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11	Multilingual Community Visualizations (MCV): A GIS Dashboard for
12	Linguistic Research and NWS Operations
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#### ABSTRACT

26 The NWS is actively expanding its multilingual outreach to better serve the 68.8 million U.S. 27 individuals who speak a language other than English at home. Among these, 26.3 million 28 individuals with Limited English Proficiency (LEP) are of particular concern, as they often rely 29 entirely on translated forecasts to make life-saving decisions. Yet identifying where these 30 populations are concentrated has remained a persistent challenge for researchers and forecasters 31 alike. To address this issue, we developed the Multilingual Community Visualizations (MCV) 32 dashboard, a geospatial tool that maps language diversity of LEP populations across all 122 33 NWS Weather Forecast Offices. Using 2019 American Community Survey (ACS) 5-year 34 estimates, we implemented a detailed data processing workflow, including dasymetric mapping to resolve Modifiable Areal Unit Problems where County Warning Area (CWA) boundaries do 35 36 not align with Census geography. The dashboard, developed in ArcGIS Online, provides 37 interactive, CWA-specific insights through data visualizations, percentage maps, and dot density 38 layers. Since its release, MCV has supported language services across the NWS and informed 39 targeted research and operations in vulnerable LEP communities. It serves as both a research tool and operational asset, demonstrating the power of GIS-integrated demographic analysis. We 40 41 conclude with a discussion of future improvements, including automating the workflow, 42 integrating updated ACS data, and incorporating broader demographic indicators. The MCV 43 dashboard represents a scalable model for leveraging demographic data to advance targeted, 44 data-driven public safety communication.

## 45

#### SIGNIFICANCE STATEMENT

46 Language barriers pose a major challenge to effective risk communication during extreme 47 weather events. This study introduces the Multilingual Community Visualizations (MCV) 48 dashboard, a novel GIS-based tool that maps limited English proficient populations across all 49 NWS jurisdictions. By displaying U.S. Census data through spatial analysis and visualization techniques, the MCV enables researchers, forecasters and emergency managers to identify 50 51 language-specific needs and improve multilingual services and outreach. The dashboard supports 52 more tailored, data-informed strategies to protect vulnerable communities and enhance resilience 53 to disasters.

25

## 54 1. Motivation

55 The United States is home to a large and growing multilingual population, with over 68.8 56 million people, or approximately one in five Americans, speaking a language other than English 57 at home (U.S. Census Bureau 2023). This linguistic diversity creates both challenges and 58 opportunities for public agencies responsible for communicating life-saving information during 59 extreme weather and climate hazards. The NWS, whose mission is to provide weather, water, 60 and climate forecasts to protect life and property, has recognized the importance of reaching 61 multilingual communities (NWS 2023a). In recent years, they have expanded their services 62 beyond English-only forecasts by establishing translation teams and developing artificial 63 intelligence tools that generate machine-translated forecasts and warnings in multiple languages, 64 available at weather.gov/translate (Trujillo-Falcón et al. 2021, 2025, in progress).

65 As the NWS continues to broaden its multilingual communication efforts, there is a 66 growing need for social science research that examines how non-English-speaking populations 67 receive, understand, and respond to extreme weather events. Recent studies have revealed that 68 the most vulnerable among these groups are individuals with Limited English Proficiency 69 (LEP)—those who report speaking English less than "very well"—as they often rely entirely on 70 multilingual information for their safety (First et al. 2025; Trujillo-Falcón et al. 2024; Villarreal 71 et al. 2025). One big challenge, however, is identifying where the 26.3 million LEP individuals 72 are located across the country (U.S. Census Bureau 2023). Without that level of detail, it 73 becomes challenging to effectively plan and implement research and operational efforts across 74 the NWS, its end users, and the broader research community (NWS 2023a).

75 As a way to address these growing challenges, our team developed the Multilingual 76 Community Visualizations (MCV), a dashboard that maps the linguistic composition of 77 communities across nearly all 122 NWS Weather Forecast Offices (WFOs). Designed to be both 78 accessible and interactive, the dashboard serves as a practical tool for researchers, forecasters, 79 and other end users to identify where language-specific communication needs may exist. The 80 dashboard has already supported the design of multilingual social and behavioral science 81 research (Trujillo-Falcón et al. 2024) and has played a pivotal role in advancing language services for the NWS (Bozeman et al. 2024). This article overviews the methodology behind the 82 83 MCV and introduces the interactive dashboard to the weather, water, and climate enterprise.

