are able to influence the probability of urbanization in surrounding gridcells. Weaknesses include potential errors due to the misclassification of data at the gridcell level, as well as limitations from predicting future growth patterns based on past drivers of growth (Agarwal and others 2001).

Cellular automata (CA) models have found increasing application in recent years (see review by Sante and others 2010), and their capabilities have expanded greatly (see, e.g., Jantz and others 2010). For example, the SLEUTH model has been applied to the San Francisco Bay Area, Washington/Baltimore (Clarke and Gaydos 1998), and the broader Chesapeake Bay drainage (Jantz and others 2010). Agent-based models (ABM) have proliferated as well (Parker and others 2003; Irwin 2010), and artificial intelligence (AI) applications are gaining wider recognition and use (Wu and Silva 2010). In combination, CA, ABM, and AI offer promising opportunities for integrating modeling approaches across disciplines by exploring how individual decision-making at the gridcell level can transform landscapes and reveal emergent properties.

For example, one AI approach, Bayesian Belief Networks (BBN), has found application in modeling drivers of urban land use change and exploring stakeholder-derived alternative planning scenarios (Kocabas and Dragicevic 2007; Ma and others 2007; McCloskey and others 2011; Pourret and others 2008). BBNs are ideal for integrating expert knowledge and empirical data (Chow and Sadler 2010; Henriksen and others 2007; Marcot and others 2006), and are also easy to calibrate, validate, and update as new information becomes available (Smith and others 2007; Steventon 2008), making them a useful tool for organizing thinking, generating hypotheses, and creating and comparing alternatives.

Despite the proliferation of UGM approaches and applications, few comparative studies are found in the literature. Modeling efforts often occur at a rapid pace, in a state of continual evolution, with limited transparency and comprehension to others (Briassoulis 2008). Land use models are also often context-dependent, which makes comparison difficult. Efforts have been made, however, to compare models within the same project. For example, Park and others (2011) developed land suitability indices for South Korea using four approaches (i.e., frequency ratio, analytical hierarchy process, logistic regression, and artificial neural networks) and found that they all produced similar results. While modeling efforts improve each year, it is important to remember that despite rising sophistication, UGMs cannot predict with certainty the spatial distribution of future land uses (Ma and others 2007). But as Irwin (2010) notes:

> [T]he goal is not to predict the exact plots of land that will be developed, since such modeling accuracy simply isn’t possible. Instead, the goal is to understand how various causal factors influence the qualitative aspects of the observed land use pattern (e.g., the degree of contiguity, fragmentation, concentration, density of various land uses) and changes over time in these pattern measures at a spatially disaggregate scale of analysis.

Methods

Modeling Urban Growth

Gonzalez (2001) used satellite imagery from the early 1970s and early-to-mid 1990s to develop a logistic regression-based UGM to estimate the probability of future development for privately owned undeveloped hectares in the 7.4 million-ha California Mojave Desert (Hunter and others 2003). Logistic regression is a variant of traditional linear regression in which the dependent variable is dichotomous (i.e., either “1” or “0,” reflecting whether or not a predetermined condition is met), and the independent variables are continuous, discrete, or both (Cramer 2003; Hosmer and Lemeshow 2000; Proctor 1992). The process yields a model that, for a set of independent variables, results in predicted values which are continuous and range between 1 and 0. These values can be interpreted as the probability of an event occurring, with “0” being no chance of occurrence, and “1” being certainty of occurrence. The general form of the logistic model is:

$$\hat{P} = \frac{1}{1 + e - \left(\hat{\alpha} + \hat{\beta} x\right)}$$

where: $\hat{P}$ is the predicted probability of an event occurring; *e* is the base of the natural logarithm; $\hat{\alpha}$ is the intercept parameter estimate; $\hat{\beta}$ is the vector of slope parameter estimates; and x is the vector of explanatory variables.

Gonzalez (2001) based his UGM on the 91,431 ha of private lands that underwent urbanization in the California Mojave Desert over the roughly 20-year interval examined. The model was constructed using a procedure similar to that described by Landis (2001) using 1-ha gridcells as the unit of analysis. Based on a review of literature, six independent variables were believed *a priori* to influence whether or not a particular hectare of undeveloped private land would be developed between the 1970s and 1990s. NEWDEV is a binary variable with a value of 1 if the gridcell was newly developed and a value of 0 if the gridcell remained undeveloped; DEVDIST is each gridcell's distance to the nearest existing 1970 developed site (m); PRIMDIST is each gridcell's distance to the nearest primary road (m); SECDIST is each gridcell's distance to the nearest non-primary road (e.g., residential streets and secondary roads) (m); PCTDEV is the percent of development surrounding a gridcell; CITYCAT is the gridcell's location inside (1) or outside (0) a city boundary; and SLOPE is simply the gridcell's slope (percent).

In general, the probability of development for gridcells close to existing development and infrastructure was higher than that of gridcells more distant, while level gridcells were more likely to be developed than steeper gridcells, *ceteris paribus*.

Generating Values for the Dependent Variable

The process used to generate values for the dependent variable consisted of spatially identifying the gridcells that were converted from undeveloped to developed status (e.g., new development) over the study interval. Two sets of satellite data were acquired from the North American Landscape Characterization Data (NALC) program—one from the early 1970s and one from the early-to-mid 1990s (Gonzalez 2001). NALC duplicates are satellite-based digital imagery from the Landsat Multispectral Scanner (MSS). Nine scenes of MSS data provided complete coverage of the Region. Each scene was masked to isolate private lands in the study area, and then examined for each time period to identify urban/suburban development. Band combinations were displayed which accentuated vegetation from watered lawns and other landscaped areas and enhanced anthropogenic features from the natural brightness or darkness of the surrounding unaltered desert landscape.

