



Optimization of United States Residential Real Estate Investment through Geospatial Analysis and Market Timing

Harrison Gale¹ · Shouraseni Sen Roy¹

Received: 1 June 2022 / Accepted: 10 July 2022 / Published online: 3 September 2022
© The Author(s), under exclusive licence to Springer Nature B.V. 2022

Abstract

In this study, we examined the long-term spatial patterns and trends of home values within the United States from 1996 to 2019. The Zillow Home Value Index (ZHVI) data were obtained from the Zillow's housing data portal. The overall trends indicated both coasts of the United States having the highest concentration of hotspots. The ideal time to sell varied seasonally across the country. We used geo-statistical analysis techniques, such as cluster analysis and emerging hot spot analysis (EHSA), to reveal the average and long-term trends in spatial patterns of home values. Washington was the only state with sporadic hot spots. The Western United States showed consecutive hotspots, most notably in California, but in surrounding states as well. The Northeast, Mid-Atlantic, and Florida were dominated by oscillating hotspots. Texas and the Southeast display new hotspots that signal change, indicative of southward migration of population. Finally, the Midwest has been a historical cold spot, but Cleveland has improved to a diminishing cold spot, pointing to the revitalization of the region. The seasonal level analysis displayed southern and coastal states as those benefiting most from winter home sales, and the colder northern states captured the most value and sold quicker in the summer months. This intuitive analysis of the country's variation in ideal sale month reveals a local view of when to sell rather than a generalized view of the entire United States.

Keywords Emerging hot spots analysis · ZHVI · Home values · United States · Real estate · Single-family homes

✉ Shouraseni Sen Roy
ssr@miami.edu

Harrison Gale
harrison.gale@icloud.com

¹ Department of Geography and Sustainable Development, University of Miami, Coral Gables, FL, USA

Introduction

Home prices in the United States have been trending upwards (Shiller, 2007) over time as the population continues to change their view of real estate as a major purchase to a worthwhile long-term investment. Residential real estate has appreciated overall but has still been subject to influential events that have affected value for both better and worse. The most notable event, the Great Recession (2008), slashed housing costs across the country and forced a plague of foreclosures and evictions. The effects of this housing bubble on home values in the United States were analyzed by Gupta et al., 2019. These values fell drastically and took quite some time to recover, as weary buyers needed to regain their trust in banks and the entire real estate market. After overcoming the traumatic recession, housing values began to rebound and have ultimately continued to follow an upward trend. This trend was amplified by the effects of COVID-19 as explored by Li and Kao (2022) and Wang (2021). The last few years of housing sales data have shown soaring prices fueled by low inventory and high consumer demand. This drastic uptick in capital required to purchase a home is precisely why it is necessary to understand when and where to invest in property. Therefore, the objective of this study is to analyze the spatial and temporal patterns of housing sales across the metropolitan areas in United States, so that informed decisions of when and where to buy and sell can be made. With the rise of data collection across companies, most now track the data beyond property sales on their websites. The two most accessible datasets, Zillow and Realtor.com, were the two sources used for this analysis. The Zillow dataset has been used widely to approximate where the overall real estate market is headed as well as looking at year-on-year changes across the United States. However, prior to this study there had not yet been a comprehensive study showing small-scale data across the entire United States over a large time-period such as the 24 years studied in this research.

Other instances of more concentrated effects on U.S. house prices include analyzing the introduction of transportation systems to certain cities and how they have greatly benefited surrounding properties, as previously difficult to access areas become attainable (Lewis-Workman & Brod, 1997; Mathur & Ferrell, 2013; Stecker, 2009). One of the studies estimated the value of properties along dams and noted the potential hazards, causing decreases in prices. (Bohlen & Lewis, 2009). Other research explores locational attributes, such as central business districts, rivers, and parks among others to decide which factors have the largest effect on home values (Orford, 2002; Shen, 2005). Another similar study looked at detention ponds turned parks and how they drove up nearby home values (Lee & Li, 2009). Other studies analyzed the values of homes within beach towns and observed the added value of ocean view by way of viewshed analysis (Crawford et al., 2014; Hamilton & Morgan, 2010). In another study, Lepczyk et al. (2007) displayed the housing growth in a portion of the Midwest from 1940 to 2000, showing the spread of the population and how the urban areas grew and expanded farther from the city center. Changes in property values within CBSAs was explored and dissected for seasonality in certain study areas by Miller and Sklarz (2012).