## 84 **2. Data and Methods**

#### 85 a. Data Source

86 The first step in the geospatial visualization process involved selecting a reliable and 87 appropriate data source, a task that often entails navigating trade-offs related to data availability, 88 quality, and privacy. For this project, the team used the U.S. Census Bureau's American 89 Community Survey (ACS) as the primary data source due to its accessibility, comprehensive 90 coverage, and widespread use as the national standard for demographic analysis (Wong and Sun 91 2013). Unlike the Decennial Census, which is collected every ten years, the ACS is a continuous survey that samples households on a rolling basis and provides annual and multi-year estimates 92 93 (U.S. Census Bureau 2021). The ACS includes variables critical for language access analyses, 94 such as educational attainment, employment, and language spoken at home.

95 This study specifically used the 2019 5-Year Estimates from Table C16001: Language 96 spoken at home for the population 5 years and older, disaggregated at both the county and 97 Census tract levels for all 50 states and Puerto Rico (U.S. Census Bureau 2019). We selected the 98 5-year estimates for their enhanced spatial (county and tract-level) and categorical (grouping of 99 languages) granularity compared to 1-year estimates. As the most recent data available at the start of the investigation<sup>1</sup>, this dataset best met the study's needs. These estimates yield more 100 101 stable and reliable measures for smaller geographic units and reflect averaged trends from 2014 102 to 2019 (U.S. Census Bureau 2020). They supported the development of detailed maps of 103 linguistic vulnerability and guided subsequent analyses of populations with LEP.

We obtained U.S. County and Census tract shapefiles from the Census Bureau's
TIGER/Line service, which is specifically designed to support integration with ACS data tables
(Bevington-Attardi and Ratcliffe 2015). We conducted our calculations using the boundaries of
NWS County Warning Areas (CWAs), which define the regions for which each WFO is
responsible for issuing forecasts and warnings. These CWAs are composed of entire counties or
portions of counties, delineated using Public Forecast Zones (NWS 2023b). While forecast zones

<sup>&</sup>lt;sup>1</sup> We began the investigation in 2023, following a period in which the COVID-19 pandemic had disrupted data collection and processing, leading to increased uncertainty in Census estimates from prior years (e.g., Asiala et al. 2021).

often align with county boundaries, they are frequently subdivided to account for local variations
in weather caused by factors such as elevation, proximity to large bodies of water, or other
geographic and climatic considerations. We obtained the CWA shapefile from the NWS GIS
website (weather.gov/gis/).

114 While the ACS provided the most appropriate foundation for this study, it is important to 115 acknowledge its limitations. Although highly reliable, ACS figures are derived from sample-116 based estimates, which means they may only approximate the characteristics of a portion of the 117 population. To enhance transparency, the ACS includes margins of error for each estimate, 118 helping users assess the reliability of the data (Spielman et al. 2014; Wong and Sun 2013). 119 Another notable limitation of the ACS is its aggregation of less commonly spoken languages into 120 broader categories. For example, languages such as Portuguese, Italian, and Hindi are grouped 121 under the general 'Indo-European' category (U.S. Census Bureau 2019). Though this simplifies 122 reporting, it obscures linguistic diversity and may reduce the visibility of smaller language 123 groups in analyses (Krohn et al. 2022; Pavlovskaya and Bier 2012). Ideally, the expanded 42-124 language grouping provided by the similarly named Table B16001: Language spoken at home 125 for the population 5 years and older dataset would allow for a more granular and inclusive 126 representation of languages. However, this level of detail is currently unavailable at sub-state 127 geographies and for multi-year estimates due to data suppression and privacy concerns. Lastly, 128 distrust of government agencies and concerns over identifiability may discourage survey 129 participation among marginalized communities, contributing to population undercounts and 130 skewed estimates (Brown 2015; Spielman et al. 2014). Therefore, we speculate that the LEP 131 population estimates reported in the ACS and displayed on the MCV may underrepresent the true 132 size of these populations.

