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To link to this article: https://doi.org/10.1080/24694452.2021.1947769

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Published online: 27 Sep 2021.

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Modeling Education Deserts for Veterans and Military Families in the Southern United States

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Despite billions of dollars invested in educational benefits for veterans and active-duty military families under the U.S. Post-9/11 GI Bill, many prospective students are not forging pathways through public institutions of higher education, and funding is disproportionately spent on for-profit colleges. To reveal patterns of lack of access and opportunity, we propose a novel, robust analysis tailored to the situation of veterans and military families in the southern United States. This methodology delineates education deserts using fuzzy algorithms and multivariate spatial analysis to move beyond simple "hotspot" identification of distance from university locations. Results and comparisons of four models confirm different patterns for veterans versus nonveterans and show dynamic regional changes from 2005 through 2017 that reflect shifting demographics, economics, and educational offerings. These insights could inform a roadmap for outreach that accounts for shifting education deserts and potentially workforce opportunities through geographic analysis. This approach represents a potential first step for academic actors, especially in the public sector, who play a role in advancing science, technology, engineering, and math; geography; and geographic information systems to enable veteran and military families to better achieve equitable rates of educational attainment. Key Words: education deserts, fuzzy analysis, STEM, veterans.

Many veterans and military families who transition to higher education or workforce pathways find it challenging to translate the knowledge, skills, and experience they acquired during service to academic or civilian settings (Simpson and Armstrong 2009; Danish and Antonides 2013; Mobley et al. 2017). Yet many returning veterans have significant expertise—including within science, technology, engineering, and math (STEM) fields and geography, mapping, and geospatial technologies, as well as place-based knowledge—because of their unique functions and service assignments. Such skills and perspectives are useful for location-aware industries, citizen science, humanitarian support, and public services. Moreover, veterans and military families might be an overlooked source of new, diverse student and workforce talent, including from among traditionally underrepresented groups in STEM fields, such as Black and Hispanic, first-generation, and disabled populations.

Aligning the transition needs of veterans with the needs of programs seeking new, diverse talent entails essential geographic considerations. Military bases and veteran communities are sometimes concentrated in certain areas that disproportionately lack opportunities to higher degree pathways and transitional civil jobs. Connecting the dots will first require better understanding of the landscape of higher education offerings and job opportunities relative to the footprint of veterans and military families’ locations and contexts (Solís and Miyares 2014). This study aims to map out these patterns for the southern United States, where significant numbers of underrepresented minority veterans reside. In doing so, we suggest a way to conceptualize what we call education deserts, areas that are characterized by multiple factors related to lack of access to higher education and related workforce pathways for a particular community, which in turn indicate regions suitable for development of new, tailored programmatic offerings.

First, we will present a rationale for this question through an overview of the context of federally funded education benefits available to veteran students and their families, highlighting key geographic aspects of how such resources relate to the location of the beneficiary, how they are not race or gender neutral, and that they result in skewed allocations to...
the for-profit education sector. Next, we lay out a conceptual framework that is inspired by ideas from sociological life course theory to include geographic concepts from education literature, to justify the case for a multivariate spatial model capable of describing this landscape, which will ultimately serve as the background context for future studies of individual pathways. We then provide methodological details for a novel geospatial approach built on comparative suitability analysis for our study area of interest. We implement fuzzy logic to understand what we characterize as "deserts" and opportunities for education, as well as employment. Subsequent sections of the article explain results for veteran and military communities compared to nonveterans’ access to higher education and the civilian workforce between 2005 and 2017 in the southern United States. The model confirms the presence or absence of education deserts that mirror employment patterns, validated with internal error measures and qualitative information. From these findings, we suggest that university geography departments and employers of geographers and GIScientists could potentially improve outreach, engagement, and inclusion activities. We discuss some limitations and implications in terms of a practical design for STEM and geography engagement that is context-aware for veterans, while pointing to areas needing future research.

The Access Context of Veterans’ Education Benefits

Federal spending on veterans’ benefits provides military families resources for access to higher education. Allocations across various programs over recent decades contextualize current education deserts. Although only a fraction of the $600 billion in federal military spending in the United States, investments in veterans’ benefits have grown significantly as a result of the Post-9/11 GI Bill, which increased by $9.5 billion (249 percent) in real terms between 2008 and 2017 ($13.5 billion) (Stauffer et al. 2019). Currently, federal spending on other programs (e.g., Montgomery GI Bill-Active Duty, Vocational Rehabilitation and Employment, Survivors’ and Dependents’ Educational Assistance) declined from $4.6 billion in 2009 to $2.4 billion in 2017 (Correll 2019), making the Post-9/11 GI Bill responsible for the lion’s share, at 82.2 percent of allocations. In 2017, the Forever GI Bill was approved to enhance the Post-9/11 GI Bill, where “forever” eliminates the fifteen-year expiration date on benefits. The enhancement includes more support for STEM education, as well as resources to generate “information on income, educational paths that yield the best return on investment as measured by civilian work-force success, disability and homelessness status, non-reliance on public assistance, educational attainment, and student debt and default rates” (U.S. Department of Veterans’ Affairs 2020, 25).

Among other changes, the latest program modifies compensation so that stipends are calculated based on the location of the campus where a student takes most classes (Gross 2017). This provision applies to veterans, active-duty military personnel and spouses alike, or family of service members killed in the line of duty since 10 September 2001. Such resources promise to extend the legacy of the original GI Bill, which historically increased the presence of veterans in higher education and is known as a long-term policy widely seen as having successfully increased opportunities for veterans of all backgrounds over the years (Altschuler and Blumin 2009). As Frey (2016) pointed out, however, the effects of the original GI Bill were not “race-neutral,” because White veterans still consistently gain higher levels of educational attainment. Frey (2016) contended that this disproportionate outcome might result in large part because veterans’ locations and the racism present in those locations have the largest effects on their ability to use benefits. Turner and Bound (2003) argued that this disparity can historically be attributed to location, where inequitable accessibility of tertiary education is generally more constricted in the South than in the North.

As women’s participation in the military grows, their access to educational benefits through these programs improves, as does the potential for better gender, racial, and ethnic representation. Patten and Parker (2011) found that 82 percent of post-9/11 women veteran and active-duty military stated that the reason they joined was to receive education benefits. Among enlisted personnel, women from under-represented minority groups are present in greater proportions than within the civilian population or among enrolled students in higher education, generally: 43 percent of male service members and 56 percent of enlisted women were Hispanic or a racial minority in 2017, an increase from 26 percent in 2004 (Reynolds and Shendruk 2018). By comparison,
40.3 percent of the U.S. population as a whole were non-White (2017), and in higher education, 44 percent were non-White in 2016 (de Brey et al. 2019).

