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Research Paper

Not seeing the forest for the trees: Modeling exurban viewscapes with LiDAR

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ABSTRACT

Viewscapes are the visible portions of a landscape that create a visual connection between a human observer and their 3-dimensional surroundings. However, most large area line-of-sight studies have modeled viewscapes using bare-earth digital elevation models, which exclude the 3-D elements of built and natural environments needed to comprehensively understand the scale, complexity and naturalness of an area. In this study, we compared viewscapes derived from LiDAR bare earth (BE) and top-of-canopy (ToC) surface models for 1000 exurban homes in a region of the Rocky Mountains, USA that is experiencing rapid low-density growth. We examined the extent to which the vertical structure of trees and neighboring houses in ToC models – not accounted for in BE models – affect the size and quality of each home's viewscape. ToC models consistently produced significantly smaller viewscapes compared to BE models across five resolutions of LiDAR-derived models (1, 5, 10, 15, and 30-m). As resolution increased, both ToC and BE models produced increasingly larger, exaggerated viewscapes. Due to their exaggerated size, BE models overestimated the greenness and diversity of vegetation types in viewscapes and underestimated ruggedness of surrounding terrain compared to more realistic ToC models. Finally, ToC models also resulted in more private viewscapes, with exurban residents seeing almost three times fewer neighbors compared to BE models. These findings demonstrate that viewscape studies should consider both vertical and horizontal dimensions of built and natural environments in landscape and urban planning applications.

1. Introduction

Viewscapes are the visible portions of a landscape that visually connect human observers to their 3-dimensional surroundings (Burcher, 2005). The premise that humans make important visual connections with the environment is central to both the theory and practice of landscape and urban planning. Viewscapes have been considered across a range of domains, from the design of built environments in landscape architecture (Garnero & Fabrizio, 2015; Lindsey, Wilson, Yang, & Alexa, 2008) and assessment of the visual character and impacts of roadways through parks and scenic areas (Chamberlain & Meitner, 2013; Martin, Ortega, Otero, & Arce, 2016), to hiding unsightly land uses, such as landfills (Alexakis & Sarris, 2014; Geneletti, 2010), or scars from extraction of natural resources, such as forest clear-cutting for timber harvest (Chamberlain, Meitner, & Ballinger, 2015; Domingo-Santos, de Villaran, Rapp-Arraras, & de Provens, 2011). Recently, Vukomanovic and Orr (2014) modeled viewscapes over large areas to understand preferences that motivate housing developments in rural regions.

Viewscapes are modeled using line-of-sight principles (Fig. 1) with varying levels of complexity and precision depending on the purpose and scale of the application. For example, landscape architects and city planners may directly measure features of a built or natural environment from one vantage point and a single line-of-sight direction of major interest, such as assessing amenities seen from a hill of a proposed park or a new neighborhood. Resulting viewscapes may be visualized as digitally manipulated photographs (Pasewaldt, Semmo, Trapp, & Döllner, 2014) or immersive virtual environments (Huang, Jiang, & Li, 2001; Tabrizian et al., 2016). For landscape-scale applications that require numerous vantage point locations and cover larger areas (e.g. several square kilometers), viewscapes are typically modeled in a geographic information system (GIS) using 360-degree line-of-sight algorithms. These algorithms identify all grid cells of a digital elevation model (DEM) surface that are visible from a given location.

Most large area line-of-sight studies modeled viewscapes using bare-earth models, which exclude the 3D structural elements of vegetation and human infrastructure needed to comprehensively understand the scale, complexity and naturalness of an area (e.g. Fisher & Tate, 2006;

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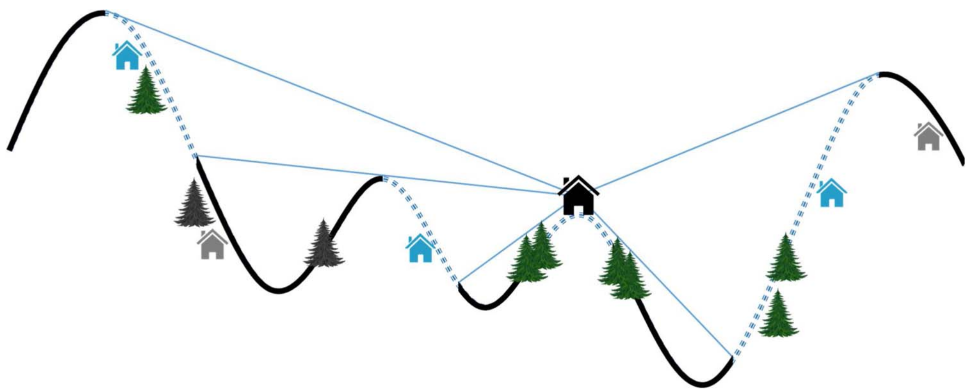