133 b. Data Processing

The data processing workflow involved four key steps: (1) data acquisition and cleanup, (2) Modifiable Areal Unit Problem (MAUP) resolution, (3) summary calculations, and (4) computed products (Fig. 1). The process began with retrieving the most recent 5-year C16001 estimates from the U.S. Census Bureau and importing them into ArcGIS Pro. While county-level estimates would typically be sufficient, spatial misalignment between CWA boundaries and

- 139 county borders required estimating populations in areas of spatial discrepancies. In particular, we
- 140 encountered the modifiable areal unit problem (MAUP), a statistical bias resulting from
- 141 aggregating data into arbitrary spatial units (Wong 2009).
- 142 A notable example occurred along the boundary between the NWS Sacramento (STO) and Reno
- 143 (REV) CWAs, where nine counties are divided due to the topography of the Sierra Nevada
- 144 mountains (Llewellyn 2023).





Fig. 1. Flowchart outlining data cleanup, processing, and joining for the MCV dashboard. Here,
blue steps are input feature layers or calculations. Green represents the output feature layers, and
yellow represents geoprocessing tools run in ArcGIS Pro.

149 To resolve MAUP-related discrepancies, we applied a dasymetric mapping approach, 150 leveraging ancillary data, such as land use, satellite imagery, and topographic information, to 151 more precisely redistribute areal population estimates (Eicher and Brewer 2001; Mennis 2009; 152 Petrov 2012). This method improves spatial resolution by reallocating population data based on 153 likely zones of habitation rather than relying solely on administrative boundaries. In the context 154 of this project, dasymetric mapping also helped mitigate the distortions introduced by arbitrary 155 county-CWA boundary mismatches. The resulting workflow involved three distinct scenarios: 156 (1) Census tracts that aligned directly with CWA boundaries, (2) unpopulated areas, and (3)

populated areas intersected by multiple CWAs. Each scenario required a tailored resolution
strategy to accurately reassign LEP population estimates within CWA boundaries (for visual
representations, see Llewellyn 2023).

In the first scenario where borders aligned well, the solution was relatively simple. A notable example comes from San Bernardino County, CA, which spans three NWS office CWAs: Phoenix, AZ (PSR), San Diego, CA (SGX), and Las Vegas, NV (VEF). For the more urbanized areas covered by SGX, we found that Census tract boundaries aligned well with the CWA boundaries. In these instances, we could use the existing tract-level counts and combine them with data from other counties in the same CWA to calculate an overall estimate. No significant modifications to the shapefiles were needed for these occurrences.

In the second scenario which included unpopulated areas, we elected to use satellite imagery to determine whether the portion of a shared county was populated. This situation arose in Northern Maine, where Somerset County spans two CWAs: Caribou (CAR) and Gray/Portland (GYX). Upon reviewing satellite imagery, we determined that the area within CAR had little to no permanent population. Based on this assessment, we split the county along CWA boundaries–assigning a population of zero to the CAR portion, while the GYX portion retained the original full population count.

174 The third scenario focusing on densely populated shared counties posed the greatest 175 challenge, as these regions had enough residents to meaningfully affect population counts. This 176 was particularly evident in Sierra and Alpine Counties in California, both of which are split 177 between the STO and REV CWAs. Complicating matters further, each county consists of only 178 one Census tract. Given their small populations, we determined that including the full population 179 of each county in both CWA totals would have minimal impact. As a result, Sierra and Alpine 180 Counties were counted in full for both the STO and REV CWAs. A similar case occurred in 181 Cayuga County, New York, where the boundary between the Buffalo (BUF) and Binghamton 182 (BGM) CWAs cut through the county, passing just south of a densely populated area. Despite 183 using tract-level data, this delineation still produced a MAUP conflict due to the artificial nature 184 of the CWA boundary. Following the rationale applied in California, we determined that 185 duplicating the tract's count across both CWAs was the most practical resolution, with limited 186 effect on the integrity of the analysis.

187 The use of multiple ancillary data sources to resolve MAUP scenarios is both expected 188 and encouraged, though each comes with its own limitations. In resolving the PSR-SGX-VEF 189 boundary conflict, for example, we relied on satellite imagery, state park boundaries, and Census 190 tract-level data to refine population estimates. While these strategies can substantially reduce 191 MAUP-related bias, completely eliminating its effects is often unattainable due to inherent 192 limitations in data availability and geographic resolution.

With MAUP addressed, we proceeded to generate summary counts for each CWA. This process began by adding a column to the county and tract shapefiles to store the three-character CWA identifier, enabling differentiation among county splits. Once each feature was assigned to a CWA, we calculated summary tables for each language group, including both total speakers and those classified as LEP. These summary tables were then joined to the corresponding CWA shapefile.