Given the uneven nature of proximity and access to higher education, these federal funding resources are not finding their way to support veterans’ pathways into public state universities. Approximately two thirds of the Post-9/11 GI Bill benefits go to private nonprofit and for-profit institutions, leaving only one third for beneficiaries attending public colleges and universities, which 70 percent of all students attend. By comparison, only 14.4 percent of funding for the Pell Grant in 2017 was distributed to private for-profit institutions, which enroll only 7 percent of all students. Specifically for veteran and military education benefits, 34.7 percent of funds were distributed to private for-profit entities (Stauffer et al. 2019). This is of particular concern to the discipline of geography and geographic information systems (GIS), which is disproportionately offered among public land-grant universities compared to other types of institutions (Solís et al. 2014). Only 14.5 percent of degrees earned by student veterans since 2001 have been in STEM-related fields, and merely 1.2 percent of these already small numbers are in technologies like geospatial fields (Student Veterans of America 2017).

Like it does for most college students and job-seekers, proximity and location matter to enlisted and veteran individuals (Solís and Miyares 2014). Many adult Americans live in education deserts. Myers (2018) found that 11.2 million adults, or 3.5 percent of the adult population, live more than a sixty-minute drive from a public college in the United States. Our study explores what this pattern of education deserts looks like specifically for veterans and military families.

Conceptual Framework: A Spatial Approach to Life Course Theory

Our analysis is informed by the preceding context and framed through a conceptual approach that takes seriously the underlying geographies of and uneven access across the higher education system (Solís et al. 2014) that reflect the lived experiences of veterans and military families over the course of their lifetimes (Mobley et al. 2017). This analysis of education deserts is formulated to reflect multiple factor realities, as a backdrop to future studies of individuals moving through this landscape.

The pipeline continues to serve as a predominant metaphor characterizing how individual students access higher education, particularly underrepresented groups in STEM disciplines, health sciences, geosciences, law, biosciences, and education, private-sector professions (Chang 2002; Alfred et al. 2005; McCarty et al. 2005; Calleros 2006; Cullinane 2009; Hinton et al. 2010). When we consider that nearly one third of all undergraduate students transfer before earning their degree, including reverse transfers (e.g., from four-year to two-year programs, per Gonzalez 2012), it becomes clear that complex patterns of student mobility and spatial behavior render the traditional linear metaphor inadequate. Similarly, it falls far short to describe the behavior of military veterans, who are highly mobile, whose geographies are constrained by the presence of bases or installations, who are often reassigned to new places without personally choosing locations, and whose postservice occupational mobility are influenced in diverse ways as a result of their service (Cunningham 2021). Nonlinear mobility and the impact of economic forces on spatial human behavior are better captured in a landscape type of analysis that serves as a “base map” for understanding how access is “geographically contingent, spatial in nature, or dynamically connected across scales” (Solís and Miyares 2014, 169).

Building on this geographic understanding, inspired by concepts from sociological life course theory, we need more nuanced ways to describe the landscape on which such “trajectories” and “transitions” of individuals unfold through informal and formal education across their lifetimes. In particular, we appreciate how life course theory underscores the importance of spatiohistorical contingencies (like proximity to educational or economic opportunities) that inflect outcomes as it relates to returning veterans, where the moments of entry and exit from service or return count as “transitions.” This, in turn, demands a focused perspective on the stage at which such experiences shape the “development of self-efficacy, interests, task values, and long-term life goals, which in turn, influence educational and career choices in STEM and non-STEM fields” or not (Wang and Degol 2013, 305; Eccles and Wigfield 2002; Farrington et al. 2012). Transitions are complex and might include many “phases of assimilation and continuous
appraisal as people move in, through, and out of it” (Anderson, Goodman, and Schlossberg 2012, 59; Hayden et al. 2014). Life course theory resonates with the lived experiences of veterans and active-duty service members and has begun to be applied to understanding how choices to pursue higher education are made in innovative ways (Robertson, Miles, and Mallen 2014; Brawner et al. 2015; Mobley et al. 2017). Some scholars have explored the role of community colleges to meet needs of post-9/11 veterans, recommending streamlining programs to create veteran-friendly campuses (Persky and Oliver 2010). Other scholars bridge the learning environments of the military and the academy (Blaauw-Hara 2017) and the transition for women veterans (Albright et al. 2019). Landscape patterns, however, for lack of access to where such opportunities exist have received little systematic attention, and there is a dearth of methodologies to shed light on systematic gaps in offerings at regional, state, or multistate scales, an important consideration for the mobility that characterizes veteran communities at certain life stages (Mortimer and Shanahan 2003; MacLean and Elder 2007).

We assert that each of these points of transition and trajectories literally take place in real locations and, as such, are integral to a fully contextualized analysis that must be understood as a landscape system that sets the stage for individual pathways. An important critique of the life course and meaning-making approaches is a lack of attention to context of where these experiences are unfolding. One rare study explores the spatiality of postmilitary identities, paying attention to discourses of loss and separation that result in transitional circumstances for individuals across the course of their lives (Herman and Yarwood 2014). Although it certainly matters to all students where universities are located, which place-based characteristics the campus location has, and the distances students must travel to attend, such geographic considerations matter in unique ways for veterans, active-duty service members, and their families. For this reason, we propose a novel geospatial approach to identify and analyze education deserts specific to their contexts (Figure 1).

A Geospatial Analytical Approach to Characterize Education Deserts

Following the preceding spatiohistorical context and conceptual framework, we argue that a geospatial analytical approach to delineate education deserts needs to be heuristic and context-sensitive and accommodate a complex system of targeted actors along with the education and workforce assets accessible to them. We explain here how our methodological design of a suitability model employing fuzzy algorithms is an appropriate option and provides insights for novel, actionable solutions.

Methodological Framework

We propose a methodological framework that draws on land suitability analysis (LSA) for mapping the landscape of access to higher education for veteran and military families. This approach is favored because it allows us to contextualize lack of access for a specific population of interest at specific timeframes, which is more aligned to our conceptual approach explained earlier than a standard “hotspot” analysis that buffers an arbitrary distance from university locations. We consider a methodological framework useful and robust if it allows us to potentially determine (1) whether education deserts are different for veterans than for nonveterans. (2) whether changes in the regional patterns of lack of access change over time. (3) whether the related landscape of workforce opportunities shows distinct patterns for the two groups and change over time, and (4) to what extent patterns of workforce opportunities are similar to or different from patterns of educational opportunities for both groups.

Approaching the question as a suitability analysis over time offers a comprehensive view of a multiplicity of characteristics and patterns of existing

Figure 1. A graduating student in uniform walks the campus at Texas Tech University in Lubbock, Texas. Photo credit: Hope Lenamon.
educational opportunities relative to how it might suit a particular audience, given that we argue that this unfolds in unique ways for veterans, active-duty service members, and their families. In addition, this approach allows for the study to be a comparative one, to juxtapose different models of the landscape as experienced by veteran compared to nonveteran populations. Together veteran and nonveteran results can give a sense of the overall opportunity landscape for a specific state, a geographic region, or the country as a whole. We anticipate different patterns of results applying such a model across a quadrant comparison (Figure 2).

In this research framework, four models are created and used to generate maps of the study area to depict patterns for comparison: educational opportunities for veteran populations (EOV), workforce opportunities for veteran populations (WOV), educational opportunities for nonveteran populations (EONV), and workforce opportunities for nonveteran populations (WONV).