The cost of using home service websites such as Zillow, as well as the accuracy of Zillow's home value estimates were tracked by Gindelsky et al. (2019) and compared to their own data as well as other big data services. According to Bin (2004), a comparison between two different regression models to determine home values revealed the detrimental effect of flood plains. Crime across major metropolitan areas was measured by Lynch and Rasmussen (2001), which showed that homebuyers pay a premium to be further from crime, but property crimes have less of an effect compared to serious felonies. Another study evaluated the proximity to hog farms and its negative impact on property values (Milla et al., 2005). An international look at a housing market showed the increase in property values near cities in Vietnam following foreign investment (Chung et al., 2018). One study noted that solar panels come at a serious cost, and this was monitored to find that this investment came with an overall greater sale price than their counterparts (Dastrup et al., 2012). Therefore, there are many studies that focus on the role of individual factors on home values and their trends over short time periods over specific areas. However, there are no studies examining the entire United States housing market and its changes over long periods of time. Therefore, in the present study we have examined the long-term spatial patterns and trends of home values within the United States from 1996 to 2019. While covering this large span of space and time, the pieces can then be put together by breaking down certain areas into case studies to see how long the areas were affected by these instances or how far beyond the study area effects were still felt. Moreover, the data goes beyond the specific dates of major events affecting the real estate market, which allows there to be an understanding of how long it took to feel the effects of an event and how quickly certain areas were able to recover after any effects subsided. This comprehensive review of the real estate market, backed by decades of data, will prove useful for planning and forecasting in the United States. It will also provide insight as to what the future real estate landscape will look like.

Study Area

The study area encompassed the United States (US), including Alaska and Hawaii. The entire study area experiences a wide range of climates, causing seasonality to be an important factor when considering home prices. The Southeast has hot-humid weather throughout the year (Rastogi et al., 2020; Sen Roy & Balling, 2005). The northern US is mostly cold with the more extreme points being very cold. The middle of the country to the Atlantic coast has mixed-humid weather that varies by season. The Southwest is hot-dry in the summer months and fades to mixed-dry before and after summer. The Pacific coastline line has a marine climate year-round. The analysis was conducted at the census neighborhood level. There was a total of 15,708 neighborhoods across the US, with home value data ranging from 1996 to 2020 (Fig. 1). In addition, there was a total of 896 metropolitan areas across the country (Figs. 4 and 5).

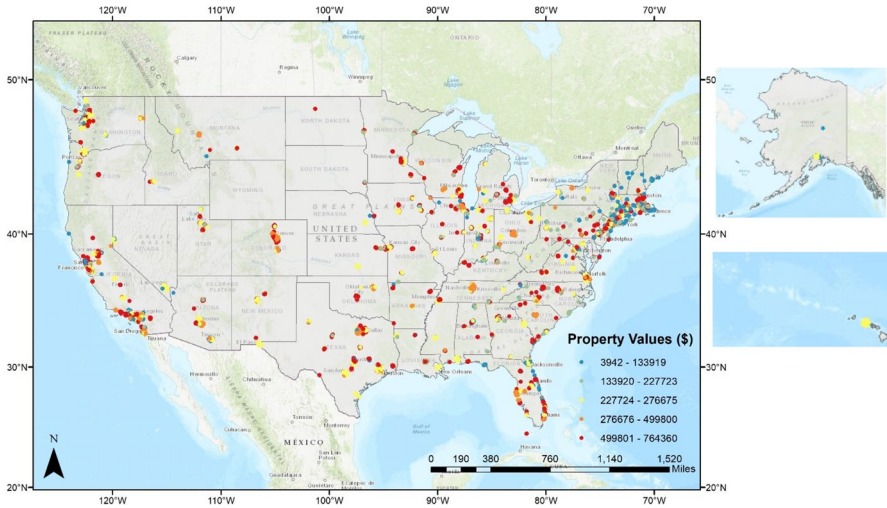


Fig. 1 General layout of the area. United States and major cities in the study area. Location of average property values in the United States from 1996 to 2020

Data and Methods

Housing Data

We used the Zillow Home Value Index (ZHVI) at the neighborhood level, which is a smoothed, seasonally adjusted measure of the typical home value and market changes across single family homes. This index reflects the typical value for homes in the 35th to 65th percentile range. This dataset was acquired from their data webpage for Zillow Research (<https://www.zillow.com/research/data/>). Each point is at the center of a neighborhood that Zillow has collected enough meaningful data to create an average home value for the neighborhood. Twenty-four years of spatial and temporal home value data, spanning from January 31, 1996 to December 31, 2019 were analyzed. To figure out which month is best to sell (high prices) or buy (low prices) for each metropolitan area, we analyzed Realtor.com metropolitan level data regarding the median listing price and median days on the market. The data offered many attributes, but since the primary concern was to address seasonal changes in home sales, we selected sale price and number of days on the market as the most meaningful measure. These sales data was acquired from their data webpage (<https://www.realtor.com/research/data/>). Each metropolitan area is denoted by a core based statistical area (CBSA) code that holds its associated median listing price and median days on the market. These housing data analyzed spans five years, from January 2017 to December 2021.

