Gulf Views: Toward A Better Understanding Of Viewshed Scope In Hedonic Property Models

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Abstract

This study examines the influence of Gulf of Mexico views on residential home sales prices in Pinellas County, Florida. We utilize Light Detection and Ranging (lidar) data to construct four continuous measures of Gulf of Mexico views—the total view, the maximum view segment, the mean view segment, and proximity to view content. Our results illustrate that residential property owners have a higher marginal willingness-to-pay for larger total views and larger continuous view segments. Results also indicate that the proximity of homes to the view content influences view valuations.

Hindsley, P., Hamilton, S., & **Morgan, A.** (2013). "Gulf Views: Toward A Better Understanding Of Viewshed Scope In Hedonic Property Models." *Journal of Real Estate Finance & Economics*, 47(3), 489-505. ISSN: 1573-045X. [DOI:10.1007/s11146-012-9365-0] Version Of Record Available At www.springer.com

Introduction

The flow of services from recreational and aesthetic amenities plays a contributing role in people's residential property choices. When compared to other locations, a disproportionate number of people in the U.S. live on or near the coast. For example, roughly 35% of the US population lives within shore-adjacent US coastal counties— an area representing only 17% of the total U.S. land area. While people have long been drawn to the coast, a lack of explicit markets for many coastal resources complicates our understanding of the how the flow of these services impact residential decisions. One way researchers have approached the challenge of valuing local environmental amenities is through the use of residential property transactions, via hedonic property models. In this paper, we use the hedonic framework to assess the influence of coastal view amenities, or viewsheds, on residential home prices.

In the valuation of viewsheds, researchers should make a concerted effort to communicate the specific view characteristics their analyses capture. Bourassa et al. (2004) discuss the failure of numerous studies to fully characterize their view measures. As an extension of their discussion, we differentiate the objective constituent components of a view into view content, scope, orientation, and content distance. These components capture the content of an individual home's viewshed (view content), the magnitude or size of a view (view scope), the direction of the existing view in relation to the home's spatial orientation (view orientation), and the distance to the relevant view content influencing the homebuyer's purchasing decision (content distance).

Our study investigates the influence of a Gulf of Mexico view on home prices in Pinellas County, Florida. We focus on two constituent components of a Gulf of Mexico view, scope and content distance. Utilizing Light Detection and Ranging (lidar) data, we construct a continuous measure of view that accounts for natural and man-made obstructions. By identifying each continuous swath of view as a view segment, we then examine three different ways in which the scope of a coastal view, in degrees, could be measured in a hedonic framework—the total view, the largest or maximum view segment, and the arithmetic mean of all view segments. In addition, we also study one type of content distance view measure. Finally, we estimate the marginal willingness-to-pay (MWTP) for these viewshed components.

Our general findings suggest that lidar-based view measures allow for significant flexibility in understanding the influence of view scope on sales prices. Households assign higher marginal valuations to their largest continuous view segment when compared to their total view. Of the three measures, we find the highest point estimates are associated with marginal increases in mean view, but this measure also captures the greatest uncertainty, as represented by the widest confidence intervals in MWTP. Last, our results indicate that content distance does influence point estimates of MWTP.

Background

Numerous studies have examined the aesthetic value of views within the hedonic framework. Over time, viewshed measures have become increasingly precise. Early research commonly captured property views by utilizing discrete variables, either through a single dummy variable, which acted as a proxy to infer the existence of a view of a resource, or through the use of a view scale, which is a type of subjective view measure, requiring a number of dummy variables to represent the quality of a view (Benson et al. 1998; Pompe and Reinhart 1995; Bond et al. 2002; Bourassa et al. 2004).2 Other studies also examined the role of distance on the value of views (Benson et al. 1998; Tyrväinen and Miettnen; Bourassa et al. 2004). The typical finding across these studies is that view amenities positively impact property values and the implicit value of a view decreases with increasing distance from a resource.

While these findings provided initial insight into the premium homeowners will pay for the view of an adjacent resource, the methods used to capture views in the hedonic property function had distinct limitations. First, constructing a view measure usually required physical inspection of the property, either by the researchers themselves or via household surveys. As such, these measures tend to suffer from the subjective nature of the researcher-derived view classification. The inclusion of dummy variables also limits the precision of these measures. In addition, the laborious nature of quantifying views within the hedonic framework meant that relevant studies were often characterized by a small sample of properties.

More recent studies have utilized advances in Geographic Information Systems (GIS) to generate view measures. These studies generate continuous view measures to provide significant improvements in precision when compared to the previous binary indicators or subjective view measures (Lake et al. 2000; Din et al. 2001; and Paterson and Boyle 2002). Most recently, researchers have captured the threedimensional characteristics of viewsheds through the use of lidar (Bin et al. 2008; Morgan and Hamilton 2011) and remote sensing (Cavailhes et al. 2009).

Bin et al. (2008) use lidar data to construct a continuous measure of view which takes into account natural and man-made obstructions. Bin et al. were initially unable to separately identify view amenities, shoreline access, and flood risk because of the high correlation among these amenities and disamenities. Motivated by the need to disentangle these spatially integrated housing characteristics, they include a continuous viewshed measure within their specification. This inclusion enabled separate identification of coastal amenities and risk within the hedonic price function. Using data from North Carolina coastal communities, they estimate a spatial autoregressive hedonic model and calculate that households are willing to pay an average of $995 for a one-degree increase in the view of the Atlantic Ocean. They argue that failure to appropriately incorporate view may bias estimates of other highly correlated environmental variables, such as access to coastal amenities.