Application of Suitability Analysis

The research literature is sparse to nonexistent when it comes to combining LSA and educational factors to define where are the most suitable and least suitable places of access. A similar paucity of studies exists for workforce opportunities. What little analysis is available does not amount to much more than coarse hotspot analysis (Myers 2018) or a treatment of multivariate but nonspatial elements of interest (Elliott, Gonzalez, and Larsen 2011; Carter-Boyd 2012; Barry, Whiteman, and Wadsworth 2014; Ford 2017; Yanchus et al. 2018). Our research seeks to address this gap by drawing on how the technique has been widely used in other applications. This study appears to be the first to apply these techniques to study educational landscapes.

Our model recognizes how other researchers use LSA to generate specific insights about various applied issues that, like our subject matter, require understanding of complex constellations of sites and actors and multiple characteristics of connectivity ( Sicat, Carranza, and Nidumolu 2005; Samanta, Pal, and Pal 2011; Qiu et al. 2014; Weerasiri, Wirojanagud, and Srisatit 2014; Aburas et al. 2017; Q. Li et al. 2017). Similar to our approach, Jamali et al. (2014) used spatial multicriteria analysis to locate suitable sites for constructing subsurface dams in Pakistan. Weerasiri, Wirojanagud, and Srisatit (2014) employed it to determine likely locations of high levels of arsenic contamination in soil in Thailand. Jafari and Zaredar (2010) used LSA to develop environmental policies for sustainable range-lands via a multicriteria spatial analytical hierarchy. These examples demonstrate the flexibility that LSA offers, used within this research study to provide better information regarding education opportunities available to military veterans in the United States.

Incorporation of Fuzzy Logic

There are several computational techniques available to analyze suitability within the LSA approach: analytical hierarchy process, fuzzy logic, multicriteria decision techniques, and ordered weighted averaging (Malczewski 2006; Attua 2010; Azizi et al. 2015). Among these options, there are three reasons why the choice of fuzzy logic suits our specific purposes for defining education deserts: (1) as a heuristic technique, it suits exploratory needs significantly better than deterministic models that require a clear physics-based or theoretical underpinning; (2) the technique allows for gradient output, because we understand that education deserts should not be depicted as binary because access to educational opportunity exists on a continuum; veterans (or nonveterans for that matter) do not typically experience lack of access in such a definitive way; and, finally, (3) multivariate, fuzzy logic techniques allow us to incorporate a large set of variables for describing the education desert, which offers the opportunity for richer comparisons than standard “hotspot” approaches. This, in turn, makes room for tailored meanings of suitability while accounting for potential uncertainty in the data sets. Given that census

<table>
<thead>
<tr>
<th>Modeling Framework</th>
<th>Multi-variate description of educational landscape</th>
<th>Multi-variate description of workforce landscape</th>
</tr>
</thead>
<tbody>
<tr>
<td>How veterans and military families experience the landscape</td>
<td>EOV</td>
<td>WOV</td>
</tr>
<tr>
<td>How non-veterans experience the landscape</td>
<td>EONV</td>
<td>WONV</td>
</tr>
</tbody>
</table>

Figure 2. Quadrant framework of models. Note: EOV = education for veterans; WOV = workforce for veterans; EONV = education for nonveterans; WONV = workforce for nonveterans.
demographic and socioeconomic data might contain uncertainty due to sampling errors, uncertainty can be compounded when using many different data sets together. Fuzzy logic is a more appropriate choice compared to spatial optimization to reflect this potential compounding of sampling uncertainties when data sets are aggregated.

**Model Implementation**

**Study Area.** We chose to apply this approach to the southern United States for empirical and opportunistic reasons. As noted earlier, the southern United States is significant in terms of its historical disparity of veteran educational access (Turner and Bound 2003). The southern United States is also of interest because of the prevalence of military bases and typically higher veteran populations. One interested audience for the results of this study is the Vice Provost’s office at Texas Tech University, for use in assessing offerings and programming for veterans, so the study centers on Texas. We define the region’s extent using the U.S. Bureau of Economic Analysis (BEA) delimitations of Southwest plus Southeast regions (Figure 3; BEA 2019). This comprises sixteen contiguous states centered on Texas, plus one additional state: Alabama, Arizona, Arkansas, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, New Mexico, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, and West Virginia. Maryland was added because it is contiguous and falls among the top states for both total defense spending and defense spending as a percentage of state gross domestic product (National Conference of State Legislatures 2018). The total population of the study area is approximately one third of the U.S. population, yet the area is home to 53 percent of all veterans, about 1,397,539 individuals (DoD Data/Reports 2019). As a central location of interest, it is worth noting that Texas has the highest number of veterans under age twenty-five (27,000 individuals) and expects the largest increase in veteran population over the next ten years (National Center for Veterans Analysis and Statistics 2017).

**Data Collection and Preprocessing.** The multivariate model accommodated an array of official data variables (Table 1) that reflect our preceding discussion regarding education and life trajectories. The American Community Survey (ACS) was a primary source for county-level total population, veteran population, and nonveteran population annually from 2005 to 2017 (2005 being the earliest year available in ACS). Each year’s data set contained complete variable data for an average of 358 counties of the total 1,467 counties included in this study. Variables used to build the suitability model were age (eighteen to thirty-four, thirty-five to fifty-four, and fifty-five to sixty-four), education (high school graduate [includes equivalency] and some college or an associate’s degree), median income, and employment status (United States Census Bureau 2019). A layer comprised of locations of military installations, ranges, and training areas (MIRTAs) was collected from the Department of Defense (2019) as a point-vector layer. A layer for colleges and universities was created from a collection of two different sources to ensure completeness, namely, from the National Center for Education Statistics (2019; part of the Institution of Education Sciences, U.S. Department of Education) and from the U.S. Geological Survey (2019). A manual review of 1,940 universities and institutions was conducted to standardize university names across sources. The boundary layer was sourced from the Texas Tech Center for Geospatial Technology (USA GIS data 2014) in shapefile format.

**Data Processing.** Four unique models (Figure 2; EOV, EONV, WOV, WONV) were constructed for each year between 2005 and 2017 across the study region to delimit presence and access where the education (E) and workforce (W) assets were located as relevant to veterans (V) or nonveteran populations (NV). The EOV and WOV models incorporate MIRTAs variables to reflect proximity to military
installations. Age ranges reflect standard working-age groups and education variables were split between high school graduates (equivalency) and those with some college or associate’s degree as an indicator of status as potential prospective student. Median income and employment status are assumed to have a positive relationship to educational attainment. The college and universities layer served to mark physical sites where education opportunities were offered. The workforce models excluded the education variable set and the college and universities layer but maintained working-age variables and MIRTA data to show the importance of distance from military bases, where active-duty service members would be currently working and commuting: The shorter the distance to bases, the more desirable the location to the model.

Five-Step Data Analysis. The analytical process to assess and map site suitability for each year was conducted for each model of the quadrant using five steps of multicriteria analysis, each of which is explained and justified in what follows and outlined in Figure 4. These steps are (1) Euclidean distance, (2) inverse distance weighted (IDW), (3) reclassify, (4) fuzzy membership, and (5) fuzzy overlay. The model was designed by the authors and built using the ArcGIS 10.6.1 platform and tools. Model validation was performed through calculating mean absolute percentage error (MAPE) and coefficient of the variation for root mean square error (CV[RMSE]), as well as with qualitative verification of results, described next.