The ZHVI data were downloaded in CSV format, and then joined by neighborhood codes, which aligned with a neighborhood shapefile from the US Census

Bureau (2022). The table allowed the data to be displayed on the map while also stacking each month's data so that every neighborhood contained data for each of the twelve months over the entire 24-year period. The Census Bureau data represented 17,057 neighborhoods across the United States, of which 15,708 were joined with the ZHVI data. The Realtor.com data were also downloaded in CSV format, and then joined to a CBSA code shapefile from the Census Bureau by means of a query table to once again stack values for each metropolitan area. The Census Bureau data represented 918 metropolitan areas, of which 896 were joined to the Realtor.com data.

Emerging Hot Spot Analysis (EHSA)

Emerging hot spot analysis (EHSA) was used to identify the trends in spatial clustering in the presence of home values across time and space. EHSA constitutes two steps: (1) a space–time cube, and (2) the actual analysis. A space–time cube is a netCDF file containing points in x and y coordinates, with a z coordinate for time. The space–time bins were used to calculate the hotspot trends among the cubes of data within the study area, thus grouping them into cold- or hot-spot variations (Bunting et al., 2018; Tullis-Joyce & Sen Roy, 2021). It takes into consideration the neighborhood distance and time step parameter values to calculate the Getis-Ord G_i^* statistic (Hot Spots Analysis) for each bin (Sen Roy, 2022; Wan & Sen Roy, 2022). The result from this analysis is useful in understanding where the presence tends to cluster in the frequency of occurrence over time (Carter et al., 2019; ESRI, 2022). We calculated the EHSA based on a time cube with a time step interval of twelve months to capture the inter-annual variability in the distribution. These cubes measure the change in home value each month from 1996 to 2020 and range in color between red (hot-spot), blue (cold spot), and white when there is no measurable pattern, as well as several patterns used to signal the type of hotspot or cold spot. The different types of hotspots identified calculated from the EHSA analysis include the following:

New hot spot: A location that is a statistically significant hot spot for the final time-step and has never been a statistically significant hot spot before.

Consecutive Hot Spot: A location with a single uninterrupted run of statistically significant hot spot bins in the final time-step intervals.

Oscillating hot/cold spot: A statistically significant hot/cold spot for the final time-step interval, which has a history of also being a statistically significant cold/hot spot during a prior time-step.

Sporadic Hot/Cold Spot: A location that is an on-again then off-again hot/cold spot.

Diminishing Cold spot: A location that has been a statistically significant cold spot for ninety percent of the time-step intervals, including the final time-step.

Local Indicators of Spatial Autocorrelation (LISA)

Home value hotspots can be clustered (spatial clusters) or exist individually (spatial outliers) (Zhang et al., 2008). The spatial patterns of local level clustering were identified using the local Moran's I index (Anselin, 1995; Getis & Ord, 1996; Levine, 2004). In this study, spatial clusters of high home values would be high values surrounded by other samples with high values. In contrast, spatial outliers of home values would be samples with a high value surrounded by samples with normal or low values (Fig. 3). The following equation includes the explanation of the calculation:

The Local Moran's I statistic of spatial association is given as:

$$I_i = \frac{x_i - \bar{X}}{S_i^2} \sum_{j=1, j \neq i}^n w_{ij}(x_j - \bar{X}) \quad (1)$$

where x_i is an attribute for feature i , \bar{X} is the mean of the corresponding attribute, w_{ij} is the spatial weight between feature i and j , and:

$$S_i^2 = \frac{\sum_{j=1, j \neq i}^n (x_j - \bar{X})^2}{n - 1} \quad (2)$$

with n equating to the total number of features.

The z_{I_i} -score for the statistics are computed as:

$$z_{I_i} = \frac{I_i - E[I_i]}{\sqrt{V[I_i]}} \quad (3)$$

where:

$$E[I_i] = -\frac{\sum_{j=1, j \neq i}^n w_{ij}}{n - 1} \quad (4)$$

$$V[I_i] = E[I_i^2] - E[I_i]^2 \quad (5)$$

where z_i is the value of the variable z at location i ; z_{-} is the average value of z with the sample number of n ; z_j is the value of the variable z at all the other locations (where $j \neq i$); σ^2 is the variance of variable z ; and w_{ij} is a weight which can be defined as the inverse of the distance d_{ij} among locations i and j . The weight w_{ij} can also be determined using a distance band: samples within a distance band are given the same weight, while those outside the distance band are given the weight of 0.

In order to conduct the LISA analysis, monthly average values, for median listing price and average median days, were calculated at the neighborhood level at the monthly scale over five years (January 2017 to December 2021). A high positive local Moran's I value implies that the location under study has similarly high or low values as its neighbors, thus the locations are spatial clusters. Spatial clusters include high-high

clusters (high values in a high value neighborhood) and low–low clusters (low values in a low value neighborhood) (Fig. 2). In home values, low–low clusters are “cool spots”, while high–high spatial clusters can be regarded as “regional hotspots.” A high negative local Moran’s I value means that the location under study is a spatial outlier. Spatial outliers are those values that are obviously different from the values of their surrounding locations (Lalor & Zhang, 2001; Perlman & Sen Roy, 2021). Spatial outliers include high–low (a high value in a low value neighborhood) and low–high (a low value in a high value neighborhood) outliers (Louderback & Sen Roy, 2017), In home values, high–low spatial outliers can be regarded as isolated “individual hotspots”.

