Dynamic Population Mapping to Advance Energy-Water Resilience

Andrew Zimmer[a], Joe Tuccillo[a], Byeonghwa Jeong[a], Sangkeun Lee[a], Marie Urban[a]

[a]Geospatial Science and Human Security, Oak Ridge National Laboratory, Oak Ridge, TN, USA

Corresponding author: zimmera@ornl.gov

Focal Area

Energy and water systems in the U.S. face stress from population growth, seasonal demand spikes, and high-demand industries under variable climate conditions. Household-level demand profiles informed by a suite of cross-sectional demographic and economic characteristics, paired with dynamic population mapping, enable more precise forecasting and resilience planning.

Existing Challenge

Energy and water systems in the United States are deeply interconnected and have multiple vulnerabilities [13, 29, 1]. Local surges in demand—from growing or temporary populations—can cascade across municipal and regional energy-water systems, creating both challenges and opportunities for efficiency and resilience [30, 4]. Propagation of these local dynamics also creates opportunities for efficiencies and resilience.

Total population size and temporal-spatial dynamics—including seasonal mobility and migration—critically shape local and regional consumption. Populations heading to cooler climates in summer can create short-term demand spikes [16, 12]. Household composition and socioeconomic characteristics, such as income and size, influence per-household energy and water use [5, 15].

Current modeling often relies on static population estimates, limiting reflection of temporal and spatial variability and reducing the ability to anticipate peak loads [32, 18, 15]. Household socioeconomic factors drive variations in energy and water use across regions [15, 26, 8]. High-resolution, temporally explicit population data integrated with household-level consumption profiles enables more accurate forecasting and identification of at-risk populations [19, 9].

Near-Term Opportunity

Oak Ridge National Laboratory has over 25 years of experience developing population data through the LandScan program, providing a strong foundation for high-fidelity population modeling [11, 2, 21, 20, 10]. LandScan produces global 1 km rasters representing ambient population counts, including U.S. day- and night-time populations [2]. These datasets and methodologies have been leveraged to project U.S. populations to 2030 and 2050 [11], generate high-resolution global population data [20], and more recently, to create synthetic populations, which capture household-level demographic and socioeconomic traits [21, 23, 22]. Such datasets and methodologies support modeling of electricity and water demand, energy-water interactions, and resilience under dynamic population scenarios [3, 13, 14, 29, 1, 30, 4, 15, 32, 19, 9].

Integrating dynamic population mapping with seasonal mobility patterns can further improve these datasets. This approach provides an opportunity to better account for population-driven demand. Coastal resort areas and second homes in southern Arizona, for example, experience substantial temporal changes in population that directly influence local energy and water loads. Modeling these flows allows energy and water use profiles to move with populations, supporting precise forecasting, targeted infrastructure planning, and improved management of peak loads and system stress [32, 6, 17, 31]. As illustrated in Figure 1a, these layers—including seasonal population dynamics, socioeconomic demand, climate shocks, and emerging industries—feed into a conceptual dynamic demand model that produces scenario-based outputs.

Over the next 3–5 years, the approach will proceed in three concrete steps: (1) integrate high-resolution population datasets with household-level demand profiles; (2) incorporate seasonal and temporary population dynamics into dynamic maps; and (3) simulate scenario-based energy-water responses under climate variability and emerging industrial demand. Implementation will involve collaboration among DOE National Laboratories, municipal utilities, academic institutions, and industry partners to validate models, share data, and evaluate resilience outcomes.

Coupling LandScan and micro-simulation with ORNL's Critical Infrastructure Resilience expertise enables assessment of both supply-side vulnerabilities and populations at risk during extreme events. This integration advances energy–water resilience by informing climate-aware planning, scenario testing, and investment decisions [27]. Incorporating real-time and forecasted weather data (e.g., from NWS or Open-Meteo) further enhances the framework, allowing dynamic adjustment of population-linked demand profiles to anticipate short-term surges during heatwaves, cold snaps, or heavy precipitation. These capabilities support municipal and utility decision-making, optimize operations to reduce peak-load stress, and promote equitable access to energy and water services, thereby mitigating societal impacts from demand fluctuations and extreme events.