Euclidean distance. Given the multistate scale of analysis and the fact that the geolocation of some data was proxy (e.g., county centroid) or interpolated, we chose to use Euclidean distance, which quantifies the absolute distance between points in dimensional space. The alternative, travel distance computed from a vector-based road network, could be used for modeling education deserts when more precise locations of target populations are known relative to sites of educational or workforce assets. This is more computationally intensive, however, and requires greater user effort, and vector-based road network distance requires a small unit of analysis (e.g., multicounty or city scale) to improve accuracy over Euclidean distance calculations (Sander et al. 2010). The study area covers a large, multistate region, and many data variables are attributed to a county or other aggregate spatial unit rather than as point data such as addresses, which would be necessary to make routing or travel distance a viable

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**Table 1. Variables and sources of data used in the suitability models**

<table>
<thead>
<tr>
<th>Category</th>
<th>Variable</th>
<th>Year</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Age (35–54)</td>
<td>(2005–2017)</td>
<td><a href="https://factfinder.census.gov/faces/nav/jsf/pages/download_center.xhtml#none">https://factfinder.census.gov/faces/nav/jsf/pages/download_center.xhtml#none</a></td>
</tr>
<tr>
<td></td>
<td>Age (55–64)</td>
<td>(2005–2017)</td>
<td><a href="https://factfinder.census.gov/faces/nav/jsf/pages/download_center.xhtml#none">https://factfinder.census.gov/faces/nav/jsf/pages/download_center.xhtml#none</a></td>
</tr>
<tr>
<td></td>
<td>Some college or an associate's degree</td>
<td>(2005–2017)</td>
<td>U.S. Geological Survey 2019 <a href="https://www.sciencebase.gov/catalog/item/4f4e4acee4b07f02db67fb39">https://www.sciencebase.gov/catalog/item/4f4e4acee4b07f02db67fb39</a></td>
</tr>
<tr>
<td></td>
<td>Employment status (18–64)</td>
<td>(2005–2017)</td>
<td><a href="https://factfinder.census.gov/faces/nav/jsf/pages/download_center.xhtml#none">https://factfinder.census.gov/faces/nav/jsf/pages/download_center.xhtml#none</a> . . . . .</td>
</tr>
<tr>
<td>U.S. boundaries</td>
<td>U.S. boundaries</td>
<td>2019</td>
<td>The Center for Geospatial Technology at Texas Tech University, accessed 2019 <a href="https://www.depts.ttu.edu/geospatial/center/USAGISData.html">https://www.depts.ttu.edu/geospatial/center/USAGISData.html</a></td>
</tr>
</tbody>
</table>
choice. We do advocate, however, when adapting this approach to finer scales such as within-state studies, or with data that include addresses, using a vector-based road network layer rather than Euclidean distance. To incorporate the spatial relationship between populations and the educational sites, Euclidean distance was thus computed from the center of the cells’ source of the colleges and university locations and MIRTA to the center of each of the neighboring cells (X. Li et al. 2019). The computation formula used to determine this distance is

\[(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2},\]  

(1)

where the function \((x, y)\) is the Euclidean distance between \(x\) and \(y\), \(x\) and \(y\) are individuals with different dimensional characteristics, \(x = (x_1, x_2, x_3 \ldots, x_n)\), and \(y = (y_1, y_2, y_3 \ldots, y_n)\) (Mesquita et al. 2017; Wei et al. 2020). In this research, it was necessary to compute the Euclidean distance for both the MIRTA layer and the NCES layer, as noted in Figure 4 (X. Li et al. 2019). As explained earlier in the conceptual approach, proximity is important to prospective students and thus critical.

Figure 4. Flowchart of data and analysis configuration of the modeling method. Note: Depicted for a single year for veteran (V) populations, implemented similarly for all other years from 2005 through 2017 and for nonveteran (NV) populations. NCES = National Center for Education Statistics; FM = fuzzy membership; MIRTA = military installations, ranges, and training area; EOV = education for veterans; IDW = inverse distance weighted; ACS = American Community Survey; FTP = feature to point; WOV = workforce for veterans. Designed by Solís and Aljaddani (2020).
in suitability models. In this case, the closer the area to the military installation or college or university, the more desirable the location in the model.

**Inverse distance weighted.** Because the data from each of the counties existed as polygons and not all of the counties had data readily available, an interpolation technique was chosen for predicting unknown values. Several studies have implemented interpolation for predicting census demographic and socioeconomic data. Examples of these techniques include areal weighting, kernel density estimation, and kriging (Cromley, Ebenstein, and Hanink 2009; Qiu, Zhang, and Zhou 2012; Liu and Martinez 2019). IDW is mathematical and statistical model commonly used by earth scientists for interpolation, recognizing that points that are close to each other are usually more alike than those that are further away (Ware, Knight, and Wells 1991). IDW was chosen as superior to other options because prediction of unknown values would be based on known points in the neighborhood of each processing cell and the large number of counties in the study permitted robust and higher resolution results (Khanbabakhani, Torkashvand, and Mahmoodi 2020). Namely, when areal interpolation was conducted for this research, it rendered a map that was low resolution, making interpretation unclear. Kriging was also not chosen because the average value should be kept from being greater or less than input values to generate realistic results. With IDW, neighboring data will be the most influential and the surface will contain a greater number of detailed features (Philip and Watson 1982; Watson and Philip 1985; Darsow, Schafmeister, and Hofmann 2009; Losser, Li, and Piltner 2014; Ikechukwu et al. 2017).

IDW is defined as

$$z_{x,y} = \frac{\sum_{i=1}^{n} z_i w_i}{\sum_{i=1}^{n} w_i},$$

where $z_{x,y}$ are the value points to be estimated, $z_i$ represents the control value for the ith sample point, and $w_i$ is the weight that determines the relative importance of each control point $z_i$ in the interpolation. This contained weighted approach gives near points comparatively more influence than distant points. Weight was defined as

$$w_i = d_{x,y,i}^{-\beta},$$

where $d_{x,y,i}$ is the distance between $z_{x,y}$ and $z_i$ and $-\beta$ is an exponent for which we choose two because the greater the squares, the more the weight decreases and the less influence the squares have on points further away (Barrier and Keller 1996; Khanbabakhani, Torkashvand, and Mahmoodi 2020), reflecting the distance decay idea in our conceptual approach. This step was applied to the ACS data, Figure 4.

**Reclassify.** To input the outputs from Steps 1 and 2 into a fuzzy model, the data must first be categorized. Reclassify is a spatial analyst tool that categorizes raster data into ordinal classes (Lupia 2012). We used quantile classification to distribute output values into ten classes, setting the range from the minimum to maximum value of each raster set. The reclassification was applied to age (eighteen to thirty-four, thirty-five to fifty-four, and fifty-five to sixty-four), education, income and employment status, colleges and universities, and MIRTAs. This step prepared the interpolated raster data for use with fuzzy logic.