Results and Discussion

Spatial Patterns of Home Value Hotspots

The value of homes increased overall across the United States, apart from the Midwest functioning as a cold spot (Fig. 2). This decline in home value is due to the unattractive winters that Midwesterners must endure along with the dying steel and coal industries that are forcing past inhabitants to move elsewhere in search of jobs (Harrison & Immergluck, 2020). Moreover, with the loss of this income, families are unable to purchase homes leading to a high vacancy rate in these Midwestern cities relative to the rest of the United States (Harrison & Immergluck, 2020). The large number of homes that sit vacant for an extended period as well as the surrounding homes that are negatively impacted in terms of price are both bringing down the average value of homes across the region. In contrast, states like Florida and Texas offer booming job markets and no state income tax. This congruence of push and pull action has led to the flow of the Northern population to the southern United States.

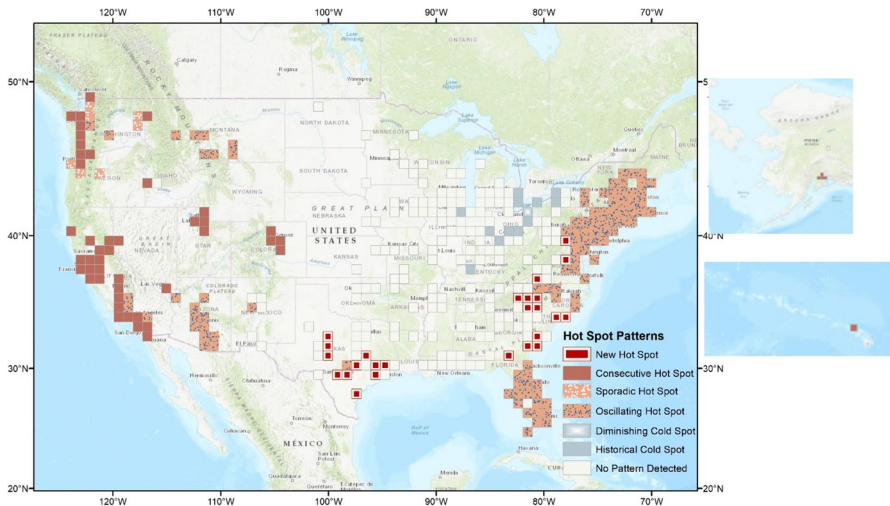


Fig. 2 Results of Emerging Hotspot Analysis at the monthly scale

In order to conduct the EHSA analysis, a space time cube was created, with each cube representing an area with a length of about 98km^2 across the country. The results of our analysis revealed the presence of different types of hot spots across the United States (Fig. 2). Further, the results revealed a more holistic view of the spatial and temporal distribution of home values during the study period. Hotspots are strewn along the east and west coasts of the United States along with a separate pocket in Texas. The variation across these hotspots is interesting as there are a few different variants appearing in clusters across the country (Fig. 2). The west coast has been a hotspot for quite a while as shown by the consecutive hotspots, which stretches eastward into Utah and Colorado. This is expected since Salt Lake City and Denver have long been cities for the wealthy to escape from the busy cities in California (Rodríguez-Pose and Storper, 2020). The consecutive hot spots in the west stretch further into Alaska and Hawaii. Shifting eastward, Texas has several new hotspots namely in Houston, Austin, San Antonio, and Corpus Christi. These new hotspots were also scattered in pockets from Virginia down to Valdosta, GA. Some large cities such as Charlotte, Asheville, Wilmington, Charleston, and Savannah represent these new hotspots. Also intriguing, are the new hotspots covering largely open areas from Virginia to Georgia, and the signs of COVID-19 that have pushed people to these remote places to escape the chaotic city life and the ease of transferring to remote work, allowing these previously difficult moves to become feasible. Oscillating hot spots appeared most frequently across the country, beginning in Maine, and flowing down to North Carolina, before picking up again in Florida. Other instances of oscillating hotspots can be found in Texas, New Mexico, Arizona, Montana, Washington, and California. All these hotspots show some variation across months but overall are upward trending, this is to be expected because states such as Arizona and Florida are very seasonal, and the markets cool down in the summer months and vice versa for the colder states (Bernard et al., 2014). Sporadic hotspots exist only in Washington and Oregon and are overall hotspots but often alternate hot then cold.

The area between Chicago, Louisville, and Buffalo experienced cold spots because it is struggling to retain the population (Fig. 2). This is to be expected as the loss of population in the Rust Belt has long been documented, since the loss of industrial and manufacturing jobs beginning in 1980 (Hegerty, 2019). However, much of the Midwest is still characterized by the lack of trend, which while not a hotspot, has yet to make a meaningful turn to signal the direction of the region. Even better, there is one sign of recovery in Cleveland, as the diminishing hotspot shows revitalization, particularly in the technology industry. Other surrounding areas have transitioned into healthcare and technology, such as Minnesota and Wisconsin, showing hope that the entire Midwestern region turn around its residential real estate markets.