Morgan and Hamilton (2011) also use lidar data and GIS techniques to construct a continuous view measure and a beach access variable for properties on Pensacola Beach, FL. Having controlled for view, they assume that any residual amenity value represents the benefit from accessing the beach for leisure purposes. However, as properties closer to the beach typically have better views (fewer obstructions), the two amenities are likely to be highly correlated, so disentangling view and access is problematical. Morgan and Hamilton's spatial autoregressive hedonic model includes beach access via a network distance parameter in order to mitigate collinearity effects between recreation and aesthetic amenities. They find households' willingness-to-pay of $1228 for a one-degree increase in viewshed and $317 for a one-meter decrease in distance to the nearest public beach access point. For non-coastal markets, numerous studies have considered a variety of landscape types observable from properties (Lake et al. 2000; Din et al. 2001; Paterson and Boyle 2002).4 Paterson and Boyle (2002) include variables representing land use/cover features (development, agriculture, forests, and surface water) and find that views of developed areas and forests detract from sales prices, while visible agricultural land and water have no statistical effect. Similarly, Cavailhes et al. (2009) develop a three-dimensional viewshed for properties in Dijon, France by integrating remote sensing data into a GIS-based model. Their model incorporates a variety of landscape types and, by relying on a few underlying assumptions, accounts for potential view obstructions. Their results indicate that content distance does influence property valuations and content within tens of meters of a property has the greatest influence.

Our study captures conditions where properties' view contents focus on an expanse of water, specifically the Gulf of Mexico. While this type of analysis captures a somewhat homogenous view content, other objective components of view are likely to differ greatly among properties. For example, one property may have a larger than average total view (measured in degrees) but due to vegetation and manmade obstructions, it is comprised of the aggregation of a number of smaller individual view segments. Conversely, a property may have a smaller than average total view which includes one large view segment. Other factors may influence perceived view quality, such as the location of obstructions and the orientation of view segments. These types of examples help motivate the need to better understand the objective constituents of views.

Site Area and Data

We obtained real estate sales data from the Pinellas County property appraiser's office for Pinellas County, Florida between the years 2000 and 2006. Pinellas County lies on a 280 squaremile peninsula separating Tampa Bay and the Gulf of Mexico. This county is highly urbanized, with 944,000 permanent residents and approximately 5 million visitors per year (Pinellas County Coastal Management 2009). Our study focuses on four barrier islands lining the Gulf of Mexico (Clearwater Beach Island, Long Key, Sand Key, Treasure Island), on which there are 10 municipalities. Figure 1 provides a map of our study area. From Fig. 1, Area A comprises the municipality of Clearwater Beach, and consists of 170 properties. Area B encompasses the municipalities of Belleaire Beach, Belleair Shore, and Indian Rocks Beach, with 260 properties, while the remaining municipalities of Madeira Beach, North Redington Beach, Redington Beach, Redington Shores, St Pete Beach and Treasure Island are contained within Area C and have 651 properties in our sample.