Fig. 1. Viewscape conceptual diagram. Portions of the landscape represented by blue, dashed lines are visible from the home of interest (black). Landscape features, such as houses (blue) and trees (green), are visible in these parts of the landscape; gray features and portions of the landscape represented by black, solid lines are obstructed by vertical elements, such as trees or peaks, and are not visible as they lie outside the line-of-sight. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Wilson, 2012). Moderate resolution (e.g. 10-m, 30-m) photogrammetry-derived DEMs are the most commonly used data in landscape-scale studies, but as finer-resolution DEMs (1-m) have become available, they are increasingly used to derive viewsheds and improve viewscape research (Wu, Pan, Yao, & Luo, 2007). Frontiers in LiDAR (Light Detection and Ranging) remote sensing are enabling researchers to map both vertical and horizontal patterns in locational data (Wehr & Lohr, 1999). LiDAR remote sensing collects 3D point clouds of the Earth's surface by measuring the travel time of laser pulses between the sensor and earth objects (Wehr & Lohr, 1999). Using multiple-return LiDAR data, Singh, Chen, McCarter, and Meentemeyer (2015) and Singh, Davis, and Meentemeyer (2015) recently measured the spatial distribution of tree biomass and invasive understory plants in urban forests to understand threats to green infrastructure in a rapidly urbanizing region. Recognizing the need to integrate this vertical dimension of vegetation into viewshed analyses, Guth (2009) argued that LiDAR data offer great potential for explicitly considering visual obstructions by vegetation and infrastructure and improving visibility across digital elevation models (DEM). Two studies have begun to explore the utility of LiDAR for modeling 3-D viewscapes, but were limited to a small sample of forest field plots on undevelopable federal land (e.g. Murgoitio, Shrestha, Glenn, & Spaete, 2013) or considered the role that 3D viewscapes play in a coastal real estate market without comparison to traditional bare-earth models (Hindsley, Hamilton, & Morgan, 2013).

In this study, we compare viewscapes measured from LiDAR-derived bare earth (BE) and top-of-canopy (ToC) surface models for 1000 exurban homes situated in a foothills region of the Rocky Mountains, USA that is experiencing rapid population growth with low-density development. We examine the extent to which the vertical structure of built and natural features in ToC models affect the size and quality of each home's viewscape. We develop spatial models that characterize terrain ruggedness and the greenness and diversity of natural vegetation in each viewscape. We further examine differences between ToC and BE viewscapes across five resolutions of LiDAR data (1, 5, 10, 15, and 30-m) to determine if results are consistent across scales. As LiDAR remote sensing and advanced techniques for line-of-sight models become increasingly accessible, this study can help guide decisions regarding whether or not to consider both vertical and horizontal dimensions of viewscapes in landscape and urban planning applications.

2. Methods

2.1. Study region

Boulder County forms part of the Colorado Front Range (COFR) on the eastern side of the Western Continental Divide of North America (Fig. 2). Protected open space, farms and ranches, and suburban residential development surround the city of Boulder (Lenth, Knight, & Gilgert, 2006). Vegetation of the COFR varies along environmental gradients of topography, geology and climate, with grasslands and shrublands dominating low elevation landscapes and forests starting at approximately 1800-m altitude to the west of the city. Lower montane forests commonly include stands of ponderosa pine (*Pinus ponderosa*), sometimes mixed with Douglas fir (*Pseudotsuga menziesii*) in more mesic areas (Burns & Honkala, 1990). Above 2500-m in upper montane forests, lodgepole pine (*Pinus contorta*), aspen (*Populus tremuloides*), limber pine (*Pinus flexilis*), and Douglas-fir communities often co-occur (Veblen & Donnegan, 2005).

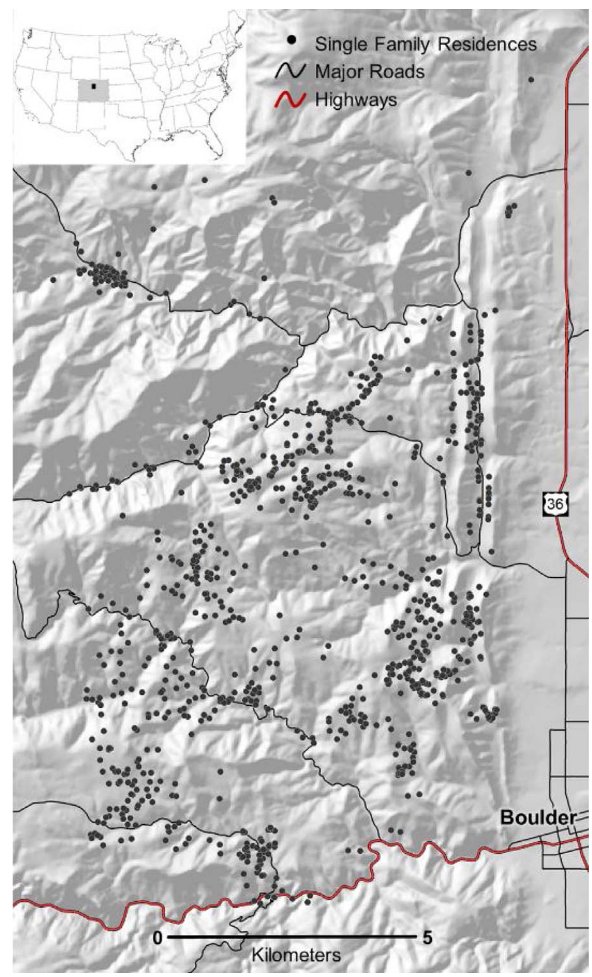

Fig. 2. Study area. Points represent 1000 randomly selected exurban homes in Boulder County, CO, situated in the forested foothills above the lower tree line (1800-m elevation).

