Visibility Analysis of Oceanic Blue Space using Digital Elevation Models

Abstract

Published evidence shows that views to blue spaces (e.g. ocean, lake, and river) have positive effects on humans' health and mental well-beings. However, quantitative assessment of blue space visibility is challenging for large spatial areas with complex terrain or built environment. The assessment approach introduced in this study applied an innovative sampling strategy which generalizes blue space as a lattice of points and calculate visibility of all the points within a continuous area. Compared to traditional viewpoint-based visibility analyses, this approach can assess blue space visibility over a large area at a fine spatial resolution. The raster output can be overlaid with data recorded at different spatial units to study the associations between blue space visibility and socio-economic and health disparities. Additionally, this approach can be applied to assess impact of buildings to blue space visibility over space by comparing outputs generated from different digital elevation models (DEM). The utility of this approach was demonstrated in a case study in the island of O'ahu, Hawaii, which finds that: (1) wealthier and older people possess higher share of ocean visibility; (2) man-made buildings have caused large shrink and redistribution of ocean visibility; (3) high-rise buildings have particularly high and extensive impact to ocean visibility. The findings suggest that improved environmental assessment processes and planning policies are needed to mitigate the inequality of visible blue space in different population groups and preserve the shrinking visible blue space in the process of urban development.

1 Introduction

The belief that viewing natural environment (such as water and vegetation) can ameliorate stress and illness dates back to the early ages, which influenced the landscaping of early cities in Persia, China and Greece (Marcus and Barnes, 1999). Contemporary psychological studies confirmed the positive effects of viewing natural scenes on stress reduction compared with viewing scenes of built environment (Ulrich, 1981, 1999, Velarde et al. 2007). Particularly, views to the aquatic elements (e.g. ocean, lake, and river) in the natural environment are often perceived with higher restorativeness (Laumann 2001), positive influence on psychophysiological states (Ulrich, 1981, Laumann 2003), and stress-reducing and mood-enhancing effects (Karmanov and Hamel, 2008). Such restorative and healing aquatic environments are referred to as blue space. The emotional, healing and restorative effects of visible blue space are systematically reviewed in (Völker and Kistemann 2011). Considering the increasing threat of stress-related diseases to our society, more attention should be paid to the benefits of visible blue space on the public mental well-being and environmental injustice associated with unequal share of visible blue space in different population groups. Investigations to these issues can be facilitated by a quantitative assessment of visible blue space in people's living environment.

The economic value of views to blue space has been widely recognized. Environmental scenes containing water are associated with higher perceived attractiveness and higher willingness to pay or/and visit than those without water (White et al. 2010). For instance, hotel rooms and residential homes with a view of blue space are higher priced (Luttik 2000; Lange and Schaeffer 2001). In the city of Honolulu, Hawaii, around 81% of serious inquiries for home purchase express a desire for ocean views (Krischke 2017). In the meantime, views to blue space are dynamically changing in the process of urban development. Waterfront buildings may create views of blue space for residents in the buildings, but interrupt views in other areas. The importance of preserving scenic landscape (including blue space) has been recognized at the policy level. The National Environmental Policy Act (1969) has determined preserving the aesthetic aspect of the environment as one of the Federal responsibilities (Council on Environmental Quality, 1969). At the state level, Hawaii Environmental Policy Act of 1969 has listed 'affecting on scenic vistas and view planes' as one of the thirteen administrative criteria to assess potential environment impact of an action (Office of Environmental Quality Control 2012). Despite the recognized importance of scenic landscape in planning documents, there is a general lack of practical methods and tools to quantify impact of man-made building to visible blue space, which is a major element of scenic landscape in many coastal cities. The social and economic implications of the change of visible blue space deserve further investigation.