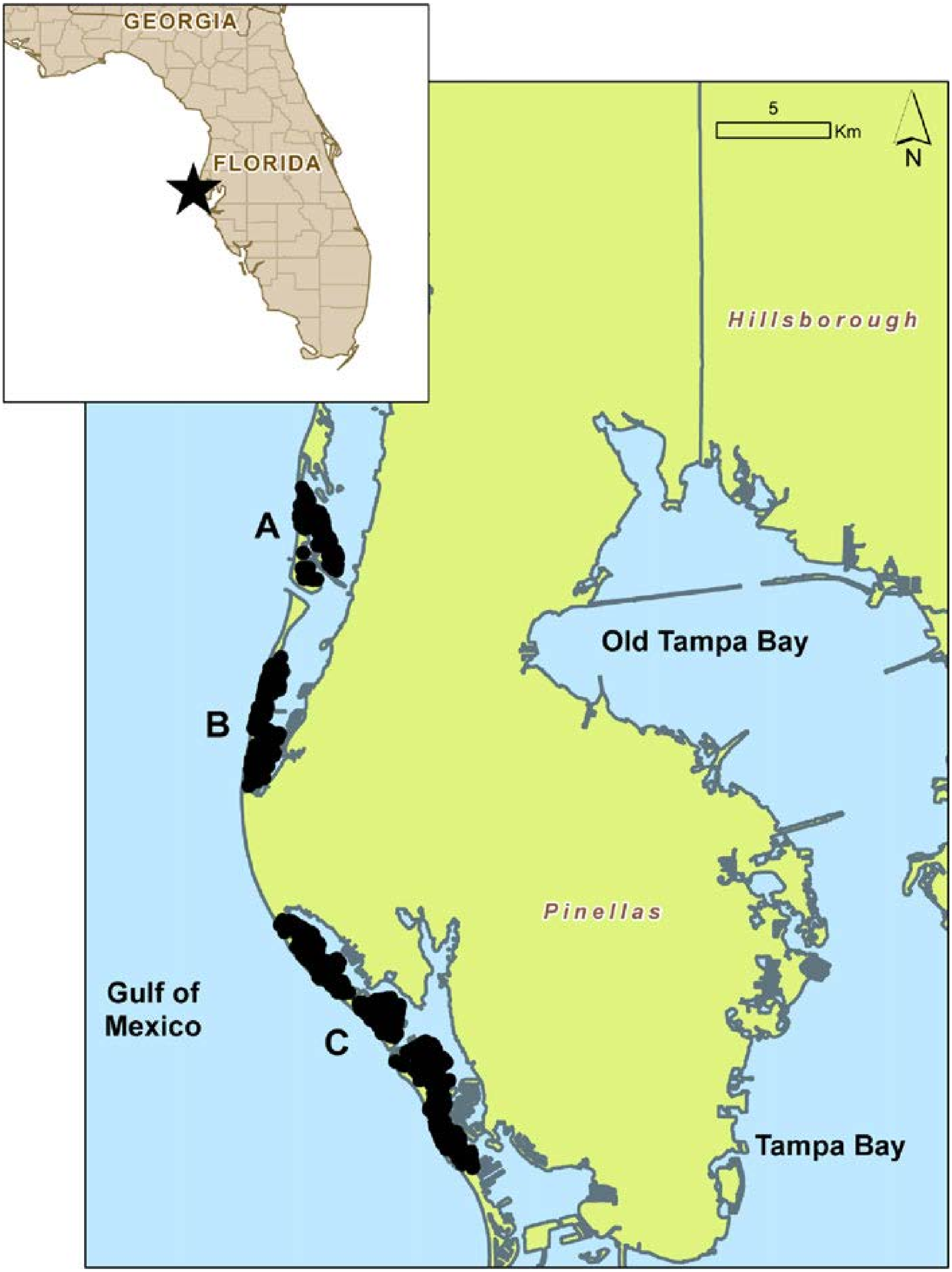

Fig. 1 Map of study area (Pinellas County Barrier Islands)

Pinellas County's barrier islands are roughly 35 miles in length. Up until the mid-20th century, the Pinellas County barrier islands experienced significant dredge-landfill activities on the back barrier bays (Pinellas County Coastal Management 2009). These dredge-and-fill activities greatly increased the total number of lots as well as the water access through an intricate series of canals. As a result, many of the single family homes sold during the 2000–2006 period are found near the backsides of these islands. In our dataset, 62% of homes have either access to a back barrier bay via canals or are found on the back barrier bays; in contrast, only 1.5% of the homes are considered Gulf front. The average home is 2157 feet from the Gulf of Mexico.

We adjust sales prices for inflation and normalized them to 2006 values. Table 1 provides summary statistics for housing sales prices as well as other variables relevant to the empirical analysis. After accounting for missing values and irregular

Table 1 Summary statistics

Variable	Mean	Std Dev	Min	Max
Price	475400	424266	50000	6540000
Clearwater (1,0)	0.16	0.36	0	1
Long Key (1,0)	0.07	0.25	0	1
Sand Key (1,0)	0.59	0.49	0	1
Treasure Island (1,0)	0.19	0.39	0	1
Year2000 (1,0)	0.15	0.36	0	1
Year2001 (1,0)	0.16	0.37	0	1
Year2002 (1,0)	0.17	0.38	0	1
Year2003 (1,0)	0.15	0.36	0	1
Year2004 (1,0)	0.16	0.37	0	1
Year2005 (1,0)	0.12	0.33	0	1
Year2006 (1,0)	0.08	0.27	0	1
Home Area	2803	1350.95	688	11611
Property Area	8036	3120	1394	40119
Stories	1.2	0.43	1	4
Bathroom Water Connections	7.5	3.22	3	30
Superior (1,0)	0.02	0.14	0	1
Excellent (1,0)	0.06	0.23	0	1
Custom Finish (1,0)	0.16	0.36	0	1
Bay Front (1,0)	0.62	0.48	0	1
Dock (1,0)	0.61	0.49	0	1
Boatlift (1,0)	0.51	0.50	0	1
Deck (1,0)	0.86	0.35	0	1
Pool (1,0)	0.46	0.50	0	1
Distance to Gulf (feet)	2157	1377.6	50	6028
Distance to Tampa (miles)	46.3	1.79	42.04	49.58
Percent White*	0.97	0.004	0.97	0.99
Percent of Homes Rented*	0.31	0.1	0.15	0.54
Percent of Households with Individuals 60+ *	0.48	0.09	0.34	0.63
Gulf View > 0 degrees (1,0)	0.79	0.45	0	1
Gulf View > 20 degrees (1,0)	0.30	0.46	0	1
Total Gulf Visibility (degrees)	26.29	502.5	0	177
Max Gulf Visibility (degrees)	13.75	34.18	0	176.15
Mean Gulf Visibility (degrees)	3.53	15.12	0	175.27

observations, 1081 properties were collected from the 2000 to 2006 time period. All 1081 properties are designated as having homestead exemptions by the Pinellas County Property Appraiser's office, meaning all homes are primary residences. The average normalized sales price for properties within this period was $475,400. The average residential property in this sample is 38 years of age, 2803 square feet in size, and has a lot size of 8036 square feet. The Pinellas County Property Appraiser's office does not collect information on the number of bathrooms or bedrooms, but it does collect information on the number of bathroom water connections. In this application, a water connection refers to a sink, tub, shower, or bidet. The average home in this dataset has just over 7 fixtures, which is approximately 2 bathrooms.