Home Value Clusters Across the United States

After looking at the hotspots, LISA was used to explain which areas were affecting others for the worse or the better (Fig. 3). High-low clusters were most prominent all over the United States, but there are low-high clusters visible in some high cost of

living areas. These low–high clusters cover much of the Northeast, the west coast, Las Vegas, Arizona, Colorado, Minneapolis, D.C., Atlanta, Charleston, and South Florida. These areas have low-value neighborhoods among an overall high value region, a lot of these are neighborhoods along the coast, which make the inland areas seem comparably affordable. South Florida is the only cluster of low–high regions that is not surrounded by high-high neighborhoods, such as California and the Northeast. Therefore, this is an opportunity to take advantage of living in this area while there are still affordable pockets on the outskirts of the general high price neighborhoods. Similar to the results of EHSA, the majority of middle-America offers affordable homes, as expressed by the large number of low clusters. That is why the low–high cluster that most stands out lies in the Minneapolis-St. Paul metropolitan area (Fig. 3). This cluster in conjunction with the diminishing hotspot in Cleveland from the EHSA analysis shed light on the possibility of a rebounding Midwest. Clearly, this area is already making a comeback as seen in the cluster analysis but has not yet had an uptrend for a prolonged time to constitute the area as a hotspot. This forecasts a similar path for Cleveland, as it edges out of cold spot status, and soon the two metropolitan areas should bridge and breathe life into the Midwest again. This is further bolstered by the example of the bridge created between Atlanta and Charleston. The results of LISA show that both cities are the only examples of low–high clusters in their surrounding areas. Moreover, the results of EHSA depicts both approximate regions as new hot-spots, while drawing surrounding cities to the same status.

Seasonality in the Value of Homes within the United States

From the analysis of data from Realtor.com, we found the overall best month to quickly sell a house July for 213 metropolitan areas, closely followed by June for

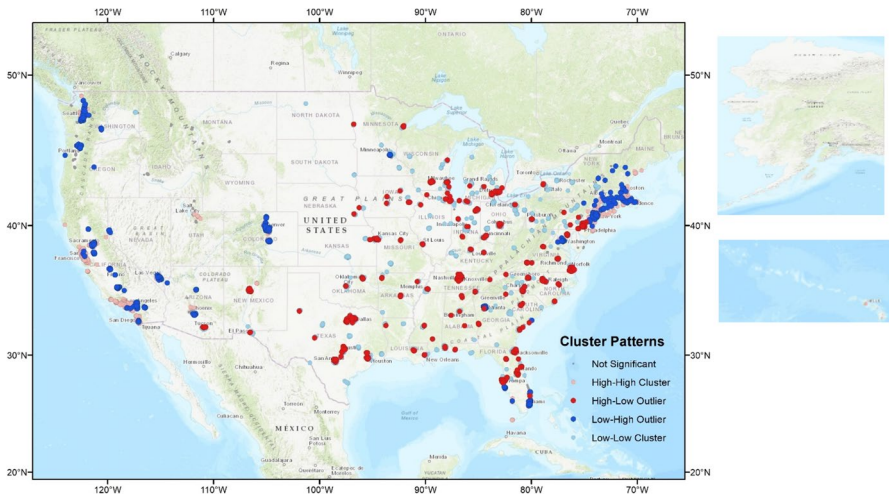


Fig. 3 Results of Local Indicators of Spatial Autocorrelation (LISA)

202 metropolitan areas. (Fig. 4). Thus, the majority of the country experienced success of summer home sales. However, areas such as Southern California, Arizona, New Mexico, Texas, and South Florida posted the winter months as the best time to sell, which matches the timeline of the older population flocking to these areas to get away from the harsh winters occurring in their home states. This migration of the elderly population to the warm American south has affected the real estate market for decades (Sullivan & Stevens, 1982). The real estate market of the southern United States performs well during the winter months, with the Northern half performing well in the summer. When looking to sell a house for the largest dollar amount, June is the best month reported by 157 metropolitan areas, followed by July with 144 areas. (Fig. 5). Surprisingly, 140 areas saw December as the best month to sell to maximize profits, but this is correlated with the warmer areas in Florida and Arizona. With this larger variation in values when looking at prices by month the map shows a more contested mosaic of red and blue, representing summer and winter months prevailing in respective areas. The general trend shows the western and southeastern United States receiving top dollar on home sales during the winter months, with middle-America and areas lying east selling for the most in the summer months. The most recognizable