Following the table joins, we developed our computed products to enhance interpretability and facilitate cross-CWA comparison. Specifically, we derived two key metrics for each CWA and corresponding language: (1) the percentage of total speakers within a CWA who are LEP and (2) the percentage of total speakers who belong to a specific language group (e.g., Spanish, Chinese, etc.) who are LEP. The equations used to compute these metrics are shown in Fig. 1. These outputs formed the basis for developing an interactive dashboard to support analysis and decision-making.

# **3. Multilingual Community Visualizations Dashboard**

To improve accessibility and usability, we developed a comprehensive, web-based dashboard using the ArcGIS Online platform (Fig. 2). Processed Census data described in Section 2 were integrated into the platform, forming the foundation for an interactive interface tailored to the needs of both end users and researchers. The dashboard supports multiple visualization options to accommodate diverse user preferences.





## 213 Fig. 2. The Multilingual Community Visualizations dashboard

Users are first presented with a national map view. Upon selecting a specific CWA, the dashboard dynamically updates to display localized information. The left-hand panel shows the WFO identifier and a General Data Viewer with updated population counts of total and LEP population for the selected area. Key data summaries appear at the top, including the five largest LEP language groups and a pie chart in the upper-right corner that illustrates the percentage breakdown of language groups. To further promote flexibility and usability, we incorporated both percentage maps and dot density map layers.

Users can explore both the LEP population and overall speaker population for a range of languages, including Arabic, Chinese (including Mandarin and Cantonese), French (including Cajun and Haitian), German and other West Germanic languages, Korean, Slavic languages, Spanish, Tagalog (including Filipino), and Vietnamese. As discussed in Section 2, the ACS aggregates many smaller languages into broader linguistic groups. To reflect this, the dashboard also includes grouped categories such as Other Asian-Pacific, Other Indo-European, and a general "Other" category to capture remaining languages not individually specified.

The release of the MCV dashboard has advanced both research and operational efforts across the weather enterprise. Since its public debut in 2024, it has been accessed over 1,100 times by both researchers and end users (Llewellyn et al. 2024). In operational settings, the MCV

- 231 dashboard has been instrumental in supporting language services for the NWS. The tool has
- 232 informed decisions on prioritizing WFOs for involvement in the agency's pilot artificial
- 233 intelligence translation initiative (Bozeman et al. 2024; Trujillo-Falcón et al. 2025, *in progress*).
- Additionally, MCV data has been further analyzed to support the development of more localized
- and tailored communication strategies at the WFO level (Fig. 3). Overall, the MCV has
- supported a more cost-efficient and targeted delivery of language services for the NWS, helping
- to maximize impact for multilingual populations through evidence-based analysis.



238

Fig. 3. Census tract-level analysis of LEP Spanish speakers within the NWS Grand Forks WFO.
The map displays the percentage of each tract's population that identifies as LEP and speaks
Spanish at home. Insets highlight the Grand Forks and Fargo/Moorhead metro areas, where
concentrations are highest. Data are derived from the 2023 ACS 5-Year Estimates, which are not
yet publicly available in the MCV but are being prepared for inclusion in an upcoming update.

In the research domain, the MCV dashboard has helped target social science fieldwork in regions identified as highly vulnerable. This has led to the discovery of previously overlooked concentrations of LEP speakers in rural areas that face elevated risks from natural hazards. For example, Trujillo-Falcón et al. (2024) used the MCV dashboard to locate Spanish-speaking communities in Arkansas and Kentucky that were affected by the December 10–11, 2021

tornado outbreak. They overlaid MCV data with tornado tracks and were able to identify

250 possible areas where language inequities may have contributed to delayed tornado warning

response. This work showcases how researchers can use the MCV as a tool to enhance their

reach and impact.

# **4. Conclusion and Future Directions**

254 The MCV, in its current form, should be used as an example of the power of leveraging 255 GIS techniques to learn more about the communities the NWS or emergency managers serve, 256 and researchers wish to study. As such, we wish in the future to incorporate continuous 257 development into this interface and dataset to allow for effective decision-making. One of the 258 highest priorities is continuous updates to the most recent ACS data available (i.e., 2023 ACS 259 data), as the MCV was built on a dataset that was released 4 years prior to this publication. In 260 addition to updating to more recent data, we are interested in exploring the automation and/or 261 simplification of the geoprocessing workflow, to cut down on the amount of time required to 262 process and address the MAUP areas and ingest more recent data into the dashboard interface during regular updates. Lastly, we would like to consider the inclusion of additional 263 264 demographic data (e.g., country of origin) and different geographic levels of data (e.g., county 265 and Census tract level estimates) in future iterations of the MCV dashboard. This has been highly 266 requested by end users to better tailor their products, and further emphasizes the desire for 267 accessible data interfaces in this field.