**Fuzzy membership.** Our conceptual model underweights the fact that lack of access to education is not a strict either-or prospect for student veterans. Thus, fuzzy logic helps to improve the concept of absolute “true or false” in Boolean logic by measuring the degree of truth (Zadeh 1975). The fuzzy set theory allows fuzzy membership to be in a range from 0 to 1 (Hong et al. 2017; Mullick, Tanim, and Islam 2019). All values in between are ranked on the likelihood of membership to the set (Wayne and Olympia 2003; Bamberger 2017). Fuzzy membership provides realistic results and allows control of input values based on the objectives of the research (Raines, Sawatzky, and Bonham-Carter 2010; Bamberger 2017; Weerasiri, Wirojanagud, and Siriatt 2014). Fuzzy membership in our work was used to identify the probability of each individual layer of potential locations across a spectrum from deserts to opportunities for veteran and nonveteran communities. Probability is allocated a value on a scale in which 1 represents more probable of being a member of the set and 0 less probable. To calculate the relationship between the observed values and fuzzy memberships, we used the small and large mathematical functions because this allows a nonlinear treatment, aligning with our conceptual model described earlier. Shorter distances between a location and the surrounding educational facilities or MIRTAs are more desirable in this study and further distances are less desirable. Fuzzy large was used to classify data in which a larger value was more desirable, such as median income. The fuzzy method thus
Table 2. Variables and attributes that determine suitability for veterans in 2017

<table>
<thead>
<tr>
<th>Category</th>
<th>Variable</th>
<th>Attribute</th>
<th>Suitability level</th>
<th>Normalized value</th>
<th>Model type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demographic data</td>
<td>Age (18–34)</td>
<td>43</td>
<td>Low</td>
<td>0.1</td>
<td>Fuzzy large</td>
</tr>
<tr>
<td></td>
<td></td>
<td>24,163</td>
<td>High</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Age (35–54)</td>
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<td>Fuzzy large</td>
</tr>
<tr>
<td></td>
<td></td>
<td>55,775</td>
<td>High</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Age (55–64)</td>
<td>141</td>
<td>Low</td>
<td>0.1</td>
<td>Fuzzy large</td>
</tr>
<tr>
<td></td>
<td></td>
<td>40,722</td>
<td>High</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Education data</td>
<td>High school graduate</td>
<td>190</td>
<td>Low</td>
<td>0.1</td>
<td>Fuzzy large</td>
</tr>
<tr>
<td></td>
<td>(includes equivalency)</td>
<td>49,881</td>
<td>High</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Some college or an</td>
<td>779</td>
<td>Low</td>
<td>0.1</td>
<td>Fuzzy large</td>
</tr>
<tr>
<td></td>
<td>associate’s degree</td>
<td>97,549</td>
<td>High</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Colleges and universities</td>
<td>3.00 (348.60 km²)</td>
<td>Low</td>
<td>0.1</td>
<td>Fuzzy small</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.064 (0.018 km²)</td>
<td>High</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Economic data</td>
<td>Median income</td>
<td>22,297</td>
<td>Low</td>
<td>0.1</td>
<td>Fuzzy large</td>
</tr>
<tr>
<td></td>
<td></td>
<td>98,127</td>
<td>High</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Employment status</td>
<td>436</td>
<td>Low</td>
<td>0.1</td>
<td>Fuzzy large</td>
</tr>
<tr>
<td></td>
<td></td>
<td>96,786</td>
<td>High</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Military data</td>
<td>Military installations, ranges,</td>
<td>3.00 (348.60 km²)</td>
<td>Low</td>
<td>0.1</td>
<td>Fuzzy small</td>
</tr>
<tr>
<td></td>
<td>and training areas</td>
<td>0.064 (0.018 km²)</td>
<td>High</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

Table 3. Variables and attributes that determine suitability for nonveterans in 2017

<table>
<thead>
<tr>
<th>Category</th>
<th>Variable</th>
<th>Attribute</th>
<th>Suitability level</th>
<th>Normalized value</th>
<th>Model type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demographic data</td>
<td>Age (18–34)</td>
<td>9,883</td>
<td>Low</td>
<td>0.1</td>
<td>Fuzzy large</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1,162,332</td>
<td>High</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Age (35–54)</td>
<td>11,547</td>
<td>Low</td>
<td>0.1</td>
<td>Fuzzy large</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1,196,613</td>
<td>High</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Age (55–64)</td>
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<td>Low</td>
<td>0.1</td>
<td>Fuzzy large</td>
</tr>
<tr>
<td></td>
<td></td>
<td>473,231</td>
<td>High</td>
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<td></td>
</tr>
<tr>
<td>Education data</td>
<td>High school graduate</td>
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<td>Low</td>
<td>0.1</td>
<td>Fuzzy large</td>
</tr>
<tr>
<td></td>
<td>(includes equivalency)</td>
<td>657,740</td>
<td>High</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Some college or an</td>
<td>7,943</td>
<td>Low</td>
<td>0.1</td>
<td>Fuzzy large</td>
</tr>
<tr>
<td></td>
<td>associate’s degree</td>
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<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Colleges and universities</td>
<td>3.00 (348.60 km²)</td>
<td>Low</td>
<td>0.1</td>
<td>Fuzzy small</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.064 (0.018 km²)</td>
<td>High</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Economic data</td>
<td>Median income</td>
<td>16,678</td>
<td>Low</td>
<td>0.1</td>
<td>Fuzzy large</td>
</tr>
<tr>
<td></td>
<td></td>
<td>65,333</td>
<td>High</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>Employment status</td>
<td>19,375</td>
<td>Low</td>
<td>0.1</td>
<td>Fuzzy large</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2,156,927</td>
<td>High</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

does not create a binary representation of the area being analyzed, so a sharp class boundary between suitable and unsuitable areas is not created but as a range instead (Hall, Wang, and Subaryono 1992). We applied the large fuzzy membership technique to age, education, median income, and employment status. We assigned these higher values to the most suitable locations. The small fuzzy membership was applied to both layers—colleges and universities and MIRTAs—for each model. Smaller distances from target locations mean the site was the most suitable and thus more desirable, and the longer the distance, the less suitable the location (Tables 2 and 3).

The midpoint of the fuzzy large recognizes a crossover point that specifies a membership of 5. A value greater than the midpoint means a higher probability of being a member of the set, and any values lower than the midpoint have a declining membership probability. The spread factor specifies the shape and character of the transition zone (Figure 3A), and the midpoint of fuzzy small recognizes the crossover point also assigned to 5. Values greater than the
midpoint on this side have a lower probability of being a member of the set and values underneath
the midpoint have a higher probability of membership. The spread parameter controls the rate at
which fuzzy membership increases from low to high (Figure 3B).

For our study, the fuzzy membership functions map the membership in a sigmoid shape (Figure 5),
in which both of the functions are based on the user specifying the value of spread \( f_1 \) and the midpoint
\( f_2 \). Fuzzy small and fuzzy large were defined in the following equations:

\[
\mu_1(x) = \frac{1}{1 + \frac{x - f_2}{f_1}},
\]

\[
\mu_2(x) = \frac{1}{1 + \frac{x - f_2}{f_1}},
\]

where \( x \) is the input raster layer that is characterized by different parameters and represents the fuzzy small
and fuzzy large calculations, respectively (An, Moon, and Rencz 1991; Mullick, Tanim, and Islam 2019;
Raines, Sawatzky, and Bonham-Carter 2020).