Key Outputs and Deliverables

Figure 1b depicts the conceptual dynamic demand model. Inputs including household profiles, seasonal mobility, climate shocks, and emerging industry growth are integrated to produce high-fidelity maps, peak-load and risk assessments, scenario planning, and resilience guidance.

High Resolution Household Demand Profiles

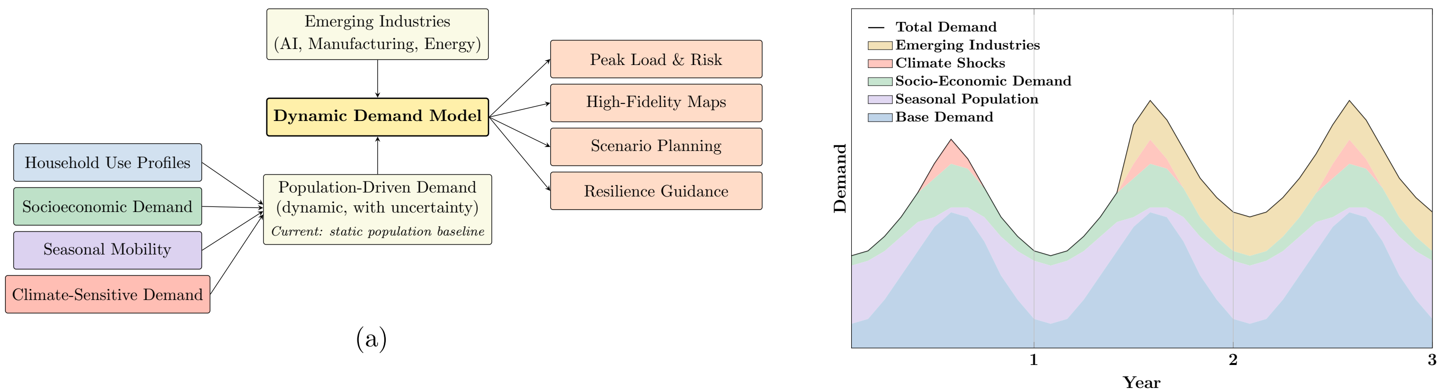
Using established methods for data fusion social survey data to synthetic populations[24], develop household-level profiles of energy and water by combining synthetic population data describing household demographic (household size, living arrangement) and economic (income and assets) characteristics matching those in social surveys focused on housing and resource use [28, 25]. Explore modeling an integrated seasonal population by estimating probable long-distance travel flows from transportation surveys [7] and assigning them to vacant second home, short-term rental, and temporary residential (e.g., hotel) locations. This integrated dataset captures spatial, temporal, and socioeconomic variability (Figure 1a), supporting multi-scale demand modeling and planning [19, 15].

Seasonal and Mobility-Driven Demand Dynamics

Dynamic population mapping quantifies seasonal and temporary population shifts linked to household demand (Figure 1b), identifying peak-load periods and areas of potential supply constraint, supporting planning for routine and extreme scenarios.

Scenario-Based Analysis

Simulation platforms integrate household demand, population dynamics, and infrastructure characteristics to evaluate system responses under diverse scenarios, including climate extremes and industrial growth. This provides actionable insights for resilience planning and operational decision-making [15].



(b)

Figure 1: Conceptual Dynamic Demand Model with Illustrative Demand Distribution

Success Measures

Successful implementation of dynamic, population-informed modeling can be measured through improved forecasting accuracy, reduced peak energy and water loads, and enhanced system efficiency. Reduced peak loads translate to lower outage risk, improved access for vulnerable populations, and better alignment with municipal planning and investment policies. Additional benefits include greater operational flexibility, improved decision-making under variable population and climate conditions, and increased resilience to disruptions. Broader success is reflected in adoption by utilities, municipalities, and partners, demonstrating practical value and scalability across the energy-water nexus.