The American West is the only U.S. region where rural population growth is increasing faster than growth in metropolitan areas (Lenth et al., 2006). Expansive exurban development has accompanied these recent changes, with 27% of Boulder County now considered part of the Wildland-Urban Interface (WUI; Radeloff et al., 2005). Residents of the Boulder WUI are wealthier, older, and more educated than the residents of the state of Colorado overall (Champ, Brenkert-Smith, & Flores, 2011). For example, 80% of the residents (average age = 55) of the Boulder County WUI hold College degrees with 48% of households having yearly incomes greater than $100,000 (Champ et al., 2011). In contrast, according to the 2010 US Census, the average age of residents in Colorado is 36, with 37% of the population holding College degrees and 9% of households earning more than $100,000/year. These socioeconomic factors contribute to exurbanites' locational freedom and their ability to make the viewscape an expression of choice in housing decisions (Vukomanovic & Orr, 2014).

2.2. Housing data

We acquired publicly available geocoded data of all recorded house sales transactions in Boulder County, Colorado, from 1950 through 2010 (Boulder County Assessor's Office, 2015). For analysis, we randomly selected 1000 single-family residences (SFRs) located above 1800-m where the lower montane forest begins above the plains (Burns & Honkala, 1990) and where most exurban housing occurs (Fig. 2). SFRs represent the vast majority of homes in exurban and rural areas of the study system; less than 1% of WUI residents in Boulder County live in condominiums, mobile homes, or apartment buildings. Approximately 98% of WUI residents own their current homes, and more than 90% of households live in their residence full-time (Champ et al., 2011). Our 1000 randomly selected residences are located in a region that meets the common definition of exurban housing density (0.68–16.18 ha per unit; Theobald, 2005). We verified locational accuracy of these data through visual inspection of high-resolution imagery from the National Agriculture Imagery Program (NAIP).

2.3. LiDAR data – bare earth and top of canopy models

We obtained 776 tiles of multiple-return LiDAR data (~1.5 × 1.5 km each) from the Colorado GeoData Cache (geodata.co.gov). The LiDAR data were acquired during May and September 2014. These data include five returns plus intensity, with a point cloud spacing ranging from 0.31-0.70 m. We used ground, and first-return LiDAR points to derive continuous BE and ToC surface models at multiple raster resolutions (1m, 5m, 10m, 15m, and 30m). We calculated the raster values for each resolution by applying a linear interpolation algorithm to a triangulated irregular network of the LiDAR point cloud (Lloyd & Atkinson, 2002). We normalized the BE model derived from the first return LiDAR points to produce a ToC model surface that includes natural and human-made features (Priestnall, Jaafar, & Duncan, 2000). We retained vertical data within a height range of 1.5–65 m above bare earth to remove understory vegetation (< 1.5 m) and human-made objects taller than 65 m (e.g. radio towers). Finally, we supplanted ToC surface model values with BE model values for a 90 × 90 m area around each home site to ensure that the 1000 single-family residences do not themselves obscure subsequent calculations of each viewscape.

2.4. Measuring exurban viewscapes with visibility analysis

We mapped several metrics of environmental conditions that characterize the visual quality of exurban viewscapes in the intermountain West: the visual scale, complexity, and naturalness of an area seen from a particular vantage point (Vukomanovic & Orr, 2014). We used visibility "line-of-sight" analysis (Fig. 1) to measure the size (visual scale) of each exurban viewscape, based on both BE and ToC models at multiple resolutions (1 m, 5 m, 10 m, 15 m, and 30 m). We limited the maximum visibility distance to 10 km in all directions and set the local observer height to 3 m above the surface to simulate a typical viewpoint from a house. Our analysis used a computationally efficient line-sweeping algorithm implemented in GRASS GIS (Haverkort, Toma, & Zhuang, 2009). We computed multiple separate processes in parallel to calculate viewscapes from 5-m resolution data and coarser. Computation of 1-m resolution viewscapes (input raster size of 400 million cells) required 38 GB of memory necessitating an alternative parallelization approach. We split the square area centered on the observer point into four square tiles with one cell-width overlap and processed these tiles in parallel. This approach produces identical results on the overlap of any two tiles and we then directly merged the resulting viewscape quadrants into a seamless viewscape. This approach sped up the computation of the 1-m resolution viewscapes by roughly four times. Finally, we vectorized each viewscape's geographical boundary resulting in 10,000 multipart polygons (1000 residences using BE and ToC data at 5 resolutions).