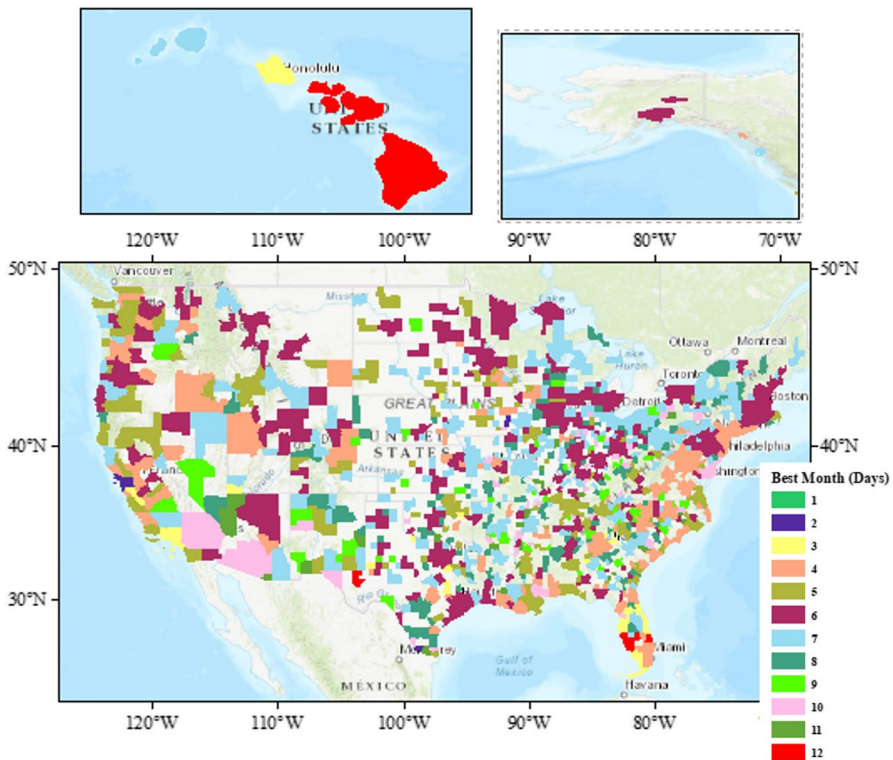


Fig. 4 Best month to sell homes in terms of days on the market

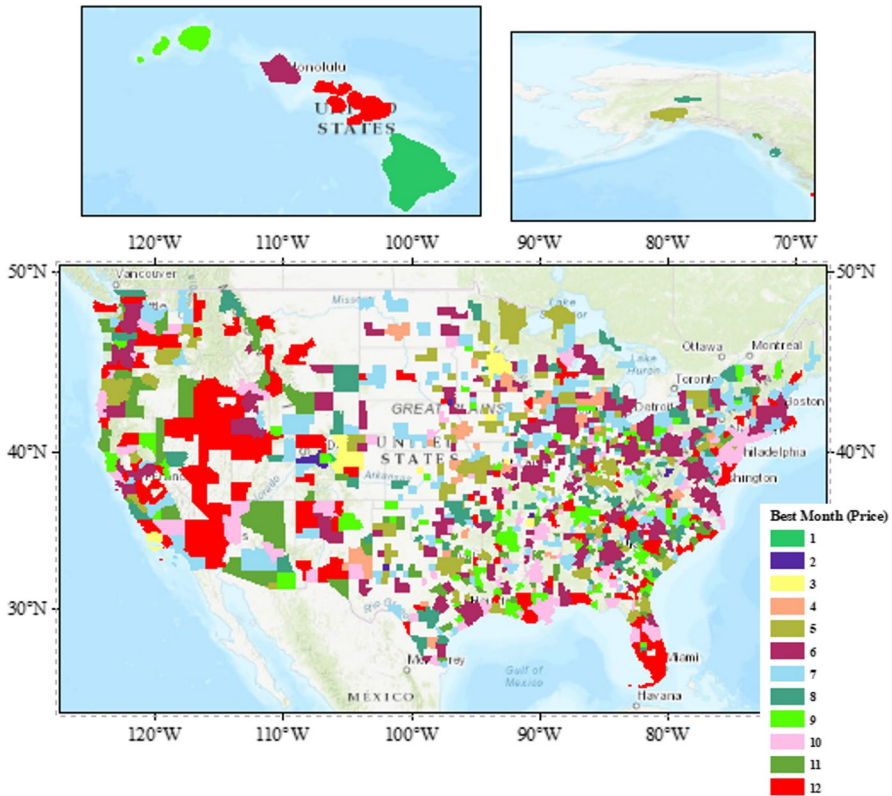


Fig. 5 Best month to sell homes in terms of selling price

exception stretches from Delaware to New York and displays fall as the best season to sell. Though for the most part Spring and Fall should be avoided when looking to sell the quickest and for the largest sum of money. On the other hand, these seasons act as value propositions for buyers, and should be taken advantage of to dodge the seasonal price increases.