Lidar data was obtained from the Florida Department of Emergency Management. The lidar flight occurred between 7/6/2007 and 8/10/2007. The vertical accuracy of the lidar elevation data meets the NSSDA DTM requirement of .9.14 cm at the 95% confidence level and was verified using a field survey by an independent survey group. For each property we construct four lidar-derived viewshed measures that account for natural and man-made features on the landscape including all structures, sand dunes, trees, other vegetation, etc. The first viewshed measure is a Gulf side individual property's view angle (IPVA°) adapted with minor modifications from Hamilton and Morgan (2010). The earlier measure of IPVA° (Hamilton and Morgan 2010) required the researcher to manually place the observer on the beach side of the home once the observer height was derived from the roof height and roof structure. This manual process limits the number of records that can be analyzed in each region and introduces a measure of subjectivity to the view measure. An adaptation to the IPVA° creation process developed for this research is the creation of a unique surface digital elevation model (DEM) for each property in the analysis area as opposed to one surface DEM for all properties. This allows each analyzed property to have its house structure reduced to zero elevation in its DEM only. Removing the analyzed property from only its DEM assures than each individual property's structure will not block its own view of the amenity and that all views including forward, backward, and to the side are accounted for in the analysis. In earlier iterations of the IPVA°, only a singular view vector could be utilized in a single orientation. This new approach produces a best possible view measure of all amenities from all faces of the home and allows for analyzing an unlimited number of properties as it is now an automated process.

The negatives of this approach over the original IPVA° are that the storage requirement is one-thousand times larger as each property requires the same storage as the entire study area in the original method. As a result, processing time increases exponentially, requiring access to cluster or parallel computing systems. For example, in this analysis the 1081 properties consumed 5TB of storage and the computational processing time per property increased from minutes in the original study to hours per property.

The IPVA° is constructed for all 1081 properties in the study areas resulting in 777 homes with Gulf of Mexico views greater than 0 degrees and 327 homes with views greater than 20 degrees.5 The IPVA° measures a home's view of the Gulf of Mexico in degrees assuming an observer location in the highest living level of the home. For example, on a two level home the observer is placed at the approximate height of the second level. Figure 2 provides a schematic detailing the IPVA° from two different properties in the sample. The property on the left is an inland property with a large IPVA° that constitutes two large view segments of differing sizes. On the right is a Gulf-front property with a large IPVA° consisting of one large single view segment. A theoretical maximum of approximately 180 degrees exists for this measure due to the almost linear nature of the Gulf shoreline in this area. It is shown that buyers prefer an increased IPVA° of the desirable amenity (Bin et al. 2008; Morgan and Hamilton 2011).

Our second viewshed measure examines each property's largest view segment of the IPVA°. The IPVA° measure was divided into segments with a minimum possible segment of 0° and a maximum of 180°. Each property was then assigned the number of segments occurring and attributes that summarize the minimum, maximum, mean and standard deviation of its view segments. We surmise that two properties may exhibit an equivalent overall view of the shoreline but due to obstructions, the size of segments in each property's viewshed differs. We hypothesize that homebuyers prefer large continuous view segments as opposed to small individual view segments. Our third measure of view scope utilizes the arithmetic mean of each property's view segments. It is our hypothesis that homebuyers not only prefer properties with one large view segment, but that they also prefer larger view segments on average. Last, we measure the influence of distance on a property's view measure (content distance) by interacting our continuous view measure with dummy variables representing distances to the Gulf shoreline.

Empirical Model

Hedonic property models are predicated on the theory that the prices of heterogeneous goods reflect the component values of those goods' characteristics (Rosen 1974). As such, price differentials reflect these component values. Hedonic property models utilize observations on property values to infer the values of home characteristics. This theory allows researchers to estimate values for non-marketed characteristics such as environmental quality. When we assume a fixed housing supply where prices are demand determined, the equilibrium hedonic price function is

(1) $$P = \boldsymbol{P}(\boldsymbol{S}, \boldsymbol{N}, \boldsymbol{E}),$$

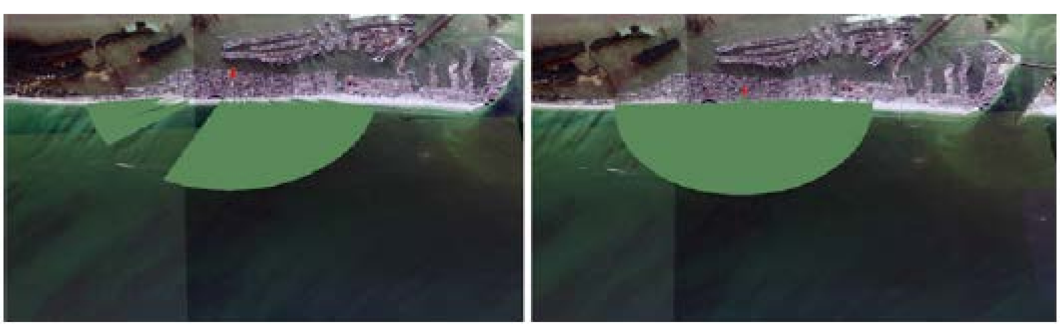

Fig. 2 Differing viewshed schematics

where P represents the price of a unit, which is a function of vectors of structural (S), neighborhood (N), and environmental (E) characteristics. Because housing supply is assumed to be fixed in the short run, the hedonic price function arises as the consequence of bidding by home buyers. Assuming the hedonic price function is continuously differentiable, Rosen (1974) postulated that the first derivative of equation (1) with respect to any continuous attribute results in an average household's marginal willingness to pay for an additional unit of that attribute.

In the last twenty years, the hedonic literature has begun to place a growing emphasis on spatial dependence in residential housing markets (Dubin 1988; Anselin and Bera 1998; Kim et al. 2003). Traditional estimation methods often fail to account for spatial autocorrelation, even with the inclusion of location-based indicators. Often home prices will cluster according to spatial characteristics. In some cases, the prices may be spatially clustered due to unobserved neighborhood characteristics such as school quality or crime rates. In other cases, structural characteristics of adjacent homes may be reflected in sales prices. Failure to account for spatial dependence can violate the assumption of uncorrelated error terms and lead to biased and inefficient coefficient estimates.