268 The MCV dashboard is a proof of concept to demonstrate the usefulness of GIS 269 technology and the ACS estimates for decision-making workflows, whether in interdisciplinary 270 research, operational settings, or any other contexts. We strongly encourage our fellow 271 researchers and end users to consider the data present in the MCV dashboard (and other 272 additional demographic information not currently present in the dashboard) in their workflows. 273 Continuous improvement of the MCV dashboard is best supported through end user feedback 274 and recommendations. Please contact the corresponding author L.E. Llewellyn 275 (liaml3@illinois.edu) to share comments or feedback, which are greatly appreciated.

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- 284 Data Availability Statement.
- 285 The GIS dashboard developed for this study is available at the following link:
- 286 <u>https://experience.arcgis.com/experience/71664444b7a74403abc592967375c3a9/</u>.

287	REFERENCES
288	Asiala, M., and Coauthors, 2021: An assessment of the COVID-19 pandemic's impact on the
289	2020 ACS 1-year data. U.S. Department of Commerce, accessed 13 July 2025,
290	https://www.census.gov/library/working-papers/2021/acs/2021_CensusBureau_01.html.
291	Bevington-Attardi, D., and M. Ratcliffe, 2015: Data visualization at the US census bureau - an
292	American tradition. Cartogr. Geogr. Inf. Sci., 42, 63-69,
293	https://doi.org/10.1080/15230406.2015.1060149.
294	Bozeman, M. L., and Coauthors, 2024: How the NWS is training artificial intelligence to address
295	language accessibility gaps in weather information. Second Symp. on the Future of
296	Weather, Forecasting, and Practice, Baltimore, MD, Amer. Meteor. Soc., J5.2,
297	https://ams.confex.com/ams/104ANNUAL/meetingapp.cgi/Paper/430227.
298	Brown, A., 2015: The unique challenges of surveying U.S. Latinos. Pew Res. Cent. Accessed 9
299	June 2024, https://www.pewresearch.org/race-and-ethnicity/2015/11/12/the-unique-
300	challenges-of-surveying-u-s-latinos/.
301	Eicher, C. L., and C. A. Brewer, 2001: Dasymetric mapping and areal interpolation:
302	Implementation and evaluation. Cartogr. Geogr. Inf. Sci., 28, 125–138,
303	https://doi.org/10.1559/152304001782173727.
304	First, J. M., A. Castillo, E. Galvez, S. Lee, M. L. Held, and K. Ellis, 2025: Examining intraethnic
305	disparities in tornado hazard understanding, reception, and response in Latinx/e
306	communities in the Southeast United States. Wea. Climate Soc., 17, 101–113,
307	https://doi.org/10.1175/wcas-d-24-0010.1.
308	Krohn, J., J. Davis-Manigaulte, C. Fulcher, and J. S. Tiffany, 2022: Visualizing diversity: spatial
309	data as a resource enabling extension to better engage communities. J. Hum. Sci. Ext.,
310	https://doi.org/10.54718/AEKV5040.
311	Llewellyn, L. E., 2023: Navigating the MAUP maze. ArcGIS StoryMaps. Accessed 13 July 2025,
312	https://storymaps.arcgis.com/stories/5382a5bf5c4147dfa8ca521205db1b5e.
313	—, J. E. Trujillo-Falcón, M. L. Bozeman, and T. D. Fagin, 2024: Diving into the linguistic