Spatial pattern was also used to detect anthropogenic features such as houses, outbuilding complexes, and commercial and industrial development. In our Region, roads typically follow a grid system, and developed areas are typically cleared in regular geometric patterns that are easily discernible from natural landscape features such as arroyos, rock outcrops, and playas. Developed areas were identified and the perimeters digitized as polygons, which were subsequently converted to raster and assigned a value of “1” for developed areas, and “0” for non-developed areas. The final result was a data coverage that contained values of “1” for areas developed during the roughly 20-year study period, and “0” for undeveloped sites.

Areas newly developed between the 1970s and the 1990s were obtained by subtracting 1970s development from that of the 1990s using ARC/INFO. These binary values (“1” for newly developed, “0” for gridcells that remained undeveloped) provided the data for the dichotomous dependent variable in the logistic regression model. Analysis of the 1970s images revealed that development covered 33,294 ha, or only 2.2% of the Region’s 1,542,337 ha of private land (Gonzalez 2001). By the 1990s, development had increased to 124,725 ha and covered 8.1% of all private lands—an increase of 91,431 ha or 275%. This rapid conversion is consistent with demographic data showing that the Region’s incorporated municipalities grew from 115,000 residents in 1970, to over 450,000 by 1990—an increase of over 350% (Gonzalez 2001). Moreover, most new development occurred in the southwestern portion of the Region in major settlements nearest to the Los Angeles metropolitan area that are the focus of this study.

Modeling the Independent Variables

The next step was to calculate the values for each independent variable for each one-ha gridcell of private land in the study area (Gonzalez 2001). Each independent variable was represented by an individual GIS data layer. The distances from each gridcell center to 1970s development, primary roads, and non-primary roads were measured with Euclidean distance functions of GRID (ESRI Inc. 1994). PCTDEV was estimated using square moving analysis windows with the number of surrounding cells set at 400 (i.e., a 20 cell x 20 cell square). This window size resulted in the best contribution to the model (as determined by R^2_{adj}) compared to other sizes examined (i.e., 3 x 3, 10 x 10, 50 x 50, and 100 x 100). CITYCAT was a categorical variable that was assigned a value of 1 for each gridcell located within a municipal boundary; otherwise the cell was assigned a value of 0. SLOPE was expressed in percent using ARCView commands. Digital elevation models (DEMs) were obtained from the California Spatial Information Library (CASIL). These DEMs were initially in a 30-m grid but were resampled to a 100-m grid for consistency with previous research. City boundaries were obtained from CASIL. Primary and secondary road geospatial data were obtained from U.S. Census Bureau TIGER files via CASIL.

Model-fitting and Evaluation

The logistic model was fit using stepwise regression (SAS Institute Inc. 1995), where gridcells, both newly developed and undeveloped, were associated with the six independent variables described above (Gonzalez 2001). The goodness-of-fit for each model was assessed using the max-rescaled R^2 (Nagelkerke 1991). The model ultimately selected was the simplest in terms of the number of independent variables used and had the best fit as indicated by R^2 (SAS Institute Inc. 1995)

Table 4 shows that each independent variable was a highly significant ($P<0.0001$) predictor of new development using the Wald Statistic. The model suggests that proximity to existing infrastructure is far more important than natural features in explaining the location of new development. Indeed, the order of importance in which the independent variables entered the model was PCTDEV, CITYCAT, PRIMDIST, DEVDIST, SECDIST, and SLOPE.

Several measures of association of predicted probabilities and observed responses were used to evaluate the model (Table 5). The dataset included 91,431 observations that were assigned a response value of "1" (i.e., the number of newly developed ha), and 1,417,612 observations with a response value of "0" (i.e., the number of undeveloped ha). These data create a total of (91,431) x (1,417,612) = 129,613,682,772 pairs of observations with different response values (Table 5). Of this total, 87.1% were concordant, 12.5% were discordant, and only 0.4% were tied (Table 5) (Gonzalez 2001). Table 5 shows four rank correlation indexes, which were estimated from the number of concordant and discordant pairs of observations. For these indices, the higher the value, the better the model's predictive ability (SAS Institute Inc. 1995).

The model's R_{adj}^2 value of 0.32 is relatively low, indicating that the independent variables had a limited ability to explain the variation of new development between the 1970s and 1990s (Table 5). In similar studies, Nelson and Hellerstein (1997) found R^2 values ranged from 0.23 (McFadden R^2), to 0.54 (Maddala R^2) and 0.56 (Cragg–Uhler R^2). Finally, a jackknife procedure indicated that 93% of predictions were correct, which suggests that although the variables included in the model had a low ability to explain the variation of new development based on R_{adj}^2, the model overall was effective in predicting new development in the Region during the period examined (Gonzalez 2001).

Projecting Future Development at the Community Scale

Given the demographic conditions and trends described above, as Hispanics comprise an increasingly larger share of the state's and county's population, the overall average family and household sizes are likely to increase (Myers 2001). As a result, the average number of persons per hectare may also increase, resulting in significantly higher settlement densities and a potentially smaller area of future development. Yet because population projections do not consider ethnicity at the sub-county level (Matyas 2004), forecasting the Hispanic and White non-Hispanic composition of new residents in our focus communities is difficult.

For example, newly released 2010 Census data revealed that some of our focus communities already had higher populations by 2010 than they were projected to have by 2020 under the SCAG (2004) projections. As a result, a "modified growth" between 2010 and 2020 was calculated for each community (Table 2). This modified growth was determined by averaging two different values for estimated population growth between 2010 and 2020. The first value was determined by assuming that the rate of growth for each community would be the same between 2010 and 2020 as it was between 2000 and 2010—that is, if a community grew by 70% between 2000 and 2010, it would grow by 70% between 2010 and 2020. The second value was determined by assuming that the populations of each community would grow at the same rate that was initially projected by SCAG (2004)—that is, if the SCAG projections estimated that a community would grow by 40% between 2010 and 2020, then the actual 2010 population was assumed to grow by 40% to determine the estimated population in 2020. These two values were then averaged for each community to determine the modified growth in Table 2. While this may be a coarse method for readjusting population projections, it does recognize that the initial projections for growth were inaccurate.