Fuzzy overlay. To assess the final results of each model, a fuzzy overlay is used to combine all of the
fuzzy membership results that have a range of values between 0 and 1 based on the specified overlay type.
Fuzzy overlay is a mathematical function that quantifies the relationship between the membership of the
variables to an explicit set that corresponds to class. The output of the fuzzy membership (Step 4) was
used as an input raster in the fuzzy overlay (Step 5, Figure 4). All of the input variables that distinguish
the fuzzy overlay are equally important in the four models. This equality among the variables is an
advantage for our empirical study, because no weighted overlay is required to specify either the relative
importance of each variable or the relative importance of the classes of the variables or the weighted sum (Carvalho et al. 2007). The second advantage of using a fuzzy overlay is that the output values range between 0 and 1 as a gradient, as explained previously. The third advantage is that the fuzzy overlay provides more consistent results than a weighted overlay, which tends toward overestimation or underestimation of potential site cita-
tions (Baidya et al. 2014).

The main function of the fuzzy overlay is to combine the results of each variable into one suitable map that has a range between 0 and 1 based on the type of the overlay (Raines, Sawatzky, and Bonham-Carter 2010; Bamberger 2017). Within the fuzzy overlay, a numeric value of 1 is more likely to be a member of the set (opportunities) and 0 is less likely to be a member of the set. These values are the output of the fuzzy logic to quantify the probability of each location belonging to each raster layer. This information exists in different input raster continuous layers in different values and is extracted to identify the relationship between the set itself (An, Moon, and Rencz 1991; Raines, Sawatzky, and Bonham-Carter 2020).

In this research, for each year between 2005 and 2017 for each of the four models—EOV, EONV,
WOV, and WONV—each of the input continuous raster layers for the fuzzy overlap were outputs of the
fuzzy membership (Araya-Muñoz et al. 2017). We implemented AND logic as an operator in the fuzzy
overlay to obtain the minimum value from all input continuous raster layers as the fuzzy AND was set to
0.50. The formula of AND in the fuzzy overlay is as follows:

\[
\mu(x) = \min(\mu_i),
\]

where \( x \) is the value of the membership for crisp measurement, and \( i \) indicated to each of the \( n \) layers (Zimmermann 1996).

Results of the Fuzzy Suitability Analysis Model

Education Deserts

The output of the EOV model depicts where educational deserts are, where lack of access for veteran
and military communities to join the higher education opportunity systems is present, and where the
landscape patterns offer a comprehensive understanding of potential suitable and unsuitable loca-
tions for new or existing program expansion to engage prospective students. To compare, results
from the EONV model that was developed for nonveterans shows different landscape patterns of oppor-
tunities and deserts for nonveteran populations.

Figures 6 and 7 present the EOV model in 2005 and 2017, respectively, to highlight the changes
between these first and last years of the study period, although the model was performed on each interven-
ing year. The earlier date shows an erratic and fragmented distribution of educational deserts and
educational opportunities. Since 2015, model results
show a remarkable expansion of the landscape of educational opportunities, especially for the eastern coast, southwest, and middle southern regions, whereas the educational deserts have shrunk in size over most of the study area. Meanwhile Figures 6 and 7 also present EONV in 2005 and 2017 to exhibit opportunities and deserts for nonveteran communities. Earlier years show a similar uneven nucleated but scattered distribution of educational deserts and opportunities for nonveterans. Similar to the landscape for veterans, from 2015, larger spots of the educational opportunities expanded remarkably while the educational deserts have shrunk, although the specific pattern is distinct.

Comparison to Workforce Opportunity Landscape

To better understand the role of potential employment relative to education desert landscapes, Figures 8 and 9 present the WOV models in 2005 and 2017, again representing the beginning and end periods, although the analysis was run for each intervening year. In 2005, the respective workforce opportunities for veterans versus nonveterans were more nucleated and scattered. In the 2017 results, a pattern that looks quite similar to the EOV/EONV results is visible, namely, larger spots of the workforce opportunities expanded remarkably for the eastern coast, southwest, and the middle southern regions, whereas workforce deserts shrank in most of the study area. Figures 8 and 9 present WONV models in 2005 and 2017 for comparison. The workforce opportunities belt of WOV and WONV was shown clearly in the center of the study area, longitudinally from north to south, mirroring changes detected in the education models.

Validation Metrics

To assess the internal validity of the model, we computed statistical cross-validation metrics based on MAPE and the CV(RMSE). This statistical calculation assesses the accuracy of the spatial interpolation by omitting each measured observation sequentially and then predicting the value of that removed observation using the remainder of data available.

The MAPE refers to the standard deviation of the prediction error and is a measure of the difference between the predictions and the measured values of a unit:

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \frac{|m_i - p_i|}{m_i} \times 100.$$  \hspace{1cm} (7)

RMSE is the standard deviation of the prediction error and measures how spread these prediction errors are:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (m_i - p_i)^2}{n}}.$$  \hspace{1cm} (8)

The CV(RMSE) consists of the ratio of RMSE to the mean ($\bar{x}$) of the dependent variable. The smaller the CV, the lower the dispersion variable. The smaller the CV, the lower the dispersion, which means the model is a good fit:
This calculation was performed for each variable and each year, as reported in Table 4 for veterans and Table 5 for nonveterans. Any of the MAPE and CV(RMSE) calculations that are less than 25 percent indicate that the model is a good fit and has a reliable and acceptable prediction capability.
As seen in the tables, the employment status variable is the only one where MAPE or CV(RMSE) exceeds 25 percent, which we find is due to outliers that skewed right. This variable was only used for the WOV and WONV models and indicates that the workforce models do not meet accuracy expectations. Future research on workforce opportunities should incorporate variables with less spatial error or

Figure 7. Suitability maps of EOV and EONV communities in 2017 in the southern United States. EOV = education for veterans; EONV = education for nonveterans.

As seen in the tables, the employment status variable is the only one where MAPE or CV(RMSE) exceeds 25 percent, which we find is due to outliers that skewed right. This variable was only used for
outliers. All other variables indicate reliable prediction capability. Thus, we consider the education deserts depicted for veterans and nonveterans (EOV and EONV models) as valid representations with low error.

We also validated the change across education deserts models with respect to qualitative information, based on whether results reflect known historical change in the education landscape at a tangible level. We note two interpretations that explain

Figure 8. Suitability maps of the WOV and WONV communities in 2005 in the southern United States. WOV = workforce for veterans; WONV = workforce for nonveterans.
visible model patterns. First, there is an educational opportunity belt of EOV and EONV displayed clearly in the middle of the study area in later years compared to earlier years, heading longitudinally from north to south (Figures 6 and 7). We interpret this pattern in part due to the significant satellite system expansion in the Texas Board of Regents System (which included Texas Tech University), Figure 9. Suitability maps of the WOV and WONV communities in 2017 in the southern United States. WOV = workforce for veterans; WONV = workforce for nonveterans.
which appears to have influenced the distinct change in deserts of education from 2005 to 2014 into opportunities from 2015 to 2017.