314	melting pot: Using GIS to identify limited English proficiency communities across NWS
315	warning areas. Second Symp. on the Future of Weather, Forecasting, and Practice,
316	Baltimore, MD, Amer. Meteor. Soc., J5.5,
317	https://ams.confex.com/ams/104ANNUAL/meetingapp.cgi/Paper/430270.
318	Mennis, J., 2009: Dasymetric mapping for estimating population in small areas. Geogr.
319	Compass, 3, 727-745, https://doi.org/10.1111/j.1749-8198.2009.00220.x.
320	NWS, 2023a: Service Assessment: August-September 2021 Hurricane Ida. National Oceanic and
321	Atmospheric Administration, accessed 9 June 2025,
322	https://www.weather.gov/media/publications/assessments/Hurricane_Ida_Service_Assess
323	ment.pdf.
324	NWS, 2023b: 10-507: Public geographic areas of responsibility. U.S. Department of Commerce,
325	accessed 9 June 2025,
326	https://www.weather.gov/media/directives/010_pdfs/pd01005007curr.pdf.
327	Pavlovskaya, M., and J. Bier, 2012: Mapping census data for difference: Towards the
328	heterogeneous geographies of Arab American communities of the New York
329	metropolitan area. Glob. Rise Local Implic. MarkOriented Conserv. Gov., 43, 483-496,
330	https://doi.org/10.1016/j.geoforum.2011.10.007.
331	Petrov, A., 2012: One hundred years of dasymetric mapping: Back to the origin. Cartogr. J., 49,
332	256-264, https://doi.org/10.1179/1743277412y.0000000001.
333	Spielman, S. E., D. Folch, and N. Nagle, 2014: Patterns and causes of uncertainty in the
334	American Community Survey. Appl. Geogr., 46, 147–157,
335	https://doi.org/10.1016/j.apgeog.2013.11.002.
336	Trujillo-Falcón, J. E., O. Bermúdez, K. Negrón-Hernández, J. Lipski, E. Leitman, and K. Berry,
337	2021: Hazardous weather communication en español: Challenges, current resources, and
338	future practices. Bull. Amer. Meteor. Soc., 102, E765-E773,
339	https://doi.org/10.1175/BAMS-D-20-0249.1.
340	, A. R. Gaviria Pabón, J. Reedy, and K. E. Klockow-McClain, 2024: Systemic

- 341 vulnerabilities in Hispanic and Latinx immigrant communities led to the reliance on an 342 informal warning system in the December 10-11, 2021, tornado outbreak. Nat. Hazards 343 Rev., 25, 04023059, https://doi.org/10.1061/NHREFO.NHENG-1755. 344 -, M. L. Bozeman, L. E. Llewellyn, S. T. Halvorson, M. Mizell, S. Deshpande, B. Manning, 345 A. Shastry, and T. Fagin, 2025, in progress: From binary to bilingual: How the National 346 Weather Service is using Artificial Intelligence to develop a comprehensive translation 347 program. Artif. Intell. Earth Syst. 348 U.S. Census Bureau, 2019: Language spoken at home for the population 5 years and over. 349 American Community Survey, accessed 14 July 2025, 350 https://data.census.gov/table/ACSDT5Y2019.C16001?q=C16001:+LANGUAGE+SPOK 351 EN+AT+HOME+FOR+THE+POPULATION+5+YEARS+AND+OVER&g=010XX00 352 US\$1400000. 353 —, 2020: Understanding and Using American Community Survey Data: What All Data Users 354 Need to Know. U.S. Government Publishing Office, accessed 21 March 2025, 355 https://www.census.gov/programs-surveys/acs/library/handbooks/general.html. 356 —, 2021: Decennial Census and American Community Survey (ACS). Census.gov. Accessed 357 13 July 2025, https://www.census.gov/programs-surveys/decennial-census/about/census-358 acs.html. 359 —, 2023: Language Spoken at Home for the Population 5 Years and Over. American 360 Community Survey, accessed 14 July 2025, 361 https://data.census.gov/table/ACSDT5Y2023.C16001?q=C16001:+LANGUAGE+SPOK 362 EN+AT+HOME+FOR+THE+POPULATION+5+YEARS+AND+OVER&g=010XX00 363 US\$1400000. 364 Villarreal, M., C. MacPherson-Krutsky, and M. A. Painter, 2025: Barriers and best practices for 365 inclusive emergency alerts and warnings. Int. J. Disaster Risk Reduct., 125, 105581,
- 367 Wong, D. W., 2009: Modifiable areal unit problem. *International Encyclopedia of Human*

https://doi.org/10.1016/j.ijdrr.2025.105581.

368	<i>Geography</i> , Elsevier, 169–174, https://doi.org/10.1016/b978-008044910-4.00475-2.

- Wong, D. W., and M. Sun, 2013: Handling data quality information of survey data in GIS: A
  case of using the American Community Survey Data. *Spat. Demogr.*, 1, 3–16,
- 371 https://doi.org/10.1007/BF03354884.