Regression diagnostics based on Ordinary Least Squares (OLS) estimation procedures tests suggest the presence of spatial autocorrelation. We estimate the hedonic price function with a log-linear specification. Lagrange Multiplier (LM) test statistics suggest the use of a spatial simultaneous autoregressive lag model.6 The formal spatial lag model is

(2) $$P = \rho \boldsymbol{WP} + \beta \boldsymbol{S} + \delta \boldsymbol{N} + \theta \boldsymbol{E} + \varepsilon$$

where P is an i×1 vector of residential sales prices for i observations, ρ is a spatial autoregressive coefficient, W is an i×i spatial weights matrix, β is an s×1 vector of structural variable coefficients, S is an i×s matrix of observations on structural home variables, δ is an n×1 vector of neighborhood variable coefficients, N is an i×n matrix of observations on neighborhood variables, θ is an e×1 vector of environmental variable coefficients, E is an i×e matrix of observations on environmental variables, and ε is an i×1 vector of independent and identically distributed random error terms. In equation 2, the spatial autoregressive coefficient, ρ, reflects the average influence of neighboring properties on sample home prices.

In the spatial lag model, marginal changes in housing characteristics must reflect the spatial spillovers or diffusions represented by ρWP. This means that spatially relevant characteristics can directly influence the price of a house in question while also indirectly influencing the price of neighboring properties. Kim et al. (2003) recommend estimating marginal effects in spatial lag models with the inclusion of a spatial multiplier, 1/(1-ρ). In our study, we are interested in estimating the marginal willingness-to-pay for view amenities. Given our log-linear specification, we measure the MWTP for a Gulf of Mexico view with θview _ P _ ð1=ð1 _ ρÞÞ. All reported values of MWTP are computed with mean home sales prices. We use the Krinsky and Robb (1986) parametric bootstrap procedure with 5000 draws from a multivariate normal distribution to generate confidence intervals for MWTP.

Results

Construction of the spatial weights matrix plays a key role in capturing the unobserved spatial characteristics that contribute to spatial dependence. We follow suggestions by Anselin and Bera (1998) in the construction of our spatial weights. After experimenting with different weight matrices, we choose a row standardized weighting scheme where neighbors are defined with a distance cutoff. The distance cutoff defines the extent of spatial spillover within the study area. We use a spatial weighting matrix that identifies properties within 1640 feet. All properties outside 1640 feet are treated as zero elements in the weighting matrix.

In our investigation of the influence of view scope, we estimate three primary model specifications with the log of sales prices used as the dependent variable. Table 2 provides the Maximum Likelihood estimation results for three hedonic property models. In each model, we address heteroskedasticity by estimating robust standard errors. Each model differs only in how it represents our primary variable of interest, scope for a Gulf of Mexico view. As such, we refer to these model specifications as the total visibility model, the maximum visibility model, and the mean visibility model.

We estimated numerous specifications and found the primary results robust to alternative functional forms. In each case, significant spatial autoregressive coefficients indicate the presence of spatial dependence. In each model, we include year and island fixed effects. The year fixed effects are statistically significant at the 1% level in all four model specifications. With one exception, the island fixed effects do not have statistically significant coefficient estimates.

Among the other variables included are a quadratic specification for home area (square feet/1000), property area (square feet/1000), and distance to the Gulf shoreline (hundred foot increments) in order to account for potential non-linear effects. The distance to the Gulf shoreline plays an important role in our specification because it controls for differences between local amenities associated with the Gulf of Mexico. Distance captures ecosystem services, such as recreation, that need to be identified separately from view. The total and mean visibility models provide evidence that homebuyers prefer homes closer to the Gulf, but the influence diminishes with increased distance.

Other variables included in each specification are the number of bathroom water connections, the distance to downtown Tampa, a Census tract level variable depicting the percentage of households with members over 60 years of age, a Census tract level variable depicting the percentage of houses rented, and a variety of indicator variables

Table 2 Spatial Lag estimation results for the total, maximum, and mean visibility models