For each of the 10,000 viewscapes, we measured privacy in terms of the number of visible neighbors and distance to closest visible neighbor. We quantified complexity as the mean terrain ruggedness (TRI) and naturalness as the mean normalized difference vegetation index (NDVI) value within each viewscape. For diversity, we measured the number of different vegetation types present in each viewscape. The TRI measures the sum change in elevation between a cell and the mean of its 8-cell neighborhood and provides a quantitative metric for assessing terrain heterogeneity (Riley, DeGloria, & Elliot, 1999). TRI values for the study area ranged from 0 ("level") to 1027 ("extremely rugged"). We calculated the naturalness (greenness) of each viewscape based on two merged NDVI Landsat products acquired during leaf-on tree phenology conditions during July and September of 2014. To fill holes caused by clouds and cloud shadows, we combined the two NDVI products and selected the maximum value. At the pixel-level, the NDVI band represents the higher NDVI values (pixel max), and for each viewscape we computed the average of the pixel max. We obtained mapped vegetation data from the LANDFIRE Existing Vegetation Type (LANDFIRE, 2014) database, which included multiple types of forest, grassland, shrubland, riparian, bare earth, and development.

2.5. Statistical analysis

We used two-sample F-tests and t-tests to determine whether viewscapes derived from high-resolution 1-m BE models (N = 1000) and ToC models (N = 1000) differ significantly in area, privacy (number of visible neighbors and distance to nearest visible neighbor) and visual quality (TRI, NDVI, vegetation diversity). We ran Student's and Welch's t-tests to compare differences in means. For each model type (BE, ToC), we also used one-way analysis of variance (ANOVA) to assess differences in viewscape area across the five resolutions of LiDAR data aggregation (1, 5, 10, 15, and 30-m). We analyzed all possible pairwise combinations of resolution differences (i.e. 1 m–5 m, 1 m–10 m, 1 m–15 m, 1 m–30 m, 5 m–10 m, etc.) using Tukey's honest significant difference (HSD) tests within each model type. For each resolution, we developed an OLS regression model of the relationship between BE and ToC viewscape areas in order to quantify overestimation bias in BE models and determine if relationships change with scale. All analyses were performed in R (R Core Team, 2013) using an alpha of 0.05, or 95% confidence interval.

3. Results

High-resolution bare-earth (BE) models produced significantly larger exurban viewscapes (4.6 times on average) compared to top-of-canopy (ToC) models (Table 1; Figs. 3 and 4). Privacy of exurban homes also differed significantly between BE and ToC viewscapes; residents could see almost three times more neighbors in BE viewscapes compared to ToC and the nearest visible neighbor in BE viewscapes was over 100 m closer on average (Table 1; Fig. 5). BE viewscapes were significantly greener (higher NDVI), with a greater diversity of

Table 1
Comparison of area and visual quality metrics for 1-m BE and ToC models.

Metric	Model	Mean	Std. Deviation	*F*-test		*t*-test		
		(*M*)	(*SD*)	(*F*)	sig.	(*t*)	df	sig.
Viewscape Area (km^2)	*BE*	7.93	12.17	12.5	†	15.47	1158	†
	ToC	1.74	3.45					
Number of Visible Neighbors	*BE*	18.5	15.9	4.72	†	20.8	1404	†
	ToC	6.9	7.36					
Distance (m) to Nearest Visible Neighbor	*BE*	228.5	423.8	0.42	†	−4.75	1712	†
	ToC	345.6	654.3					
Terrain Ruggedness Index (TRI)	*BE*	2.47	1.36	0.04	†	−61.7	1078	†
	ToC	12.26	11.3					
Greenness (NDVI)	*BE*	0.600	0.148	0.65	†	3.85	1911	†
	ToC	0.583	0.144					
Number of Vegetation Types	*BE*	7.2	1.30	0.9	0.11	6.89	1998	†
	ToC	6.8	1.37					

† = $p < 0.0001$.