Conclusions

The main findings of the study are summarized below:

- (1) The spatial patterns of home values varied seasonally in concentration and dispersion. These patterns in general correlated with climate, and economic conditions.
- (2) Overall, most of the United States experienced rising prices in home values between 1996 and 2020, except for the Midwest which is in the process of

recovering from dying industries. Most of the United States showed oscillating hotspots, with pockets of new hotspots and consecutive hotspots. In general, high-high clusters covered the map with the major exceptions being California, the Northeast, and South Florida.

- (3) In terms of seasonality, the northern half of the U.S. performed well in the summer months for both days on the market and sale price. This was the opposite for most of the southern United States which excelled in the winter months in terms of days on the market and sale price.

Declarations

Conflict of Interest All authors declare that they have no conflicts of interest.

References

- Anselin, L. (1995). Local indicators of spatial association—LISA. *Geographical Analysis*, 27(2), 93–115.
- Bernard, R. M., & Rice, B. R. (Eds.). (2014). *Sunbelt cities: Politics and growth since World War II*. University of Texas Press.
- Bin, O. (2004). A prediction comparison of housing sales prices by parametric versus semi-parametric regressions. *Journal of Housing Economics*, 13(1), 68–84.
- Bohlen, C., & Lewis, L. Y. (2009). Examining the economic impacts of hydropower dams on property values using GIS. *Journal of Environmental Management*, 90, S258–S269.
- Bunting, R., Chang, O. Y., Cowen, C., Hankins, R., Langston, S., Warner, A., Yang, X., Louderback, E. R., & Sen Roy, S. (2018). Spatial Patterns of Lar-ceny and Aggravated Assault in Miami-Dade County, 2007–2015. *Professional Geographer*, 70(1), 34–46. <https://doi.org/10.1080/00330124.2017.1310622>
- Carter, J., Louderback, E. R., Vildosola, D., & Sen Roy, S. (2019). Crime in an Affluent City: Spatial Patterns of Property Crime in Coral Gables, FL. *European Journal on Criminal Policy and Research*, 26, 547–570. <https://doi.org/10.1007/s10610-019-09415-5>
- Chung, Y. S., Seo, D., & Kim, J. (2018). Price determinants and GIS analysis of the housing market in Vietnam: The cases of Ho Chi Minh City and Hanoi. *Sustainability*, 10(12), 4720.
- Crawford, T. W., Bin, O., Kruse, J. B., & Landry, C. E. (2014). On the importance of time for GIS view measures and their use in hedonic property models: Does being temporally explicit matter? *Transactions in GIS*, 18(2), 234–252.
- Dastrup, S. R., Zivin, J. G., Costa, D. L., & Kahn, M. E. (2012). Understanding the Solar Home price premium: Electricity generation and “Green” social status. *European Economic Review*, 56(5), 961–973.
- ESRI (2022) Emerging Hot Spot Analysis (Space Time Pattern Mining). <https://pro.arcgis.com/en/pro-app/latest/tool-reference/space-time-pattern-mining/emerginghotspots.htm> (accessed on May 16, 2022).
- Getis A, Ord J K 1996 Local spatial statistics: an overview. In Longley P, Batty M (eds) Spatial analysis: modelling in a GIS environment. Cambridge (UK), *Geoinformation International*: 269–85
- Gindelsky, M., Moulton, J., & Wentland, S. A. (2019). Valuing housing services in the era of big data: A user cost approach leveraging Zillow microdata. In *Big Data for 21st Century Economic Statistics*. University of Chicago Press.
- Gupta, A., Nguyen, L., Dunning, C., & Chan, K. M. (2019). Quantifying the Effects of the 2008 Recession using the Zillow Dataset. *arXiv preprint arXiv:1912.11341*.