Forecasting Ethnic Composition at the Community-Level

Mean household and family size varies for each of the seven Mojave communities, although in all cases the sizes are larger for Hispanics than for White non-Hispanics (Table 6). Adelanto has the highest mean household and family sizes for Hispanics—4.08 and 4.40 persons, respectively. Yucca Valley has the lowest mean household size for Hispanics (2.69), while Twentynine Palms has the lowest mean family size (3.37). For White non-Hispanics, Adelanto has the highest mean household and mean family size (3.00 and 3.41, respectively), with Yucca Valley having the lowest (2.30 and 2.85, respectively). Percentages offer another means of comparison between the seven communities. For mean household size, the differences range from Hispanic households being 17% larger than White non-Hispanic households in Yucca Valley, to 39% larger in Hesperia. Hispanic women in California have a total fertility rate of 2.8, while the total fertility rate for women in California is 2.2, both of which exceed the replacement rate of 2.1 (Hill and Johnson 2002).

Several approaches were considered when attempting to forecast future ethnic composition in our focus communities. One approach is to simply assume that community ethnic population growth mirrors ethnic composition at the county level. Unfortunately, given the variation in demographic growth between 1990 and 2000—when Hispanics accounted for over one-half of the new population in five of the seven communities and roughly one-third of the new growth in the other two—it is doubtful that future ethnic composition will mirror county-wide patterns. And any divergence from county-level patterns would likely be amplified by differences in fertility rates between White non-Hispanics (1.62) and all categories of Hispanics (ranging from a high of 2.80 for White Hispanics to 1.68 for American Indian Hispanics).

In the absence of finer-scale population projections, the approach adopted here was to simply hold constant the current percent ethnic composition of each community. Hence, as new residents are added to communities, the ethnic mix observed during the 1990-2000 Census period is maintained—an approach which better reflects the current ethnic composition of each community.

Determining Future Settlement Densities to Project Community-Level Development

Hunter and others (2003) used the development probabilities described here to project future development by allocating the projected population growth on the landscape at a historic settlement density of 3.76 persons/ha for private lands across the entire 73,989 km^2 Mojave Desert area. This settlement density was determined by dividing the 469,697 residents living in the Mojave study area in 1990 by the 124,725 ha that were classified as developed at that time—a broad measure of the Region's development "footprint" that includes residential areas, roads, schools, parks, industrial sites and businesses.

Unfortunately, this approach does not recognize the temporal and geographical variations in the development density of Mojave communities. An improved method, developed here, is to divide the total population of each of the seven communities in 2001 by the existing hectares of development at that time. As shown in Table 7, the resulting "existing" densities represent an increase over the "historic" level of 3.76 persons/ha reported by Hunter and others (2003).

Another limitation of projecting future growth using a density of 3.76 persons/ha is that it is unlikely to reflect socio-economic trends over time and within communities since it simply averages all variation in settlement due to ethnicity, income or wealth. Instead, a "demographic futures" scenario would recognize that different ethnic groups have different household sizes, as well as varying domestic habits (Borjas 1994; Hill and Johnson 2002). For example, as shown above, considerable differences in family size and household size exist between the Hispanic and the White non-Hispanic components of the population. In San Bernardino County, for example, the average family size is 3.58 persons (U.S. Census Bureau 2004)—roughly the same as the per/ha settlement density used by Gonzalez (2001). However, the average family size for White non-Hispanics is 3.12 persons, while the average family size for Hispanics is 4.26 persons—a difference of 37%. Likewise, the average household size for White non-Hispanics is 2.63 persons, while the average household size for Hispanics is 4.09 persons, a difference of 55%.

As Hispanics form an increasingly larger percentage of the population in the Region, the overall average family size and average household sizes will likely increase (Myers 2001). Correspondingly, the average number of persons/ha of developed land will likely also increase, resulting in significantly higher settlement densities and a smaller area of open space converted to future development. Table 7 shows the demographic futures densities based on the demographic growth characteristics of each community between 1990 and 2001. Populations for 1990 were taken from the actual 1990 U.S. Census; populations for 2001 were taken from population estimates for that year taken from Census Bureau revised estimates released in September 2010 (U.S. Census Bureau 2011).

Spatially Allocating Households at the Community Scale

Gonzalez (2001) and Hunter and others (2003) recognized just two land cover classes for the Mojave region, developed and undeveloped. Here, we used finer-scale GIS data for San Bernardino County provided by SCAG, which divides the Region into approximately 100 land use classifications. These classifications were grouped into the four general land use categories found in Table 8. Using Arc-Map (Minami 2000), SCAG land use data from 1990 and 2001 were analyzed. Summaries of the number of hectares for each of the selected land use groupings in 1990 and 2001, and the changes that occurred in the 11-year period for each of the seven communities, are found in Table 8.

These four categories formed the within-community occupied land that was considered unavailable for future development or open space preservation. A “vacant” condition was assigned to all other lands, public and private, that were not in the four categories in Table 8. Note that a parcel of land that is considered vacant does not necessarily lack evidence of development or urbanization and, in fact, may have been considered “developed” in previous studies. It does, however, fall into a category that would allow it to be either preserved as future open space or developed for residential, commercial, or industrial uses. These vacant lands included: (1) open, undeveloped land surrounded by development; and (2) cropland, pastureland, orchards, vineyards, and other agricultural lands.

Because no reliable methodology exists to estimate settlement densities based on demographic variables, the best available estimates of changes in settlement densities due to the sharp expected increase in the Hispanic population of the seven communities may be reflected in the changes in persons/ha between 1990 and 2001. During this period, the Hispanic population increased in all seven communities in raw numbers as well as in percentage, a trend which is projected to continue. During the period 1990 to 2001, settlement density increased in all communities except Barstow. This is largely due to the fact that 85% of the new development in Barstow during that period was in commercial and industrial categories of land use change, reinforcing Barstow's position as a retail, commercial, and transportation service center. In comparison, only 9% of new development in Barstow was in residential categories. New residential development in the other six communities ranged from a low of 46% in Adelanto to a high of 87% in Victorville; new commercial and industrial development in the other six communities ranged from a low of 12% in Apple Valley to a high of 54% in Adelanto.