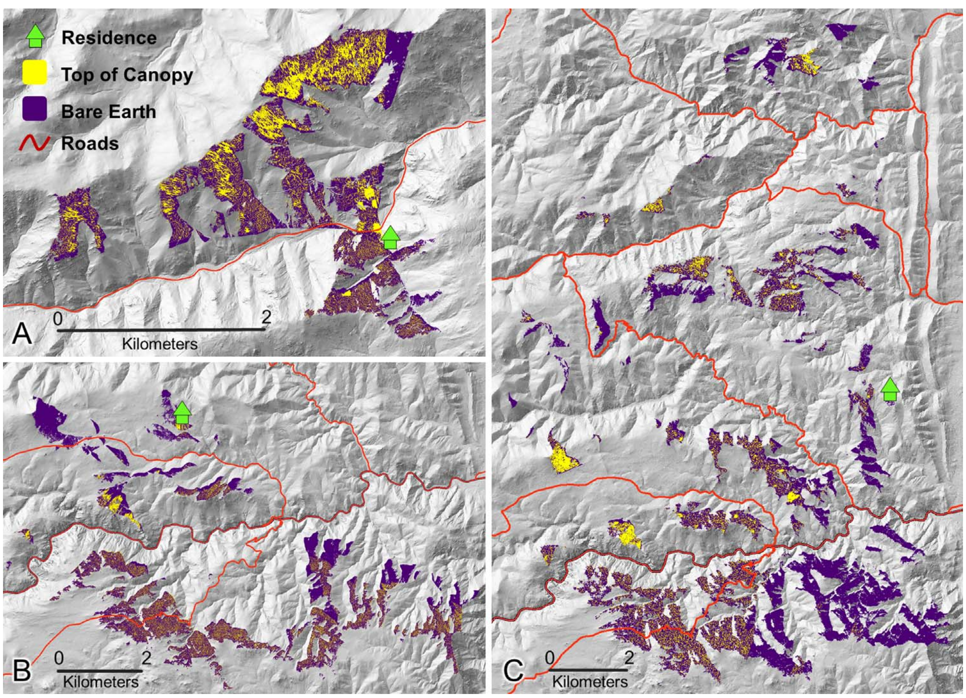

Fig. 3. Viewscape perspectives from three exurban residences demonstrate differences in 1-m BE and ToC representations between (A) small (BE = 2.1 km^2; ToC = 0.6 km^2), (B) medium (BE = 8 km^2; ToC = 1.5 km^2), and (C) large (BE = 21.1 km^2; ToC = 3.3 km^2) viewscapes.

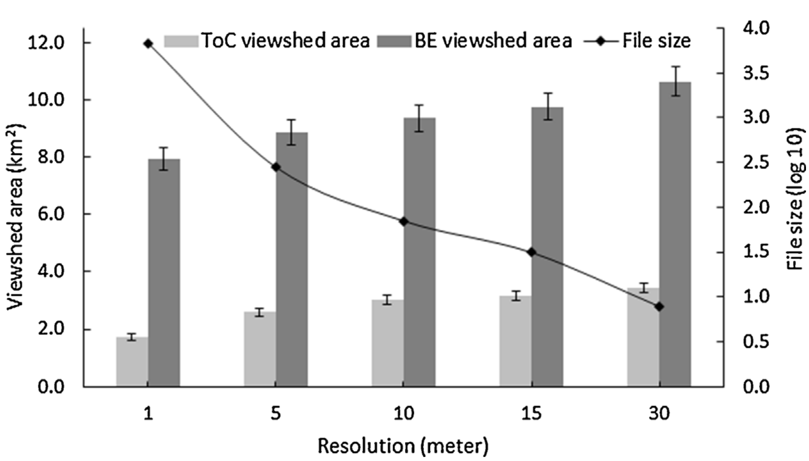

Fig. 4. Viewscape area and data volume as a function of model type and data resolution.