Views of blue space are unevenly distributed in space. In geographical information systems (GIS), visibility analysis (also called viewshed analysis) can be performed in digital terrain models to determine areas visible from one or multiple specified observation locations (viewpoints). However, viewshed analysis in current GIS cannot be directly applied to assess visibility of blue space for two main reasons. First, analyzing the amount of visible blue space in an area can be computing-intensive. The computation of viewshed from a viewing area (e.g. a coastal area) to a target area (the ocean surface) includes a huge number of line-of-sight (LOS) analyses, which would result in a long processing time. Second, the output of viewshed analysis is a binary raster in which 0 stands for invisible from the observation point(s) and 1 means visible, which, however, does not consider visual significance from a human perspective. The visual significance of an object decays as its distance to a human observer increases due to the shrinking size of the object in the observer's vision, the aspect of the object (e.g. standing, laying or siding), and atmospheric interference.

This study introduced an innovative approach to assess visibility of aquatic blue space with a flat surface (e.g. ocean, lake, and calm rivers). This approach applies a reverse sampling strategy which generalizes blue space as a lattice of points and aggregates visibility of all the points within a continuous area. The computed visibility takes into account the distance and vertical aspect of blue space to observers. Compared to traditional visibility analyses based on viewpoints, this approach can calculate blue space visibility within a spatial large area at a fine resolution. The utility of the approach was demonstrated in a case study of analyzing ocean visibility on the island of O'ahu, Hawaii, which led to 5m-resolution rasters of ocean visibility for the entire island. The derived ocean visibility rasters were then overlaid with other spatial data to analyze the relations between ocean visibility and a number of socio-economic and mental health variables. Furthermore, we demonstrated the utility of this approach in assessing the impact of man-made buildings to ocean visibility by comparing outputs generated using different digital elevation models (DEMs). The introduced approach can be potentially applied as a planning tool to assess building impacts to visible blue space in the environment. It can also benefit scientific research about the health, social disparities and environmental justice issues associated with blue space visibility.

2 Related Work

Viewshed analysis (also known as visibility analysis) is a common terrain analysis function in GIS. Conventional viewshed analysis generates a binary output including visible areas (denoted as 1s) and non-visible areas (0s). Viewsheds of multiple observation points can be combined to a cumulative viewshed representing the number of times a location can be seen from the observation points (Wheatley 1995). Viewshed analysis has been widely used in terrain-based spatial modeling, such as locating the best site for an observation tower for forest fire or diseases (Lee 1991), planning a scenic path planning in a national park (Stucky 1998), and selecting locations for telecommunication towers (Floriani et al. 1994) and radar antenna (Lubczonek 2011). The binary viewshed and cumulative viewshed become standard terrain analysis tools in prevalent GIS packages such as ArcGIS® and QGIS®.

However, the binary output of conventional viewshed analysis does not express the degree of visibility from a human perspective, which is termed Visual Magnitude (VM) in the field of graphic design. Iverson (1985) defined VM as a measure of visible landscape combining the distance, aspect of a land plane or object from the observer and times seen. Iverson (1985) cited the VIEWIT program developed by Travis et al. (1975) for calculating visual perception sensitivity (a similar concept to VM) based on manually digitized terrain data. Later, efforts have been made to incorporate VM into GIS-based viewshed analysis. For instance, Fisher (1994) applied fuzzy set theory to model the decreasing clarity of the view of objects in different distances due to atmospheric conditions. Similarly, Kumsap et al. (2005) modelled the effect of distance decay in visibility analysis for 3D forest landscape, utilizing viewshed analysis in GIS. However, these methods only consider distance decay of visual magnitude but do not take into account the relative aspect of the object to a viewer.

More recently, Domingo-Santos et al. (2011) proposed an algorithm to quantify visual exposure (a similar concept of VM) of terrain within a viewshed. Instead of a binary output, the visual exposure is described by numerical scores, according to the angle or covered surface area on the retina of an observer. Chamberlain and Meitner (2013) conducted a route-based visibility analysis that compares standard viewshed (binary output), cumulative viewshed (times seen), and VM which is evaluated by slope, aspect, and distance of a terrain to a viewer. The VM-based analysis can identify areas in landscape that are potentially more apparent and attention-grabbing seeing along a route. Nutsford et al.'s approach (2015 and 2016) incorporates both distance decay and aspect of terrain surface to provide personalized visibility analysis for green and blue space. This approach was applied to estimate the visibility of blue and green spaces at centroids of meshblocks (the finest geographic division in New Zealand) as viewpoints, which is then health and social variables. However, the uncertainty of the analysis needs further evaluation, especially in a complex terrain or built environment where the visibility changes dramatically within a short distance and visibility at a viewpoint may not represent entire spatial unit (e.g. meshblock).