Once the probability of future development was determined for the Region as a whole, each community was clipped to allow detailed growth projections. This process was followed because, for example, roads or existing development located outside of municipal boundaries would affect development probabilities within the municipality. This raster file was then converted to a shapefile depicting the development probability of each gridcell in the seven communities. Areas of development present in 2001 were then erased from the shapefile, leaving only non-developed hectares. Projected population growth was allocated for each of the seven communities at all three settlement densities—"historic," "existing," and "demographic futures"—beginning with the gridcells that had the highest probability of development and continuing until the projected population increase, or "modified growth," was exhausted.

Results and Discussion

Using the process described above, we projected future settlement patterns for each of the seven Mojave Desert focus communities using the modified growth values shown in Table 2 for three settlement densities: (1) an "historic" scenario reported in earlier research that uses a Mojave-wide average settlement density of 3.76 persons/ ha; (2) an "existing" scenario based on community-specific settlement densities as of 2001; and (3) a "demographic futures" scenario based on community-specific settlement densities that explicitly model the Region's changing ethnicity (Figs. 3, 4; Table 9).

As shown at the bottom of Table 9, the total developed area across our focus communities comprised 34% of the area within 2001 municipal boundaries. Developed area varied by town, with Twentynine Palms just 12% developed, and Hesperia 60% developed.

As expected, an inverse relationship predominated between assumptions in area-based settlement densities and the number of acres of undeveloped or vacant land converted to development (Table 9). In all communities except Barstow, the area developed decreases as one moves from the "historic" settlement density of 3.76 persons/ha, to the "existing" and then "demographic futures" settlement densities. For example, in Adelanto, all of the community's 2001 incorporated area would be developed under the "historic" settlement density scenario, while just 37% would be developed under the demographic futures. Note that communities experiencing complete "build-out" are revealed in Table 9 by negative values for 2020 projected undeveloped land—these include Adelanto, Hesperia, and Victorville. Also note that region-wide, focus communities are expected to increase from 34% developed in 2011, to 47, 60, or 100% by 2020 (see bottom of Table 9).

Community impacts resulting from the settlement densities examined here ranged widely. The broadest range across the density scenarios is exhibited by Adelanto, which transitions from 16% developed in

2001 to 100, 43, or 37% developed under the “historic,” “existing,” and “demographic futures” scenarios, respectively (Table 9). In contrast, Twentynine Palms transitions from 12% developed in 2001, to 30, 16, and 13%, respectively—values that are lower than those for the other communities perhaps due to the community’s distance from interstate highway transportation routes and relative isolation from the Los Angeles metropolitan area. Hesperia, already 60% developed as of 2001, faces complete build-out under two of the three density scenarios (Table 9).

Projecting future populations under our three settlement densities resulted in a range of future development “foot-prints” for each community. Figures 3 and 4 show spatial development footprints for 2001 and projected developed areas for 2020 for Apple Valley and Twentynine Palms. For Apple Valley (Fig. 3), all three depictions of future development show the UGM’s propensity to locate new development near existing development and roads. Comparing Fig. 3 with Table 9 reveals the strong influence of higher settlement densities, with 2020 developed area falling from 79% under the “historic” scenario to 47% under the “demographic futures.” A similar effect is seen in Fig. 4 for the community of Twentynine Palms, where new development is barely noticeable under the demographic scenario, while far more significant under the “historic” trend.

The spatial depictions of 2001 and 2020 development shown in Figs. 3 and 4 should be interpreted with caution. For example, it is important to note that the 2001 developed areas shown in grey actually include designated open spaces (Table 8). Indeed, Apple Valley and Twentynine Palms contained roughly 150 and 75 ha of designated open space, respectively, in 2001. Moreover, between 1990 and 2001 the area of designated open space grew by 78 and 44%, respectively, for the two communities. Region-wide, designated within-community open space grew from 452 ha in 1990, to 579 ha in 2001, an increase of 28% (Table 8). In short, what appears to be the total elimination of open space—especially for undeveloped lands within the urbanized 2001 core of these communities—actually includes designated open space lands.

The 28% increase in Region-wide designated open space between 1990 and 2001 raises another issue. Indeed, as communities grow, they typically become more proactive in identifying and designating new parks and open spaces—a community response we have not modeled here. In fact, it is likely that setting-aside dedicated open space will accelerate as “smart growth” planning tools such as cluster zoning and mixed-use become more accepted by town officials, builders, and residents. These tools can be highly effective in preserving open spaces, and may also be used to preserve newly created open spaces resulting from more-dense redevelopment within the urban core (Platt 2004). In fact, many older neighborhoods developed under earlier municipal plans gave little consideration to open space preservation (Press 2002). Finally, for communities bordering the Region’s military installations, the need to conserve “compatible use buffers” may present opportunities to protect both resident quality-of-life and the long-term viability of local bases (Knott and Natoli 2004). A similar case could be made for Twentynine Palms along its southern border with Joshua Tree National Park (Stein and others 2007). As development fuels efforts to conserve remaining open spaces, opportunities could improve for the protection of open space that serve multiple needs—ecological, social, and economic (Cronan and others 2010).

As with all modeling efforts, caveats are warranted. First, our method of allocating future population projections across our focus communities did not allow for “excess population” in a built-out community to be allocated to another community that had existing vacant land. Using Hesperia as an example, persons in excess of the maximum build-out at existing density were not “re-settled” in the surrounding communities of Adelanto, Apple Valley, Victorville, or elsewhere, because doing so would have introduced a source of additional growth not accounted for in the projections.

In practice, fast-growing communities often annex surrounding lands as an effective means of providing additional space. Such a practice would likely emerge across the study region, although some limitations would apply. For example, Adelanto, Apple Valley, Hesperia and Victorville share common boundaries, which limit possible expansion of those communities to areas beyond the four-community core. Also, some communities are further restricted by the proximity of public lands. Apple Valley's northern boundary and much of Barstow exhibit such constraints. Most constrained, however, is Twentynine Palms, which is sandwiched between Joshua Tree National Park, the Marine Corps Air Ground Combat Center, and BLM lands.