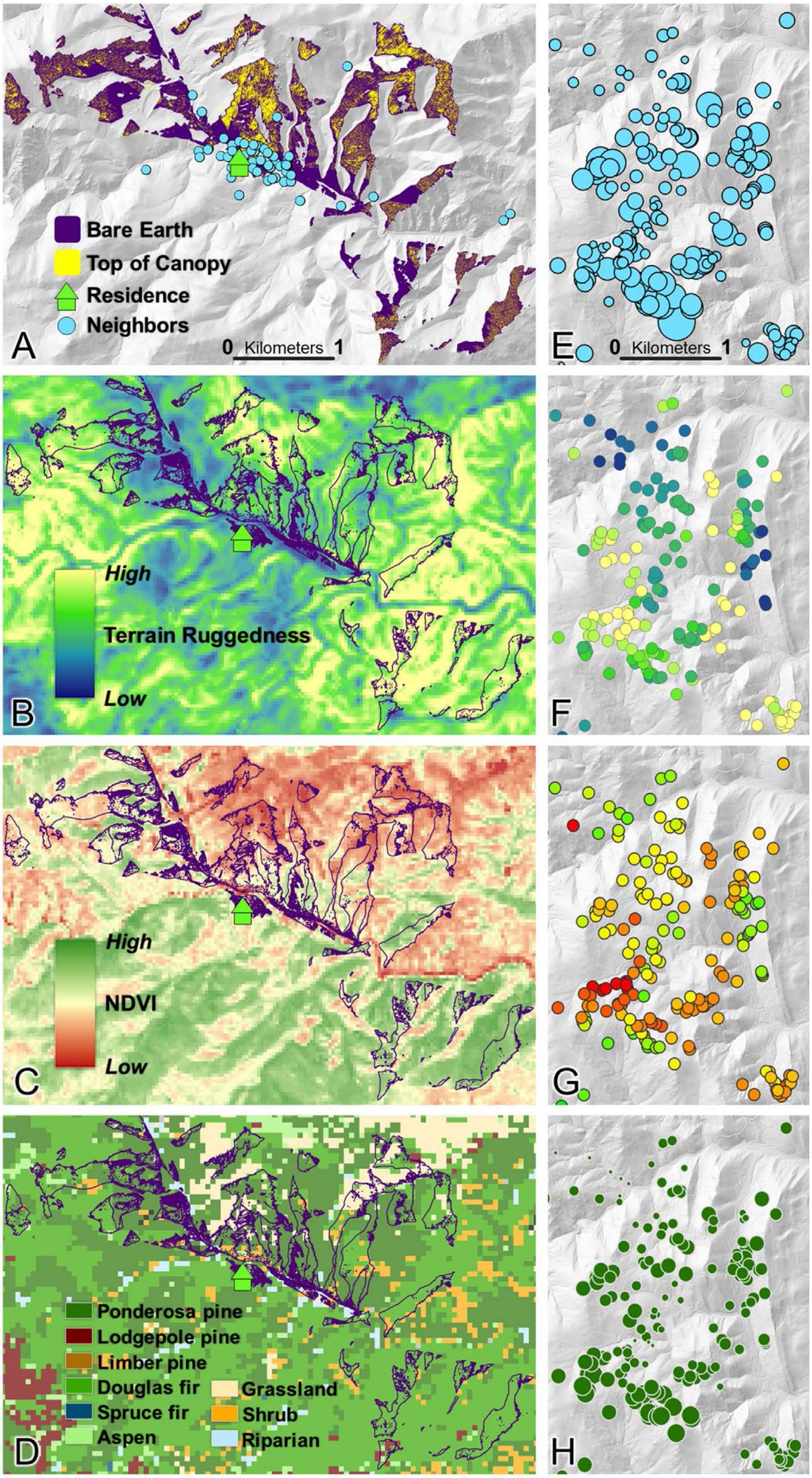

Fig. 5. Visual quality metrics of the exurban landscape seen from a single residence (A–D) and from multiple residences (E–H). The number of visible neighbors (A and E), mean terrain ruggedness (B and F), mean NDVI (C and G) and number of visible vegetation types (D and H) depend on the size and configuration of each viewscape. Purple polygons delineate the single residence's viewscape (A–D). Proportional circles represent the numbers of visible neighbors (E) and visible vegetation types (H) of multiple residences' viewscapes. Graduated colors show mean terrain ruggedness (F) and mean NDVI (G) of those viewscapes. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

vegetation types compared to ToC viewscapes (Table 1; Fig. 5). ToC viewscapes were significantly more "rugged" with average TRI values over four times greater than BE viewscapes (Table 1).

Viewscape area varied significantly across the five data resolutions for both BE [$F(4, 4995) = 4.89$, $p = 0.0006$] and ToC [$F(4, 4995) = 19.98$, $p = 0.0000$] model types. For all resolutions, ToC models produced significantly smaller viewscapes compared to BE (Fig. 4; Fig. 6). Regression relationships between the area of BE and ToC

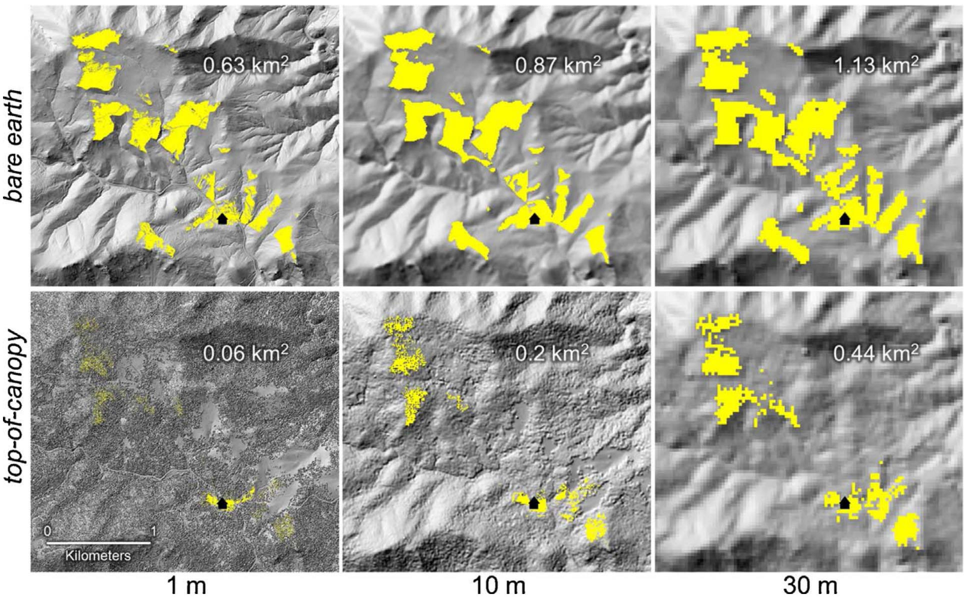

Fig. 6. Exurban viewscapes as a function of model type and data resolution. The house symbol denotes the house location for this single representation.

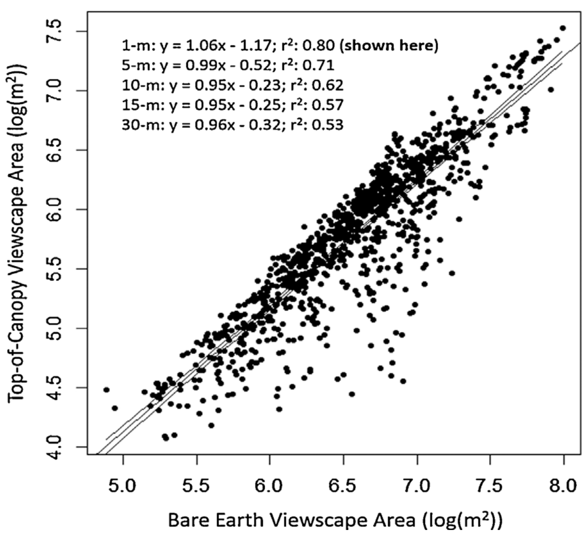

Fig. 7. Regression relationship between ToC and BE viewscape areas based on 1-m resolution LiDAR data. Model fit decreases as resolution coarsens from 1-m to 30-m.