Conclusion

Dynamic population mapping, combined with household-level energy and water demand profiling, provides a scalable framework for improving U.S. energy–water resilience. By capturing seasonal mobility, socioeconomic variability, and climate-sensitive behaviors, this approach enables more accurate forecasting, targeted infrastructure planning, and equitable resource allocation. Applied in regions with strong seasonal population dynamics, it reveals vulnerabilities, optimizes system performance, and supports climate-aware decision-making across interconnected energy–water systems.

References

[1] D. Bauer, M. Philbrick, B. Vallario, H. Battey, Z. Clement, F. Fields, J. Li, and et al. The water-energy nexus: Challenges and opportunities. US Department of Energy, Washington, DC, USA, 2014.

[2] B. L. Bhaduri, E. A. Bright, P. R. Coleman, and M. L. Urban. Landscan usa: A high resolution geospatial and temporal modeling approach for population distribution and dynamics. *GeoJournal*, 69(1-2), 2007.

[3] D. Cawthorne, A. R. de Queiroz, H. Eshraghi, A. Sankarasubramanian, and J. F. DeCarolis. The role of temperature variability on seasonal electricity demand in the southern us. *Frontiers in Sustainable Cities*, 3:644789, 2021.

[4] S. Cohen, A. Miara, V. Tidwell, S. Turner, N. Voisin, and A. Dyreson. Water and climate impacts on ercot long-term systems assessment. Technical Report NREL/TP-6A20-79581, National Renewable Energy Laboratory, Golden, CO, 2022.

[5] A. Cominola, E. S. Spang, M. Giuliani, A. Castelletti, J. R. Lund, and F. J. Loge. Segmentation analysis of residential water-electricity demand for customized demand-side management programs. *Journal of Cleaner Production*, 172:1607–1619, 2018.

[6] P. Deville, C. Linard, S. Martin, M. Gilbert, F. R. Stevens, A. E. Gaughan, V. D. Blondel, and A. J. Tatem. Dynamic population mapping using mobile phone data. *Proceedings of the National Academy of Sciences of the United States of America*, 111(45):15888–15893, 2014.

[7] Federal Highway Administration. 2022 National Household Travel Survey. `https://nhts.ornl.gov`, 2022.

[8] Federation of American Scientists. Keeping people cool in a heating world, 2024. Accessed: 2025-10-17.

[9] T. Fuentes, K. McCord, M. Martell, and C. Antonopoulos. A dataset for understanding self-reported patterns influencing residential energy decisions. *Scientific Data*, 12, 2025.

[10] V. Lebakula, K. Sims, A. Reith, A. Rose, J. McKee, P. Coleman, J. Kaufman, M. Urban, C. Jochem, C. Whitlock, M. Ogden, J. Pyle, D. Roddy, J. Epting, and E. Bright. Landscan global 30 arcsecond annual global gridded population datasets from 2000 to 2022. *Scientific Data*, 12(1):495, 2025.

[11] J. McKee, A. Rose, E. Bright, T. Huynh, and L. Bhaduri. Locally adaptive, spatially explicit projection of us population for 2030 and 2050. *Proceedings of the National Academy of Sciences of the United States of America*, 112, 2015.

[12] C. Miralles. The footprint of tourism: A review of water, carbon, and ecological impacts. *Journal of Environmental Management*, 345:116307, 2023.

[13] K. Mongird, J. S. Rice, K. Oikonomou, and J. Homer. Energy-water interdependencies across the three major united states electric grids: A multi-sectoral analysis. *Utilities Policy*, 85:101673, 2023.

[14] L. B. S. Morais, G. Aquila, V. A. D. de Faria, L. M. M. Lima, J. W. M. Lima, and A. R. de Queiroz. Short-term load forecasting using neural networks and global climate models: An application to a large-scale electrical power system. *Applied Energy*, 348:121439, 2023.

[15] R. Obringer, R. Nateghi, J. Knee, K. Madani, and R. Kumar. Urban water and electricity demand data for understanding climate change impacts on the water-energy nexus. *Scientific Data*, 11(1):1–12, 2024.