As described earlier, the UGM represents a state-change model where new development between two points in time is used to derive a logistic regression equation, which is then used to calculate the probability of future development on vacant lands based on features such as distance to roads and existing development. While such models can be effective in explaining past development and projecting future changes, they are somewhat static because they assume development drivers active between the two points in time are unchanged over the projection period. For example, the approach is limited by its inability to consider the construction of new roads, or even the upgrading of a secondary road to primary status. Also problematic is the rigidity of municipal boundaries and the inability to model the impacts of land scarcity on market prices and more space-efficient development patterns. In short, communities such as Adelanto grow, they will improve and expand road networks, annex surroundings lands, and experience rising land values that will moderate land-extensive development. Communities undergoing such changes can also accommodate new growth by redeveloping existing developed land. This, too, has not been considered in the analysis.

Finally, as we write in late 2011, the lingering effects of the 2008 financial crisis are still evident in California and across the nation. The historic collapse of housing starts and decline in housing prices provides an important lesson for anyone who assesses the past as a way of predicting the future. While population increases in the study area are likely to continue, the character of new development will probably be altered for a decade or more as strained household budgets cause families to locate in more affordable areas and housing types (e.g., multi-family dwellings and multi-generational living arrangements). National, state and municipal budgets will likely continue to be strained as well, further dampening the expansion of infrastructure like sewers, roads, and schools that is necessary to support new growth in residential development. One factor that may operate in the opposite direction, however, is that as Hispanic populations increase and become more acculturated to U.S. life, income and housing preferences may grow to be more reflective of overall lifestyles.

Conclusion

State agencies in California are required to use the projections provided by the Department of Finance when, for example, planning for infrastructure construction and maintenance (Hill and Johnson 2002). Often neglected is the consideration of alternative settlement densities stemming from ethnically-derived household size and housing preferences—an important consideration in many fast-growing regions of California. Indeed, non-econometric models tend to generalize ethnic compositions and therefore densities, conditions that can significantly affect the extent of future development. Dividing a population into discrete categories based on projected demographic futures is one method of refining the data used to estimate settlement densities and the associated urban development. This sort of “fine-tuning” may provide a more accurate assessment of how a geographic region is settled by incorporating variables that have heretofore been largely unaccounted for in UGM efforts.

Here we used a spatially explicit, logistic regression-based UGM to explore how community-specific demographic trends and population projections interact to affect future development patterns and the loss of open space. Within our seven focus communities, considering differences in settlement densities and housing preferences between Hispanics and White non-Hispanics led to significantly smaller future development footprints. For example, projecting settlement using a demographic futures scenario resulted in 53% (39,077 ha) of the study area remaining undeveloped by the year 2020, while a scenario using existing densities resulted in 40% (29,460 ha) of the study area remaining undeveloped, and a scenario incorporating historic research resulted in a deficit of developable lands.

The modeling of demographic futures is especially suited for fast-growing regions experiencing clear socio-demographic characteristics and trends. These conditions are found in many multi-ethnic urbanizing areas, areas that have become an important focus for scholars studying landscape and urban change, and simulation modeling. As demonstrated here, the modeling of demographic futures expands urban and environment-related management realms. In doing so, it provides an important perspective in understanding the future of open space planning in light of urban dynamics in multi-ethnic regions, which is an area of growing interest for today’s urban planners.

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Fig. 1 Greater Mojave bioregion in California studied by Gonzalez (2001)

Fig. 2 Communities and land ownership in the Mojave Desert Region of San Bernardino County, CA

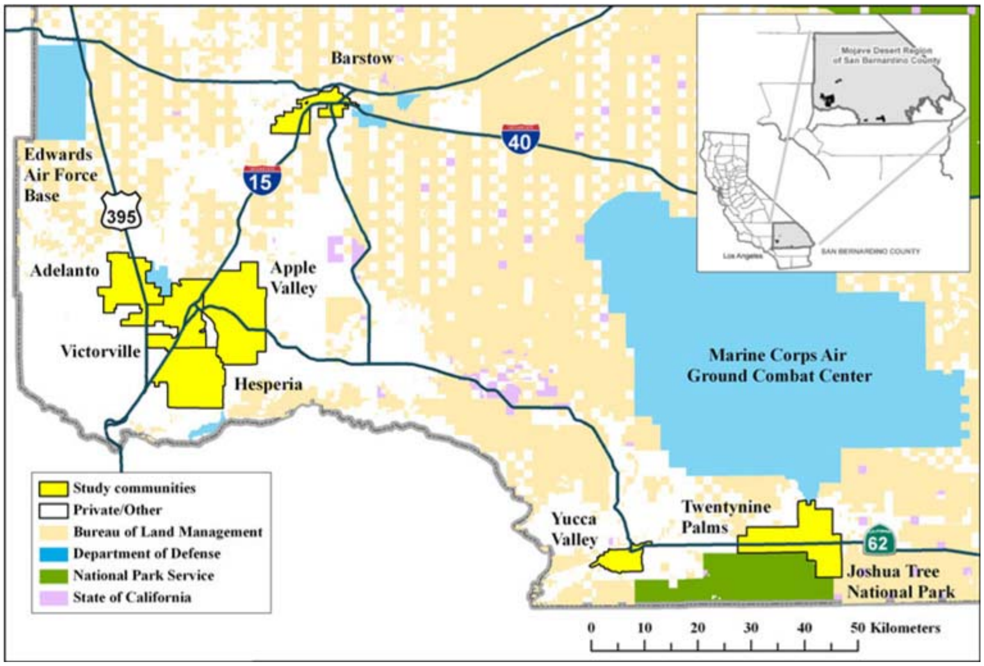

Table 1 Projected population growth in thousands by White non-Hispanic and Hispanic ethnicity for California and San Bernardino County