Variable	Total visibility model		Maximum visibility model		Mean visibility model	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Constant	1.381 [b]	0.54349	1.5254 [a]	0.53756	1.8213 [a]	0.53337
Sold in 2001	0.1969 [a]	0.03266	0.1808 [a]	0.03222	0.1858 [a]	0.03212
Sold in 2002	0.3227 [a]	0.0363	0.3103 [a]	0.03573	0.3282 [a]	0.03559
Sold in 2003	0.4882 [a]	0.03482	0.4812 [a]	0.03395	0.4883 [a]	0.03374
Sold in 2004	0.6606 [a]	0.03577	0.6487 [a]	0.03521	0.6491 [a]	0.03474
Sold in 2005	0.8932 [a]	0.04171	0.8842 [a]	0.04107	0.9002 [a]	0.04126
Sold in 2006	0.9633 [a]	0.05187	0.9522 [a]	0.05137	0.9575 [a]	0.05109
LONG KEY	−0.0932	0.06311	−0.1070 [c]	0.06256	−0.0890	0.06239
SAND KEY	−0.0665	0.05598	−0.0835	0.05500	−0.0724	0.05435
TREASURE ISLAND	−0.1143	0.08042	−0.1277	0.07992	−0.0861	0.07866
Total housing square footage	0.2127 [a]	0.04565	0.2200 [a]	0.04214	0.2657 [a]	0.04209
Total housing square footage ^2	−0.0173 [a]	0.00517	−0.0185 [a]	0.00476	−0.0207 [a]	0.00473
Bathroom water connections	0.0182 [a]	0.00647	0.0180 [a]	0.00629	0.0194 [a]	0.00629
Total Lot square footage	0.0399 [b]	0.0200	0.0404 [b]	0.01938	0.0275	0.01921
Total Lot square footage ^2	−0.0004	0.00086	−0.0005	0.00083	−0.0002	0.00081
Superior Quality	0.4400 [a]	0.15112	0.4638 [a]	0.13966	0.4096 [a]	0.14339
Excellent Quality	0.1613 [a]	0.06076	0.1575 [a]	0.05986	0.1781 [a]	0.06318
Custom Finish	0.0768 [c]	0.0396	0.0699 [c]	0.03924	0.0912 [b]	0.03926
Pool	0.0374	0.02565	0.0372	0.02558	0.0420	0.02572
Deck	0.0612 [c]	0.03601	0.0740 [b]	0.03618	0.0758 [b]	0.03632
Soundfront Only	0.3471 [b]	0.13958	0.3478 [b]	0.14461	0.3436 [b]	0.14409
Soundfront (with Dock)	0.5425 [a]	0.04872	0.5435 [a]	0.04863	0.5394 [a]	0.04874
Soundfront (with Dock & Boatlift)	0.5406 [a]	0.03535	0.5416 [a]	0.03506	0.5375 [a]	0.03475
Distance To Gulf	−0.0097 [b]	0.00442	−0.0064	0.00428	−0.011 [b]	0.00431
Distance To Gulf^2	0.0002 [a]	0.00007	0.0001 [b]	0.00006	0.0002 [a]	0.00007
Distance To Tampa	−0.0079	0.0173	−0.011	0.01721	−0.0199	0.01697
Percent of Households with Residents over age 60	0.4694	0.42383	0.4598	0.42409	0.6198	0.41701
Percent of Houses that are rented	0.6093	0.41704	0.5949	0.41553	0.7313 [c]	0.41086
Gulf IPVA	0.0023 [a]	0.00051				
Maximum Visibility			0.0036 [a]	0.00061		
Mean Visibility					0.0052 [a]	0.0018
Rho	0.1431	0.04785	0.1413	0.04725	0.15004	0.048105
Log Likelihood	−401.394		−386.628		−394.8173	
Akaike Info Criterion	864.79		835.26		853.63	
Observations	1081		1081		1081	

depicting structural and spatial characteristics, including two Pinellas County property assessor variables depicting superior and excellent home condition, homes with a custom interior finish, homes with decks, pools, a variable depicting sound front homes with no dock or boatlift, soundfront homes with docks only, and soundfront homes with both docks and boatlifts. While some coefficients are not statistically significant, all coefficients exhibit the expected signs.

Table 2 presents the results from the three view scope models. First, the total visibility model incorporates a view measure that captures the total Gulf of Mexico view for properties (GULF_IPVA) in degrees. This measure aggregates all view segments in a home's view with a theoretical minimum of 0 degrees and a maximum of 180 degrees. The coefficient estimates indicate that the total Gulf of Mexico view for a property has a positive effect on property values with significance at the 1% level.

Next, the maximum visibility model incorporates a view measure that captures the largest Gulf of Mexico view segment for properties in degrees. Our results indicate that the maximum Gulf of Mexico view for a property has a positive effect on property values at the 1% level. Our final measure, the mean visibility of the Gulf of Mexico, represents the average of all view segments for a property. Mean visibility has a positive impact on property valuations at the 1% level. Each view measure coefficient coincides with our hypothesis that homebuyers prefer large views and large view segments.

In addition to view scope, we also estimate seven models capturing varying magnitudes of content distance. We retain our previous total visibility model specification, with the exception of our content distance measures. In order to capture content distance, we create indicator variables based on different distances from the Gulf of Mexico. Table 3 depicts the results of these estimation procedures. The seven measures represent a sensitivity analysis for content distance in that they estimate the influence of interacting different distance bands (1500 ft, 1000 ft, 900 ft, 800 ft, 700 ft, 600 ft, and 500 ft) with our total visibility measure. For example, our model that uses 1500 ft distance bands is specified to include two variables that interact distance-based indicator variables with the Gulf IPVA measure. The first distance based indicator variable represents homes within 1500 feet of the Gulf of Mexico and the second represents homes between 1500 and 3000 feet of the Gulf. These measures are meant to capture the total views for the homes within different distance bands. In general, as the distance band closest to the Gulf of Mexico gets smaller in size, the coefficient gets larger. This indicates that content distance does influence price.

MWTP estimates for our Gulf of Mexico visibility measures can be found in Table 4. We estimate standard errors using the Krinsky-Robb method, where 5000 random variables are computed from our parameter estimates (Krinsky and Robb 1986). In the total visibility model, MWTP for total visibility is $1300 per degree of view (95% Confidence Interval: $706–$1894. MWTP for maximum visibility is $2015 per degree of view (95% Confidence Interval: $1266–$2765). MWTP for mean visibility is $2881 per degree of view (95% Confidence Interval: $884–$4879). Figure 3 provides graphical depictions of MWTP for total, maximum, and mean visibility.