Second, another change visible in comparison of Figures 6 to 7 and 8 to 9 depicts increased education and workforce opportunities from 2005 to 2017 that occurred for veterans but not nonveterans, which took place near El Paso, Texas. We interpret that this pattern verifies the model in that it captures the fact that Texas Tech University’s satellite presence in El Paso received about $80 million in tuition revenue bonds from the state legislature in 2015 (Welsh 2015). These statistical and qualitative observations validate that our approach can detect the kinds of changes that matter to our study population at the temporal and spatial scale applied.

### Table 4. Cross-validation table for variables used in education for veterans and workforce for veterans, 2005–2017

<table>
<thead>
<tr>
<th>Date</th>
<th>Statistical methods</th>
<th>Age 18–34</th>
<th>Age 35–54</th>
<th>Age 55–64</th>
<th>Employment status</th>
<th>High school</th>
<th>Median income</th>
<th>Some college</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>MAPE</td>
<td>9.25</td>
<td>18.39</td>
<td>14.75</td>
<td>127.41</td>
<td>23.32</td>
<td>15.07</td>
<td>15.64</td>
</tr>
<tr>
<td></td>
<td>CV(RMSE)</td>
<td>13.49</td>
<td>20.60</td>
<td>18.53</td>
<td>124.97</td>
<td>26.91</td>
<td>19.23</td>
<td>18.69</td>
</tr>
<tr>
<td></td>
<td>CV(RMSE)</td>
<td>14.23</td>
<td>20.57</td>
<td>16.42</td>
<td>134.92</td>
<td>22.00</td>
<td>17.08</td>
<td>16.95</td>
</tr>
<tr>
<td>2007</td>
<td>MAPE</td>
<td>53.50</td>
<td>17.70</td>
<td>14.15</td>
<td>125.50</td>
<td>19.16</td>
<td>13.85</td>
<td>15.25</td>
</tr>
<tr>
<td></td>
<td>CV(RMSE)</td>
<td>46.38</td>
<td>19.78</td>
<td>16.61</td>
<td>136.00</td>
<td>22.27</td>
<td>16.97</td>
<td>17.80</td>
</tr>
<tr>
<td>2008</td>
<td>MAPE</td>
<td>53.82</td>
<td>20.35</td>
<td>14.80</td>
<td>125.72</td>
<td>20.10</td>
<td>15.13</td>
<td>13.43</td>
</tr>
<tr>
<td></td>
<td>CV(RMSE)</td>
<td>46.94</td>
<td>22.02</td>
<td>18.03</td>
<td>134.77</td>
<td>23.53</td>
<td>18.55</td>
<td>16.26</td>
</tr>
<tr>
<td>2009</td>
<td>MAPE</td>
<td>64.37</td>
<td>20.08</td>
<td>13.73</td>
<td>127.52</td>
<td>19.38</td>
<td>14.84</td>
<td>12.80</td>
</tr>
<tr>
<td></td>
<td>CV(RMSE)</td>
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<td>21.96</td>
<td>16.96</td>
<td>134.57</td>
<td>23.51</td>
<td>18.97</td>
<td>15.24</td>
</tr>
<tr>
<td>2010</td>
<td>MAPE</td>
<td>54.67</td>
<td>21.81</td>
<td>15.13</td>
<td>126.45</td>
<td>21.31</td>
<td>14.44</td>
<td>14.45</td>
</tr>
<tr>
<td></td>
<td>CV(RMSE)</td>
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<td>23.60</td>
<td>18.42</td>
<td>132.80</td>
<td>25.50</td>
<td>18.17</td>
<td>16.85</td>
</tr>
<tr>
<td>2011</td>
<td>MAPE</td>
<td>70.64</td>
<td>24.02</td>
<td>16.22</td>
<td>136.86</td>
<td>21.79</td>
<td>14.07</td>
<td>14.09</td>
</tr>
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<td></td>
<td>CV(RMSE)</td>
<td>54.66</td>
<td>24.83</td>
<td>20.13</td>
<td>137.01</td>
<td>26.24</td>
<td>18.64</td>
<td>17.17</td>
</tr>
<tr>
<td>2012</td>
<td>MAPE</td>
<td>91.40</td>
<td>21.82</td>
<td>14.12</td>
<td>136.07</td>
<td>20.79</td>
<td>14.79</td>
<td>14.21</td>
</tr>
<tr>
<td></td>
<td>CV(RMSE)</td>
<td>49.46</td>
<td>22.91</td>
<td>17.51</td>
<td>134.80</td>
<td>24.70</td>
<td>19.17</td>
<td>16.91</td>
</tr>
<tr>
<td>2013</td>
<td>MAPE</td>
<td>78.33</td>
<td>22.99</td>
<td>18.41</td>
<td>135.53</td>
<td>23.05</td>
<td>15.29</td>
<td>13.77</td>
</tr>
<tr>
<td></td>
<td>CV(RMSE)</td>
<td>52.63</td>
<td>24.35</td>
<td>21.41</td>
<td>135.17</td>
<td>25.64</td>
<td>18.87</td>
<td>16.43</td>
</tr>
<tr>
<td>2014</td>
<td>MAPE</td>
<td>109.58</td>
<td>24.43</td>
<td>20.12</td>
<td>138.43</td>
<td>22.55</td>
<td>15.06</td>
<td>14.93</td>
</tr>
<tr>
<td></td>
<td>CV(RMSE)</td>
<td>56.26</td>
<td>26.13</td>
<td>22.96</td>
<td>132.49</td>
<td>25.07</td>
<td>19.25</td>
<td>17.67</td>
</tr>
<tr>
<td>2015</td>
<td>MAPE</td>
<td>72.22</td>
<td>27.80</td>
<td>25.20</td>
<td>146.04</td>
<td>24.75</td>
<td>15.67</td>
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<td>27.84</td>
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<td>27.48</td>
<td>20.01</td>
<td>17.47</td>
</tr>
<tr>
<td>2016</td>
<td>MAPE</td>
<td>107.69</td>
<td>27.87</td>
<td>24.69</td>
<td>147.66</td>
<td>24.32</td>
<td>16.16</td>
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<td>27.67</td>
<td>20.30</td>
<td>18.64</td>
</tr>
<tr>
<td>2017</td>
<td>MAPE</td>
<td>61.64</td>
<td>28.70</td>
<td>25.88</td>
<td>148.12</td>
<td>24.29</td>
<td>15.24</td>
<td>15.04</td>
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<td>CV(RMSE)</td>
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<td>27.48</td>
<td>26.78</td>
<td>136.37</td>
<td>27.83</td>
<td>19.12</td>
<td>17.90</td>
</tr>
</tbody>
</table>

*Note: MAPE = mean absolute percentage error; CV(RMSE) = coefficient of the variation for root mean square error.*

which appears to have influenced the distinct change in deserts of education from 2005 to 2014 into opportunities from 2015 to 2017.

Second, another change visible in comparison of Figures 6 to 7 and 8 to 9 depicts increased education and workforce opportunities from 2005 to 2017 that occurred for veterans but not nonveterans, which took place near El Paso, Texas. We interpret that this pattern verifies the model in that it captures the fact that Texas Tech University’s satellite presence in El Paso received about $80 million in tuition revenue bonds from the state legislature in 2015 (Welsh 2015). These statistical and qualitative observations validate that our approach can detect the kinds of changes that matter to our study population at the temporal and spatial scale applied.