	California		San Bernardino County	
	Total	% of total	Total	% of total
2000 U.S. Census Bureau results[a]	33,872		1,709	
White non-Hispanic	15,817	46.7	752	44.0
Hispanic	10,967	32.4	669	39.2
2010 U.S. Census Bureau results[a]	37,254		2,035	
White non-Hispanic	14,956	40.1	678	33.3
Hispanic	14,013	37.6	1,001	49.2
2020 population projections[b]	45,449		2,747	
White non-Hispanic	18,123	39.9	1,016	37.0
Hispanic	17,778	39.1	1,258	45.8
2030 population projections[b]	51,869		3,426	
White non-Hispanic	18,222	35.1	1,065	31.1
Hispanic	22,547	43.5	1,761	51.4
2040 population projections[b]	58,731		4,202	
White non-Hispanic	18,005	30.7	1,093	26.0
Hispanic	28,091	47.8	2,375	56.5

[a] *Source* U.S. Census Bureau (2011)

[b] *Source* California Department of Finance (2002)

Table 2 Population for focus area communities in the Mojave Desert Region

Location	US Census Bureau[a]				SCAG Projections total population[b]	Modified growth[c]
	1990	2000	2001[d]	2010	2020	2010–2020
Adelanto	8,517	18,130	18,399	31,765	30,980	31,515
Apple Valley	46,079	54,239	55,967	69,135	71,406	27,079
Barstow	21,472	21,119	22,805	22,639	34,528	3,470
Hesperia	50,418	62,582	64,394	90,173	116,536	60,888
Twentynine Palms	11,821	14,764	27,500	25,048	22,473	9,188
Victorville	40,674	64,029	67,771	115,903	125,700	116,698
Yucca Valley	13,701	16,865	17,286	20,700	22,793	6,741
Totals	192,682	251,728	274,122	375,363	424,416	255,579

[a] *Source* U.S. Census Bureau (2011)

[b] *Source* SCAG (2004)

[c] Represents the projected population growth between 2010 and 2020

[d] Estimated population, U.S. Census Bureau (2011)

Table 3 Change in ethnic demographics in the Mojave Desert Region, 1990–2000

Location	Year	Total	Hispanic (%)	White non-Hispanic (%)	African-American (%)	Other (%)
Adelanto	1990	8,517	1,475 (17)	5,430 (64)	1,156 (14)	456 (5)
	2000	18,130	8,299 (46)	6,616 (36)	2,305 (13)	910 (5)
Apple Valley	1990	46,079	5,813 (13)	37,059 (80)	1,727 (4)	1,480 (3)
	2000	54,239	10,067 (19)	36,710 (68)	4,141 (8)	3,321 (6)
Barstow	1990	21,472	6,726 (31)	11,550 (54)	2,120 (10)	1,076 (5)
	2000	21,119	7,708 (36)	9,163 (43)	2,349 (11)	1,899 (9)
Hesperia	1990	50,418	9,573 (19)	38,612 (77)	1,183 (2)	1,050 (2)
	2000	62,582	18,400 (29)	39,057 (62)	2,388 (4)	2,737 (4)
Twentynine Palms	1990	11,821	1,219 (10)	8,959 (76)	998 (8)	645 (5)
	2000	14,764	2,202 (15)	9,548 (65)	1,313 (9)	1,701 (12)
Victorville	1990	40,674	9,353 (23)	25,827 (63)	3,750 (9)	1,744 (4)
	2000	64,029	21,426 (33)	30,382 (47)	7,431 (12)	4,790 (7)
Yucca Valley	1990	13,701	976 (7)	12,229 (89)	191 (1)	305 (2)
	2000	16,865	1,922 (11)	13,829 (82)	350 (2)	764 (5)
Total	1990	192,682	35,135 (18)	139,666 (72)	11,125 (6)	6,756 (4)
	2000	251,728	70,024 (28)	145,305 (58)	20,277 (8)	16,122 (6)
Change	Number	59,046	34,889	5,639	9,152	9,366
	Percent	31	99	4	82	139

Source U.S. Census Bureau (2004)

Table 4 Logistic regression results for the development probability model (from Gonzalez 2001)

Independent variable	Coefficient	Standard error	Wald (Pr > Chi-square)	Significance (Pr > Chi-square)	Odds ratio
Intercept	−2.20830	0.01410	24,473.7125	<0.0001	–
PCTDEV	5.43690	0.04810	12,790.8440	<0.0001	229.727
SLOPE	−0.04850	0.00186	681.7802	<0.0001	0.953
DEVDIST	−0.00003	4.317E−7	5,608.7175	<0.0001	1.000
CITYCAT	0.92880	0.00880	11,133.9864	<0.0001	2.532
SECDIST	−0.00382	0.000031	15,098.4040	<0.0001	0.996
PRIMDIST	−0.00013	1.136E−6	12,587.8025	<0.0001	1.000

Table 5 Measures of association of predicted probabilities and observed responses, and rank correlation indexes (Gonzalez 2001)

Measures of association	Observed responses	Correlation indexes	Rank
Pairs	129,613,682,772	Somer's ID	0.746
Percent concordant	87.1	Gamma	0.749
Percent discordant	12.5	Tau-a	0.085
Percent tie	0.4	c	0.873
R^2_{adj}	0.32	–	–

Table 6 Mean household and family sizes for Hispanics, White non-Hispanics, and overall, 2000

Location	Mean household size			Mean family size		
	Hispanic	White non-Hispanic	Overall	Hispanic	White non-Hispanic	Overall
Adelanto	4.08	3.00	3.53	4.40	3.41	3.89
Apple Valley	3.60	2.72	2.90	3.86	3.10	3.27
Barstow	3.11	2.35	2.71	3.56	2.98	3.27
Hesperia	3.93	2.83	3.12	4.11	3.22	3.47
Twentynine Palms	2.99	2.52	2.60	3.37	3.07	3.12
Victorville	3.61	2.72	3.03	3.93	3.17	3.47
Yucca Valley	2.69	2.30	2.38	3.39	2.85	2.94
San Bernardino Co.	4.09	2.63	3.15	4.26	3.12	3.58
California	4.06	2.38	2.87	4.27	2.95	3.43
United States	3.62	2.43	2.59	3.93	2.97	3.14