Computational efficiency is a long-standing challenge for viewshed analysis. s direct viewshed algorithm consists of numerous line-of-sight (LOS) analyses projected from a viewing point to all other points in the terrain. The direct algorithm (also called R3 algorithm) is inefficient as the algorithm repeats the visibility calculations of points closer to the viewing points when estimating the visibility at a farther point. Thus, the computation of R3 is proportion to not only the size of the grid, but also the distance from the viewing point (Izraelevitz 2003). Alternatively, the R2 and XDraw algorithm make an approximation of the visibility at a point based on previously calculated visibility of points closer to the viewing point (Franklin and Ray 1994). R2 and XDraw are substantially more efficient than R3 but are criticized for their lower accuracies (Franklin and Ray 1994; Kaučič and Zalik 2002). Variants of these viewshed algorithms with different optimization techniques have been developed (Izraelevitz 2003; Andrade et al. 2011; Feng et al. 2015). Please refer to Chamberlain and Meitner (2013) for a more extensive review of viewshed algorithms and applications.

3 Method

3.1 Digital Elevation Models

The DEM used for this study are processed from point cloud captured by airborne Light Detection and Ranging (LiDAR) systems. LiDAR is an active remote sensing technique that uses laser light to sample the surface of the earth, producing highly accurate x, y, z measurements which are called point cloud. Laser pulses emitted from a LiDAR system reflect from objects both on and above the ground surface. One emitted laser pulse can generate one or many returns. Digital Surface Model (DSM, such as Figure 1, left) is generated using the highest returns from different cells of a raster. Digital Terrain Model (DTM, such as Figure 1, right) is generated using the last returns reflected from the ground. Both DSM and DTM share a generic term digital elevation model (DEM). The specific methods of deriving DSM and DTM are documented in (Dong and Chen 2017).

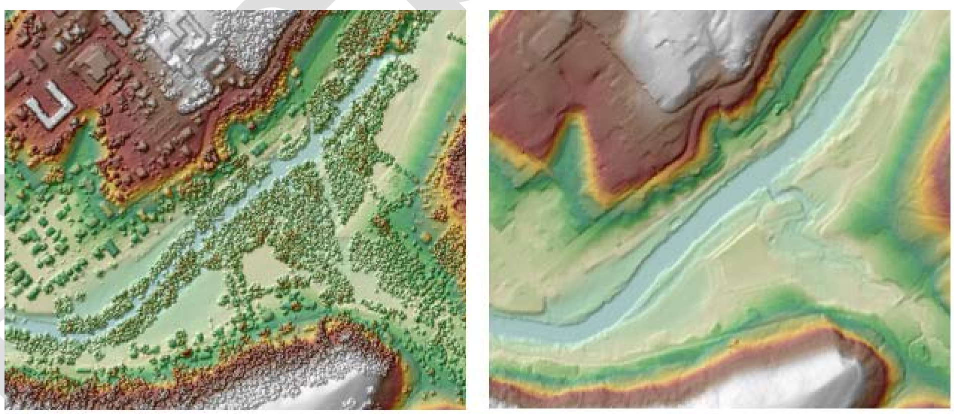

Figure 1: Example of digital surface model (left) and digital terrain model (right)

LiDAR point cloud data used to create the DEMs are publicly available in the online archive of NOAA Digital Coast (https://coast.noaa.gov/htdata/lidar1_z/). The LiDAR data were acquired from June to August 2013 and cover most low-lying coastal areas on the island of O’ahu