Table 4 also provides MWTP estimates for our content distance measures. We compute measures for the distance band closest to the Gulf of Mexico. We use the total visibility model for all properties as a point of comparison. When we constrain total visibility to the first 1500 feet, MWTP for total visibility is $1324 per degree of view (95% Confidence Interval: $725–$1922), only slightly higher than the measure with no distance constraints. We generally observe an increase in MWTP as the size of the distance band decreases. In the smallest distance band, 500 feet, MWTP for total visibility is $1901 per degree of view (95% Confidence Interval: $1150–$2651). Figure 4 provides graphical depictions of MWTP for total visibility within each distance band.

Discussion/Conclusions

While the scholarly literature on hedonic property models has established the positive/negative values of numerous local environmental amenities/disamenities, from amenities such as beach width (Landry and Hindsley 2011; Gopalakrishnan et al. 2011) to disamenities such as flood risk (Bin and Polasky 2004; Bin et al. 2008), appropriately capturing and measuring the value of a property's view has proven to be difficult. Recent advances in GIS techniques have enabled continuous and replicable measures of view which supersede previously subjective classifications. In this study, we attempt to add to the existing literature by examining two specific view components: scope and content distance. We provide more precise insight into the valuation of these view components. Results suggest that households' valuation of different types of view scope and content distance follow our preconceived hypotheses. These findings are consistent with our expectation that homebuyers not only prefer larger total views, but also larger continuous view segments. Results also indicate that distance to the view content also influences homebuyers' purchasing decisions.

Table 3 Spatial Lag estimation results for the total visibility measure when limited to distance bands

Variable	Coefficient	Std.Err	Log Lik.	AIC	Percent of sample in distance band
Total View	0.0234 [a]	0.00051	−401.39	864.79	100%
1500 ft Threshold	0.0239 [a]	0.00044	−400.08	864.16	38%
1000 ft Threshold	0.0264 [a]	0.00055	−398.55	863.09	24%
900 ft Threshold	0.0274 [a]	0.00056	−397.25	860.51	21%
800 ft Threshold	0.0265 [a]	0.00056	−397.99	861.98	17%
700 ft Threshold	0.0272 [a]	0.00061	−396.85	859.7	13%
600 ft Threshold	0.0312 [a]	0.00059	−392.97	851.94	10%
500 ft Threshold	0.0340 [a]	0.00063	−388.39	842.77	7%

Table 4 Marginal willingness-to-pay estimates for mean, max, and total visibility, by distance bands

	Primary models			Total visibility models with distance bands						
	Mean visibility	Max visibility	Total visibility	1500 ft	1000 ft	900 ft	800 ft	700 ft	600 ft	500 ft
Upper Bound	$4,879	$2,765	$1,894	$1,922	$2,108	$2,176	$2,131	$2,230	$2,422	$2,651
Mean	$2,881	$2,015	$1,300	$1,324	$1,461	$1,511	$1,464	$1,498	$1,713	$1,901
Lower Bound	$884	$1,266	$706	$725	$815	$847	$797	$767	$1,004	$1,150

The first measure of view, total visibility, picks up the total view for a property. The MWTP point estimate for total ocean visibility of $1300 per degree of view is comparable to the MWTP of $995 per degree view that Bin et al. (2008) estimated for North Carolina properties. In this study, the valuation of view amenities per degree has a higher dollar value, but the average home price is also greater in our sample.

In addition to our total visibility model, we also created a content distance measure by interacting total visibility with distance-based indicator variables. In general, we find that homes in closer proximity to the Gulf of Mexico have higher per degree view valuations. Our findings indicate that content distance does in fact influence the assessment of views. It is difficult to make a direct comparison to other studies due to differences in view content. Our study only targets one type of view, while other

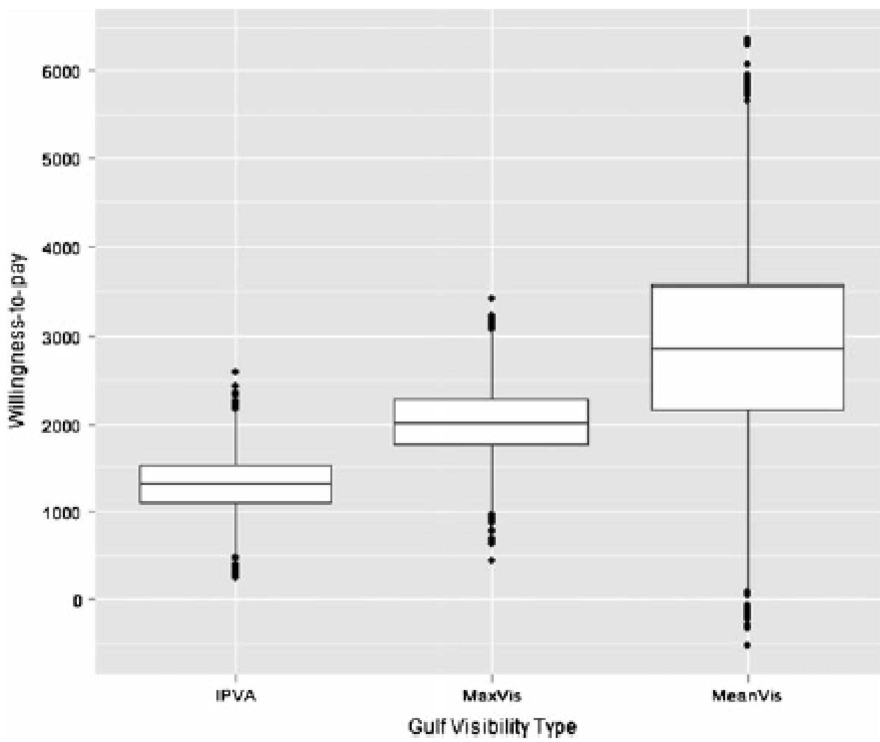

Fig. 3 Distribution of MWTP for Total Visibility (IPVA), Maximum Visibility (MaxVis), and Mean Visibility (MeanVis). The Krinsky-Robb procedure is used with 5000 draws from a multivariate normal Distribution