Source U.S. Census Bureau (2004)

Table 7 Persons per developed hectare in 1990, between 1990 and 2001 (demographic futures), and in 2001 (existing)

Location	Persons per developed hectare			Percent change between 1990 and 2001
	1990	1990–2001	2001	
Adelanto	9.6	15.4	12.0	25.0
Apple Valley	7.9	14.9	8.6	8.9
Barstow	13.9	6.4	13.0	(6.5)
Hesperia	7.4	19.6	8.6	16.2
Twentynine Palms	7.5	116.7	16.0	113.3
Victorville	10.2	60.5	15.3	50.0
Yucca Valley	8.6	48.8	10.4	20.9
All communities	8.7	28.2	10.9	25.3

Table 8 Area within various land use categories, 1990 and 2001

Location	Land use category	Occupied ha		Change	
		1990	2001	Ha	Percent
Adelanto	Designated open space	10.4	11.5	1.1	10.6
	Residential	282.3	577.1	294.8	104.4
	Commercial/industrial	598.0	943.8	345.8	57.8
	Other developed	0	0	0	0
	Total	890.7	1532.4	641.7	72.0
Apple Valley	Designated open space	83.9	149.6	65.7	78.3
	Residential	5034.4	5553.0	518.6	10.3
	Commercial/industrial	719.0	801.3	82.3	11.4
	Other developed	17.6	15.7	(1.9)	(11.0)
	Total	5854.9	6519.6	664.7	11.4
Barstow	Designated open space	43.3	54.8	11.5	26.6
	Residential	689.2	708.2	19.0	2.8
	Commercial/industrial	813.0	990.2	177.2	21.8
	Other developed	0	0	0	0
	Total	1545.5	1753.2	207.7	78.3
Hesperia	Designated open space	84.2	97.1	12.9	10.3
	Residential	5700.6	6246.0	545.4	9.6
	Commercial/industrial	1015.1	1171.4	156.3	15.4
	Other developed	4.4	4.4	0	0
	Total	6804.3	7518.9	714.6	10.5
Twentynine Palms	Designated open space	50.9	73.4	22.5	44.2
	Residential	1283.9	1370.2	86.3	6.7
	Commercial/industrial	248.6	274.2	25.6	10.3
	Other developed	0	0	0	0
	Total	1583.4	1717.8	134.4	8.5
Victorville	Designated open space	125.5	134.6	9.1	7.3
	Residential	2135.8	2524.8	389.0	18.2
	Commercial/industrial	1683.2	1748.3	65.1	3.9
	Other developed	26.4	11.4	(15.0)	(56.8)
	Total	3970.9	4419.1	448.2	11.3
Yucca Valley	Designated open space	54.0	58.4	4.4	8.1
	Residential	1271.5	1314.1	42.6	3.4
	Commercial/industrial	259.2	285.7	26.5	10.2
	Other developed	0	0	0	0
	Total	1584.7	1658.2	73.5	4.6
All communities	Designated open space	452.2	579.4	127.2	28.1
	Residential	16397.7	18293.4	1895.7	11.6
	Commercial/industrial	5336.1	6214.9	878.8	16.5
	Other developed	48.4	31.5	(16.9)	(34.9)
	Total	22234.4	25119.2	2884.8	13.0

Source Raw geospatial data provided by the Southern California Association of Governments

Fig. 3 Settlement based on historic trend, existing trend, and demographic futures for Apple Valley