### Discussion and Roadmap

Overall, these results can provide an assessment of past change that can potentially serve as a base map to design a future roadmap for education opportunity development, tailored to our population of interest. These patterns provide a context within which individual life trajectories can be interrogated. In general, we can conclude from the results that (1) education deserts are different for veterans than for nonveterans, (2) they are dynamic and have changed over the period from 2005 to 2017 to appear as increasingly consolidated regions, (3) the related landscape of workforce opportunities similarly shows distinct patterns for the two groups and also change over time, and (4) patterns of workforce opportunities as depicted by our models have grown more similar to the patterns of educational opportunities for both groups, even though differences persist, caveated by the observation that internal validity of the workforce model contains data errors that exceed accuracy thresholds. Examination at different scales across these models, and improvement of variables to better depict the workforce landscape would enlighten different regional and even local contexts.
Because the fuzzy overlay can pick up on major changes in the education landscape at a legible resolution, and because the model can differentiate between veteran and nonveteran populations, this approach can provide a context for assessing and understanding individual trajectories, essentially enabling a spatial context for life course analyses. Furthermore, it can assist departments and universities to better understand the potential future impacts of decisions to engage or invest in communities of interest, be it for growth in student enrollment or improved inclusion of veterans, traditionally underrepresented minorities, or other potential student populations. Ideally, such actions should be attentive to the patterns of educational deserts in general, for an interest group in particular, and use corresponding levels of data detail for the scale of analysis. Similarly, collective action across institutions and sectors should be attentive to systems-level change and cognizant of the education desert landscape and consider monitoring shifts over time. For purposes of discussion, Figure 10 extracts the 2017 education deserts experienced by veterans and active-duty military families from the EOV-17 model, overlaid by the sites of public/nonprofit versus private colleges and universities to illustrate the collective opportunity for increasing the public higher education share of the growing Post-9/11 GI Bill resources. The brown areas (education deserts) where blue dots (public or nonprofit colleges) coincide reflect our interest in the application of this methodological approach, namely, where our model predicts unmet demand among veterans and military families for public universities like Texas Tech.

Although our methodology could inform programs that seek to engage or expand support to veterans and military families, there are important limitations. Most notable, in the wake of the shock of unemployment that began in early 2020 due to the COVID-19 pandemic, and in reflection of the systemic racism that the movements of Black Lives Matter compel us to reflect on, it is clear that institutions of higher education will have to innovate to understand and respond to a “new normal” at best

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<th>Age 18–34</th>
<th>Age 35–54</th>
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<th>Employment status</th>
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Note: MAPE = mean absolute percentage error; CV(RMSE) = coefficient of the variation for root mean square error.
and a “better forward” that redresses historic lack of access patterns. Such innovations should take into account the different educational deserts of key underserved populations, whether they are veterans, underrepresented minorities, older adults looking to upgrade skills, or others, at the same time offering opportunities for interinstitutional cooperation across the public university sector (Bothwell 2020). New offerings for online degree programs, or hybrid modalities, can benefit from better understanding of these unique landscapes, too. Although our study depicts brick-and-mortar sites of colleges and universities, our methodology could be creatively adapted to support various goals by different choices of data sets (like broadband access) and configurations of audiences (like unemployed residents with some college but no degree). Further research and adaptation are also needed to test results at different scales of analysis to understand the impact on the choice of study area and size on the outcomes.

Beyond these caveats, it is critical to emphasize that simply understanding education deserts is only a starting point for analysis at individual or systems scales, and for deeper engagement efforts. The data models do not portend to fully capture the military family or veteran experience but simply to improve how we might understand the context for such experiences. It is insufficient to apply these results to outreach without also understanding the particular needs of the prospective students of interest. High-risk characteristics of this important audience of veterans and military families—who might suffer reintegration challenges such as posttraumatic stress, physical rehabilitation, suicide, and homelessness (Brenner et al. 2008) or even potential political radicalization among those who leave the service frustrated or disenchanted (Jones 2019; Lipinski 2019; Allam 2020)—make finding answers to our driving questions even more compelling.

**Conclusion**

Without a robust and innovative spatial methodology to assess in detail the complex landscape of education deserts, public institutions of higher education might be missing significant opportunities to grow enrollments, increase inclusion of traditionally underrepresented minority students, and leverage the

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**Figure 10.** Education deserts: Results from the EOV 2017 model overlaid with locations of U.S. colleges and universities, by type (NCES 2019; USGS 2019). EOV = education for veterans.
significant and growing investment in education benefits for veteran and active-duty military families—resources that are disproportionately spent at for-profit colleges and universities. Meanwhile, without a clear understanding of the opportunity landscape, many veterans and military members are missing the chance to overcome a lack of access to degree programs that are in reasonable proximity, that lead to civilian workforce prospects, and especially that build on their unique global and technical experiences acquired during service, such as STEM in general or geography and GIS in particular. The impetus is clear to forge location-aware analysis and to explicitly apply what we know about distance, places, and regions to implement more supportive, proactive, and knowledge-based offerings for all students, especially women and minorities and certainly among veterans of our armed forces. Finally, our approach offers a response to the important critique of life course theory’s lack of attention to a context of where these experiences are unfolding. This study used our design of a suitability analysis with fuzzy logic methods to identify education deserts for the southern United States from 2005 to 2017. The results paint a picture of a dynamic and geographically variable landscape of access that is able to account for multivariate spatial analysis of characteristics of a particular group of interest: veteran status, age, education, median income, and employment status; proximity to physical sites of higher education and bases; and other important factors that can relate to the ability to pursue higher education—with the Post-9/11 GI Bill supporting them.

Departments and universities, especially in the public sector, can use or further refine this approach to increase enrollments and grow more diverse student cohorts, goals that are even more critical in a postpandemic economic recovery era experiencing growing cognizance of racial and ethnic justice. We also believe that this education desert approach opens a data-informed space for conversations about the relative needs of different groups of interest, and we advocate for our findings to spark dialogues around inclusion, retention, equity, and alignment as an explicit spatial dimension of educational outreach. Continuing to refine the knowledge that these results suggest for the present dynamic moment in higher education promises to be as transformative for prospective students as for our understanding of the landscape of education deserts.

Supplemental Material

This set of maps presents each of the four models run for every year from 2005 to 2017. The models depict veterans and nonveterans (V/NV) by education and workforce factors (E/W). A map of colleges and universities and a map of military installations is also included for reference. See https://texastech.maps.arcgis.com/apps/MapSeries/index.html?appid=d054076e183b4d06ba383779256f3730.

Acknowledgments

We are grateful for the support provided by Dr. Dennis Patterson (co-PI), Dr. Melanie Hart (co-PI), David R. Hankins, Deb Crosby, and Jamiesha Granberry, as well as the military families and veteran students who informed and inspired this work.

Funding

We express appreciation to the National Science Foundation for award NSF DRL 1810587, for which Dr. Patricia Solis, PhD, serves as the PI and Amal Aljaddani is Graduate Research Assistant.

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