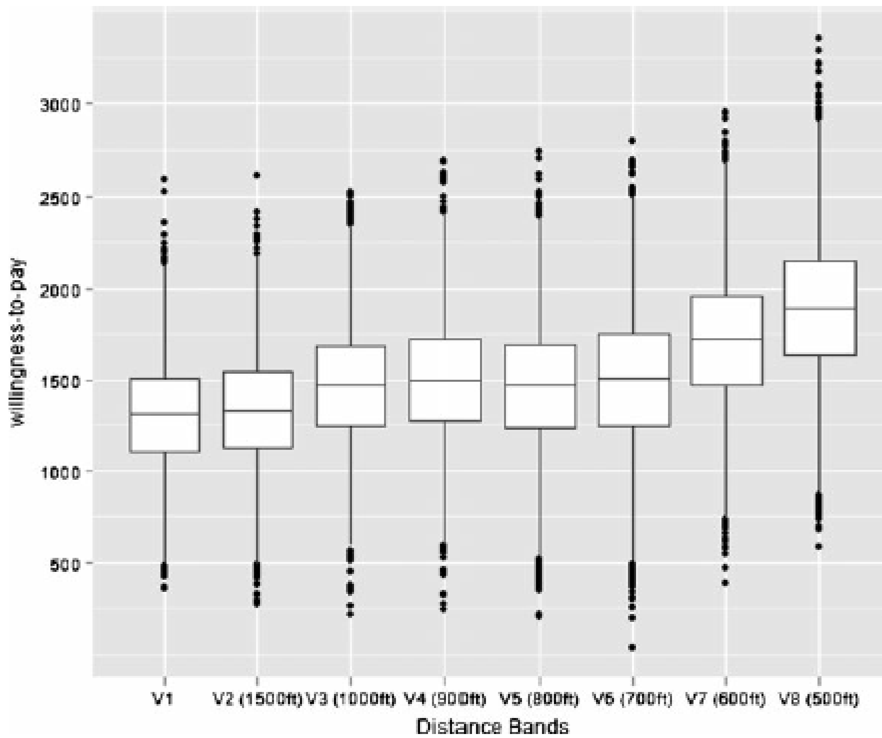

Fig. 4 Distribution of MWTP for Total Visibility (IPVA) when controlling for content distance. Total visibility (V1) for the entire sample is compared to different cutoff distances (V2-V8). The Krinsky-Robb procedure is used with 5000 draws from a multivariate normal distribution

studies investigating content distance account for more heterogeneous views for adjacent viewscapes. Both Benson et al. (1998) and Bourassa et al. (2004) interact distance with view quality dummy variables and find that distance negatively influences the valuation of a view. Cavailhes et al. (2009) find a similar relationship between distance and view content. They create a continuous measure that accounts for view type within adjacent areas through the use of remote sensing.

The maximum visibility measure represents the largest view segment in a property's viewshed. Two homes with equal measures of total view in degrees could have views comprised of different quantity and sized view segments. We hypothesize that homeowners prefer large view segments to small segments. As a consequence, we surmise that, all else equal, a view with fewer large segments would be preferred to one with more numerous small segments. Our total view measure does not allow us to identify these differences. We utilize the maximum visibility measure to test this hypothesis. Our findings show that households have a greater willingness-to-pay for a marginal change in their maximum view segment than their total visibility. This clearly suggests that home buyers consider multiple dimensions of view scope when making purchasing decisions. Homebuyers not only prefer larger total views, but also larger continuous views.

The final view type represents the mean visibility of each property. In comparison to the other two view scope measures, estimates associated with mean visibility offer less precision. The mean visibility measure is represented by an average of all view segments. This measure does indicate that homebuyers' prefer larger view segments on average; however, each individual average value can represent numerous combinations of different sized view segments. For example, one property may have four view segments (in degrees of 40, 10, 5, and 5) compared to a property with just two (in degrees of 20 and 10). While both have a mean visibility of 15 degrees, clear differences exist in the variance of segment size. This uncertainty manifests itself as a larger standard error in MWTP. The interpretation of this value is also more obscure. While a marginal increase in total and maximum visibility truly represents a one degree increase, the true value of a marginal increase in mean visibility is dependent on the number of view segments. As the number of segments increase, the absolute change associated with a marginal increase also increases. This increases the variance of MWTP and makes it difficult to directly compare the MWTP value of mean visibility with either total or maximum visibility.

GIS techniques have allowed us to measure the continuous characteristics of a coastal view within a hedonic property model. Our findings provide a promising look at the influence of scope on household valuations for viewsheds. These valuations coincide with our preconceived hypotheses related to view scope in that homeowners prefer not only larger total Gulf of Mexico views, as seen in previous studies (Bin et al. 2008; Morgan and Hamilton 2011), but also larger continuous view segments. In its present form, our viewshed method does not account for different types of view content. Future research is needed to integrate heterogeneous view content with lidarbased viewshed measures.

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