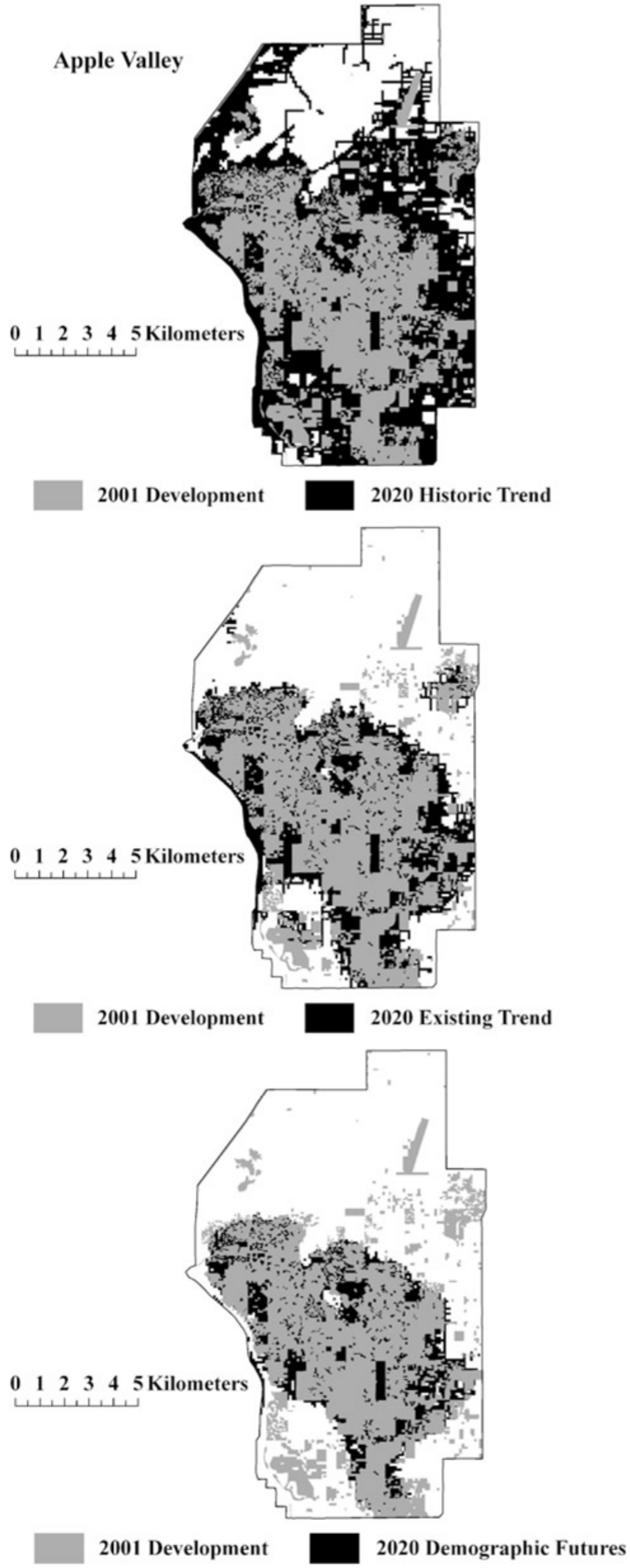

Fig. 3 Settlement based on historic trend, existing trend, and demographic futures for Apple Valley

Fig. 4 Settlement based on historic trend, existing trend, and demographic futures for Twentynine Palms

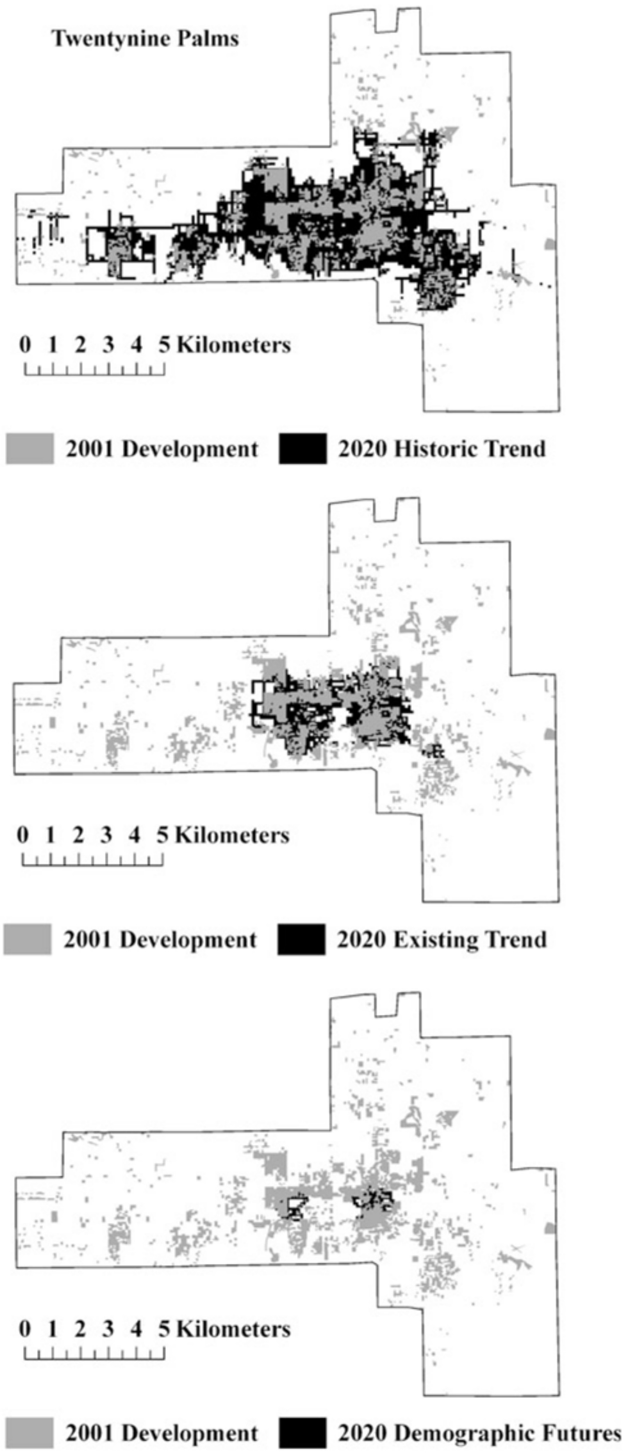

Fig. 4 Settlement based on historic trend, existing trend, and demographic futures for Twentynine Palms

Table 9 Projected area and percentages of developed and vacant land under the "historic," "existing," and "demographic futures" settlement densities (ha)

Location	Total ha	2001, actual developed ha (and %)	2020, projected developed ha	2020, projected vacant ha	2020, projected % developed
Adelanto	9558	1532.4 (16%)			
Historic[a]			9913.9	(355.9)	100[b]
Existing			4157.2	5400.8	43
Demographic futures			3578.8	5979.2	37
Apple Valley	17404	6519.6 (37%)			
Historic[a]			13721.6	3682.4	79
Existing			9674.1	7729.9	56
Demographic futures			8340.0	9064.0	47
Barstow	5961	1753.2 (29%)			
Historic[a]			2676.1	3284.9	45
Existing			2020.0	3941.0	34
Demographic futures			2293.9	3667.1	38
Hesperia	12513	7518.9 (60%)			
Historic[a]			23712.6	(11199.6)	100
Existing			14628.5	(2115.5)	100
Demographic futures			10632.2	1880.8	84
Twentynine Palms	13999	1717.8 (12%)			
Historic[a]			4161.5	9837.5	30
Existing			2291.8	11707.2	16
Demographic futures			1796.6	12202.4	13
Victorville	10838	4419.1 (41%)			
Historic[a]			32754.6	(21916.6)	100
Existing			9327.3	1510.7	86
Demographic futures			6349.4	4488.6	59
Yucca Valley	3591	1658.2 (18%)			
Historic[a]			3450.9	140.1	96
Existing			2304.8	1286.2	64
Demographic futures			1796.6	1794.6	50
All communities	73864	25119.2 (34%)			
Historic[a]			90391.2	(16527.2)	100
Existing			44403.7	29460.3	60
Demographic futures			*34787.5*	39076.7	47

[a] *Source* Gonzalez (2001)

[b] 100% of land developed indicates that no vacant land remains