viewscapes revealed overestimate bias in the BE models and showed that model fit decreases at coarser resolutions (e.g. 1-m r2 = 0.80 and 30-m r2 = 0.53; Fig. 7). Viewscape area also increased with coarser resolution for both model types (Fig. 4), but not all resolutions within a given model type produced significantly different viewscape areas (Table 2). Pairwise comparisons showed that 1-m ToC viewscape area differed significantly from all other resolutions (Table 2). Data volume decreased exponentially with coarser resolution, with concomitant increases in viewscape area (Fig. 4). For example, 5-m file size inputs to a viewscape model are 96% smaller than 1-m inputs, but produce 12% and 49% larger viewscapes on average using BE and ToC models, respectively.

4. Discussion

As viewscapes become more commonly used to improve understanding of how humans perceive the visual quality of landscapes, there will be a heightened need for more realistic Top-of-Canopy (ToC) models. For example, proximity to water bodies often attracts amenity migrants to a particular location (McGranahan, 2008; Real, Arce, & Sabucedo, 2000), but a lake that is 'seen' from a house in a BE modeled viewscape may not be visible after accounting for the presence of vertical features, such as trees and neighboring houses that can obstruct the view of the lake. This does not mean that the lake is not an important amenity in the area; however, a trade-off may exist between desirable features and those with which the homeowner has a visual connection. In this example, it may be more important for the homeowner to feel secluded and nestled within a grove of trees. Of course, many factors will influence a single housing location decision – zoning, the availability of lots for sale, home price, etc. However, by taking a landscape perspective and considering hundreds or thousands of homes, some of the trade-offs between amenity preferences may become more clear. Other applications of viewscapes, such as planning scenic views of paths or hiding unsightly land uses will similarly benefit from improved modeling of vertical features and the use of ToC models.

Several consequences arise from our finding that BE models greatly exaggerate the size of viewscapes, which significantly affect metrics of viewscape visual quality. Greenness is an element of naturalness, a common and widespread aesthetic preference that is known to enhance landscape preference (Ode, Fry, Tveit, Messager, & Miller, 2009; Purcell & Lamb, 1998; Vukomanovic & Orr, 2014). Greenness is also positively associated with mental (van den Berg et al., 2016) and physical (Tsai, Floyd, Leung, McHale, & Reich, 2016) health and amenity migrants value natural areas that provide opportunities for rest and

Table 2
Comparison of viewscape area (km^2) across resolutions within each model type.

	Resolution Comparison	1 m–5 m	1 m–10 m	1 m-15 m	1 m–30 m	5 m–10 m	5 m–15 m	5 m–30 m	10 m–15 m	10 m–30 m	15 m–30 m
BE	Difference of Means	0.95	1.43	1.83	2.71	−0.48	−0.88	−1.76	0.41	1.29	0.88
	Adjusted p-value	0.58	0.18	0.04	0.00	0.95	0.65	0.05	0.97	0.27	0.65
ToC	Difference of Means	0.86	1.29	1.45	1.70	−0.43	−0.58	−0.84	0.16	0.41	0.25
	Adjusted p-value	0.00	0.00	0.00	0.00	0.25	0.04	0.00	0.95	0.29	0.75

relaxation (Purcell, Peron, & Berto, 2001; van den Berg, Koole, & van der Wulp, 2003). Terrain ruggedness contributes to viewscape complexity, which describes the diversity and richness of landscape elements and features, and enhances landscape preference. More complex terrains – those with more variation and greater complexity of patterns and shapes – are generally considered more appealing (McGranahan, 2008; Stamps, 2004). Larger BE viewscapes are significantly greener and have a greater number of vegetation types than the smaller ToC viewscapes (Table 1). On the other hand, the presence of vertical natural and human features in ToC models resulted in viewscapes with higher terrain ruggedness values (Table 1). Naturalness and complexity are important visual quality metrics, and the study of preferences related to these metric should reflect both a more realistic viewscape size as well as the vertical structure of landscape features. Decades of scenic analysis studies have led to a number of detailed assessment metrics and models with well-established visual preference theory and conceptual models. Examples include evaluating scenic beauty (Arthur, Daniel, & Boster, 1977), managing natural landscapes for scenic preferences (Shafer & Brush, 1977), and mathematical modeling of multiple landscape parameters using synthetic data (e.g. Guldmann, 1980). To date, these studies have relied mainly on data collection from photographs and/or required field access for direct measurement, but their conceptual underpinnings are important for grounding the development of new analytics. Advances in spatial computing and fine-grain spatial data, such as LiDAR, present an exciting new frontier to apply mathematical and conceptual models of visual quality to large areas (100 s to 1000 s km^2).