- Hamilton, S. E., & Morgan, A. (2010). Integrating lidar, GIS and hedonic price modeling to measure amenity values in urban beach residential property markets. *Computers, Environment and Urban Systems*, 34(2), 133–141.
- Harrison, A., & Immergluck, D. (2020). The Battle of the Belts: Comparing Housing Vacancy in Larger Metros in the Sun Belt and the Rust Belt since the Mortgage Crisis, 2012 to 2019. https://scholarworks.gsu.edu/urban_studies_institute/47/ (accessed on May 12, 2022).
- Hegerty, S. W. (2019). The Rust Belt, the Sunbelt, and the Concentration of Poverty Within Large US Cities. *Review of Regional Studies*, 49(3). <https://eds.s.ebscohost.com/eds/pdfviewer/pdfviewer?vid=0&sid=70563772-4d98-49d5-8bf8-796380d35f59%40redis>
- Lalor, G. C., & Zhang, C. (2001). Multivariate outlier detection and remediation in geochemical databases. *Science of the Total Environment*, 281(1–3), 99–109.
- Lee, J. S., & Li, M. H. (2009). The impact of detention basin design on residential property value: Case studies using GIS in the hedonic price modeling. *Landscape and Urban Planning*, 89(1–2), 7–16.
- Lepczyk, C. A., Hammer, R. B., Stewart, S. I., & Radeloff, V. C. (2007). Spatiotemporal dynamics of housing growth hotspots in the North Central US from 1940 to 2000. *Landscape Ecology*, 22(6), 939–952.
- Levine N. CrimeStat III: a spatial statistics program for the analysis of crime incident locations. Ned Levine & Associates, Houston, TX, and the National Institute of Justice, Washington, DC; 2004. November 2004.
- Lewis-Workman, S., & Brod, D. (1997). Measuring the neighborhood benefits of rail transit accessibility. *Transportation Research Record*, 1576(1), 147–153.
- Louderback, E. R., & Sen Roy, S. (2017). Integrating social disorganization and routine activity theories and testing neighborhood crime watch program effectiveness: Case study of miami-dade county, 2007–2015. *British Journal of Criminology*, 58(4), 968–992.
- Li, X., & Kao, C. (2022). Spatial Analysis and Modeling of the Housing Value Changes in the US during the COVID-19 Pandemic. *Journal of Risk and Financial Management*, 15(3), 139.
- Lynch, A. K., & Rasmussen, D. W. (2001). Measuring the impact of crime on house prices. *Applied Economics*, 33(15), 1981–1989.
- Mathur, S., & Ferrell, C. (2013). Measuring the impact of sub-urban transit-oriented developments on single-family home values. *Transportation Research Part a: Policy and Practice*, 47, 42–55.
- Milla, K., Thomas, M., & Ansine, W. (2005). Evaluating the effect of proximity to hog farms on residential property values: A GIS-based hedonic price model approach. *URISA Journal*, 17(1). https://go.gale.com/ps/i.do?id=GALE%7CA177439929&sid=googleScholar&v=2.1&it=r&linkaccess=abs&issn=10458077&p=AONE&sw&sw=&userGroupName=miami_richter
- Miller, N., & Sklarz, M. (2012). Integrating real estate market conditions into home price forecasting systems. *Journal of Housing Research*, 21(2), 183–213.
- Orford, S. (2002). Valuing locational externalities: A GIS and multilevel modelling approach. *Environment and Planning b: Planning and Design*, 29(1), 105–127.
- Perlman, J., & Sen Roy, S. (2021). Analysis of Human Movement in the Miami Metropolitan Area Utilizing Uber Movement Data. *Cities*. <https://doi.org/10.1016/j.cities.2021.103376>
- Rastogi, D., Lehner, F., & Ashfaq, M. (2020). Revisiting recent US heat waves in a warmer and more humid climate. *Geophysical Research Letters*, 47(9), e2019GL086736.
- Rodríguez-Pose, A., & Storper, M. (2020). Housing, urban growth and inequalities: The limits to deregulation and upzoning in reducing economic and spatial inequality. *Urban Studies*, 57(2), 223–248.
- Sen Roy, S. (2022). Spatial patterns of Malaria incidence in India 1995–2013. *Geo Journal*. <https://doi.org/10.1007/s10708-022-10624-5>
- Sen Roy, S., & Balling, R. C., Jr. (2005). Analysis of diurnal patterns of trends in winter precipitation across conterminous United States. *Monthly Weather Review*, 133, 707–711.
- Shen, G. (2005). Location of manufactured housing and its accessibility to community services: A GIS-assisted spatial analysis. *Socio-Economic Planning Sciences*, 39(1), 25–41.
- Shiller, Robert J. (2007). Understanding recent trends in house prices and home ownership.
- Stecker, N. S. (2009). A GIS Analysis on the Effects of the Hiawatha Light Rail on Single-Family Residential Property Market Values. <https://gis.smu.edu/GradProjects/SteckerN.pdf>. Accessed 2 Aug 2022
- Sullivan, D. A., & Stevens, S. A. (1982). Snowbirds: Seasonal migrants to the Sunbelt. *Research on Aging*, 4(2), 159–177.

- Tullis-Joyce, P., Sen Roy S (2021) Occurrence of *Karenia brevis* near Southwest Florida coast 1953 to 2017: A Geospatial Analysis. *Journal of Coastal Conservation*, 25 (57). <https://doi.org/10.1007/s11852-021-00844.-1>
- US Census Bureau. (2022). TIGER/Line Shapefiles. <https://catalog.data.gov/dataset/tiger-line-shapefile-2019-2010-nation-u-s-2010-census-urban-area-national>. Accessed 24 Mar 2022.
- Wan, C., & Sen Roy, S. (2022). Geospatial characteristics of fire occurrences in southern hemispheric Africa and Madagascar during 2001-2020. *Journal of Forestry Research*. <https://doi.org/10.1007/s11676-022-01487-0>
- Wang, B. (2021). How does COVID-19 affect house prices? A cross-city analysis. *Journal of Risk and Financial Management*, 14(2), 47.
- Zhang, C., Luo, L., Xu, W., & Ledwith, V. (2008). Use of local Moran's I and GIS to identify pollution hotspots of Pb in urban soils of Galway, Ireland. *Science of the Total Environment*, 398(1–3), 212–221.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.