[16] D. E. Rupp, S. J. Dundas, L. C. Mazaud, and S. de Szoeke. How tourists 'escaping the heat' may drive future increases in municipal water demand in oregon coastal communities. *Discover Water*, 4:72, 2024.

[17] D. Stathakis and P. Baltas. Seasonal population estimates based on night-time lights. *Computers, Environment and Urban Systems*, 68:133–141, 2018.

[18] D. B. Steffelbauer, E. J. M. Blokker, S. G. Buchberger, A. Knobbe, and E. Abraham. Dynamic time warping clustering to discover socioeconomic characteristics in smart water meter data. *Journal of Water Resources Planning and Management*, 147(6):04021026, 2021.

[19] S. Thorve, Y. Baek, S. Swarup, H. Mortveit, A. Marathe, A. Vullikanti, and M. Marathe. High resolution synthetic residential energy use profiles for the united states. *Scientific Data*, 10, 2023.

[20] J. Tuccillo, J. Moehl, D. Adams, A. Cunningham, M. Urban, S. Walters, C. Woody, A. Reith, J. Kaufman, J. Epting, J. Gonzales, P. Dias, C. Clark, H. Yang, R. Stewart, D. Lunga, E. Weber, and B. Bhaduri. LandScan HD: A high-resolution gridded ambient population methodology for the world, 2025. Preprint.

[21] J. Tuccillo, R. Stewart, A. Rose, N. Trombley, J. Moehl, N. Nagle, and B. Bhaduri. UrbanPop: A spatial microsimulation framework for exploring demographic influences on human dynamics. *Applied Geography*, 146:102844, 2022.

[22] J. V. Tuccillo and J. D. Gaboardi. Likeness: a toolkit for connecting the social fabric of place to human dynamics. In *Proceedings of the 21st Python in Science Conference (SciPy) 2022*, 2022.

[23] J. V. Tuccillo and J. D. Gaboardi. Spatial microsimulation and activity allocation in python: An update on the likeness toolkit. In *Proceedings of the 22nd Python in Science Conference (SciPy) 2023*, 2023.

[24] K. Ummel, M. Poblete-Cazenave, K. Akkiraju, N. Graetz, H. Ashman, C. Kingdon, S. Herrera Tenorio, A. S. Singhal, D. A. Cohen, and N. D. Rao. Multidimensional well-being of us households at a fine spatial scale using fused household surveys. *Scientific Data*, 11(1):142, 2024.

[25] U.S. Census Bureau. American Housing Survey, 2023.

[26] U.S. Department of Energy. Low-income household energy burden varies among states — efficiency can help in all of them, 2019. Accessed: 2025-10-17.

[27] U.S. Department of Energy. 2021 climate adaptation and resilience plan. Technical report, U.S. Department of Energy, 2021. Accessed: 2025-10-18.

[28] U.S. Energy Information Administration. 2020 Residential Energy Consumption Survey: Consumption and Expenditures Technical Documentation Summary, 2025.

[29] D. Van Vuuren, D. Bijl, P. Bogaart, E. Stehfest, H. Biemans, S. Dekker, J. Doelman, D. Gernaat, and M. Harmsen. Integrated scenarios to support analysis of the food–energy–water nexus. *Nature Sustainability*, 2:1132–1141, 2019.

[30] N. Voisin, A. Dyreson, T. Fu, M. O'Connell, S. W. Turner, T. Zhou, and J. Macknick. Impact of climate change on water availability and its propagation through the Western U.S. power grid. *Applied Energy*, 276:115467, 2020.

[31] D. Woods, A. Cunningham, C. E. Utazi, M. Bondarenko, L. Shengjie, G. E. Rogers, P. Koper, C. W. Ruktanonchai, A. J. Tatem, J. Steele, and A. Sorichetta. Exploring methods for mapping seasonal population changes using mobile phone data. *Humanities and Social Sciences Communications*, 9, 2022.

[32] G. Zhou, Z. Li, W. Wang, Q. Wang, and J. Yu. Understanding the impact of population dynamics on water use utilizing multi-source big data. *Journal of Hydroinformatics*, 26(3):549–566, Jan 2024.