Privacy is an important driver of exurban development, particularly in the intermountain West where the frontier idyll still looms large (Hines, 2007; Kondo, Rivera, & Rullman, 2012). The visibility of neighbors not only impacts perceptions of privacy, but also other related visual quality metrics, such as naturalness or intactness (Real et al., 2000). Our results indicate that vertical dimensions of the built and natural environment are important for assessing the privacy of locations. Our case study of exurban homes shows that almost three times more neighbors are visible in BE viewscapes compared to those derived from ToC models. In this landscape, forest vegetation obstructed the visibility of neighboring homes more than human-made structures, but in other areas with higher density development, the reverse might be true. Not only were more neighboring homes visible in BE viewscapes, but the nearest visible neighbors are significantly closer. These differences between models could lead to dramatically different interpretations in viewscape studies. For example, there are many nearby visible neighbors in the BE visualization, which might suggest that residents are seeking to live close to neighbors and to maximize social interaction. However, ToC models are better representations of how vegetation creates privacy and seclusion. Although many neighbors may be nearby, only a third are visible in this case, and those that are visible are typically further away. Forested mountain regions provide a range of privacy contexts to consider. Homes may be scattered in low-density exurban patterns, but in some cases, clustering of homes is necessary due to limited road access, localized potable water for wells, or wildfire hazard concerns. In contrast, grassland systems where landowners can – and do – construct their own roads and/or large aquifers allow for wells to be established, may not necessitate clustering (e.g. Vukomanovic, Doumas, Osterkamp, & Orr, 2013). The addition of an economic perspective could help further our understanding of visual quality preferences and clarify whether differences between ToC and BE model representations better explain differences in real estate value. Hedonic price analyses, for example, could reveal the roles that viewscape size and visual quality characteristics play in determining housing markets.

The degree to which relationships are generalizable across scales of observation (i.e. scale invariance) has never been examined in viewscape modeling studies. Our finding that the area of viewscapes increases with coarser data resolution (Fig. 4) suggests that LiDAR line-of-sight models are resolution dependent and subsequent measurements of visual quality may not be generalizable across scales. However, we found that differences between the areas of BE and ToC viewscapes from the same vantage point are fairly consistent across resolutions in that BE viewscapes are approximately four times larger than ToC viewscapes. This suggests that the error in BE viewscapes could be approximated in this setting. For example, our regression models, or even a simple "4× correction coefficient", could be useful in situations where LiDAR data are not available. The strong relationship between ToC and BE viewscapes at fine scales (1-m $r2 = 0.80$) suggests that modelers can be more confident of using such a correction for fine-scale BE surfaces, but should be cautious at coarser resolutions with substantially weaker relationships (30-m $r2 = 0.53$; Fig. 7). We recognize that these correction coefficients are calibrated based on viewscape characteristics (e.g. terrain, vegetation, and housing density) of this study system in Colorado and therefore may not be generalizable to other regions. We encourage additional studies to test the scale invariance of viewscape relationships in new places.

We also encourage future work in regions with different forest types (e.g. mixed evergreen/broadleaf forest and deciduous forest) and densities of the built environment (e.g. urban and suburban areas) to assess the broader generalizability of our Top-of-Canopy LiDAR approach. An advantage of the ToC approach is its ability to represent viewscape conditions of numerous sites. However, it may incompletely represent viewscapes where horizontal visibility is important, such as in urban settings (e.g. Yu et al., 2016). Future work that investigates if and where the ToC approach is incomplete could inform innovative toolkits for landscape design and visual quality assessments across a range of landscape and urban settings.

To date, computational barriers and limited access to LiDAR data over large extents have contributed to the prominence of traditional bare-earth viewscape models. LiDAR data collection is costly and coverage has typically included only specific areas of interest. In many cases, LiDAR data are proprietary. Additionally, unique expertise is often required due to the data- and computationally-intensive nature of LiDAR analyses (Singh, Chen, Vogler, & Meentemeyer, 2016), which may pose an obstacle for many studies. Our findings that ToC viewscapes produce significantly smaller viewscapes with more realistic visual quality compared to BE viewscapes suggest that LiDAR-derived ToC viewscapes can be a better option for many landscape and urban planning studies. In cases where it is not feasible to use ToC models, our results suggest that 1-, 5-, and 10-m BE models can be used interchangeably since area measurements between these resolutions were not significantly different (Fig. 4). While data volumes and computational costs of LiDAR decrease exponentially with coarser resolution, model error significantly increases; we therefore recommend modeling viewscapes using fine-scale 1-m ToC LiDAR data.

Digitally modeled viewscapes are being increasingly used in landscape and urban planning, but with little attention to the important roles that data representation and the vertical dimension of built and natural environments play in their measurement. We found significant differences in the size of viewscapes derived from LiDAR bare-earth (BE) and top-of-canopy (ToC) models, which in turn influenced our measurements of visual quality. Viewscapes computed using BE models were significantly larger than those computed with ToC models – a pattern that was consistent across multiple resolutions of LiDAR data aggregation. Vegetation and human-made features obstruct visibility in the real world, and when models incorporate these features, they too produce smaller viewscapes that more realistically reflect the visible portions of the landscape. Our findings suggest that the vertical and horizontal dimensions of viewscapes should be considered across the range of domains that are informed by the visual connections that humans form with their environment.

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