(Figure 2). In this study, the LiDAR point cloud data were processed into three DEMs at a 5-meter resolution. This resolution is sufficient to portray outlines of buildings on the ground and can control the data size and computational workload at a moderate level. First, a DTM was created to represent the bare terrain without aboveground features. Second, a DSM was created to represent the ground surface with aboveground features. We acknowledge that other aboveground objects (e.g. trees) also have impact to ocean visibility. In order to focus on the impact of buildings to ocean visibility, only building heights were included in the DSM and tree canopies were removed. The separation between building heights and tree canopies was guided by a land cover layer from the C-CAP database of NOAA. The elevation of the derived DSM represents building heights in only impervious (developed) land in the land cover data. In undeveloped areas, DTM and DSM are identical, both representing bare ground height. Similar methods of building detection are reviewed in (Yan, Shaker, and El-Ashmawy 2015). Third, an additional DSM was created to represent ground surface excluding buildings higher than 50 meters. This DSM was specifically used for analyzing the impact of buildings higher than 50 meters to ocean visibility. The void areas (mostly in the mountains) in the LiDAR data were filled by resampling 10-meter DEM data acquired from USGS (Figure 2).

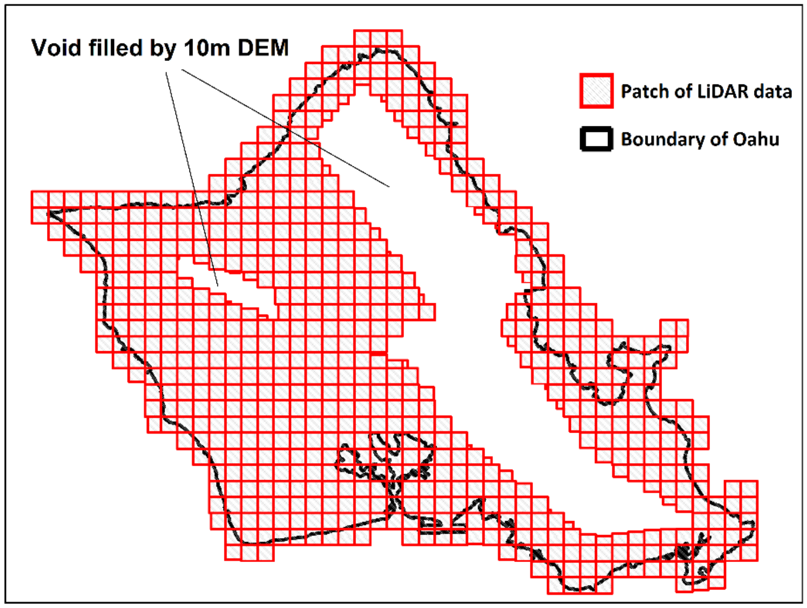

Figure 2: Coverage of LiDAR data in O’ahu.

3.2 Ocean Surface Modeling

Ocean surface is nearly a flat plane with slight curvature of the spherical earth. Assuming the earth is a sphere with a 6,371km mean radius, the furthest visible distance in the island is 123.7 km, which is at the peak of Mount Ka’ala (highest point in O’ahu, 1226 meter above sea level). At this position, more than 95% of the visible ocean surface is within 20 km from the coast line. Beyond 20km, ocean visibility decays rapidly due to the earth curvature and atmospheric interference (e.g. air moisture, air quality, and cloud). Lower areas in the island have even shorter visual distance in the ocean. Thus, a 20km buffer area from the coast line was used to represent ocean area.

The ocean area includes an infinite number of visible points. Computing visibility from the island to every point in the ocean is computationally impossible and unnecessary. In our approach, the ocean surface was generalized into a lattice of points, each of which represents an 8km^2 hexagon area in the ocean surface (Figure 3). The distance from a point to the nearest neighbor point is 3.039km. In total, 530 hexagons were created within the 20km buffer area and their centroids were selected to represent the ocean surface. Thereby, visibility analysis to the ocean surface is reduced to visibility analysis to the 530 representative points.

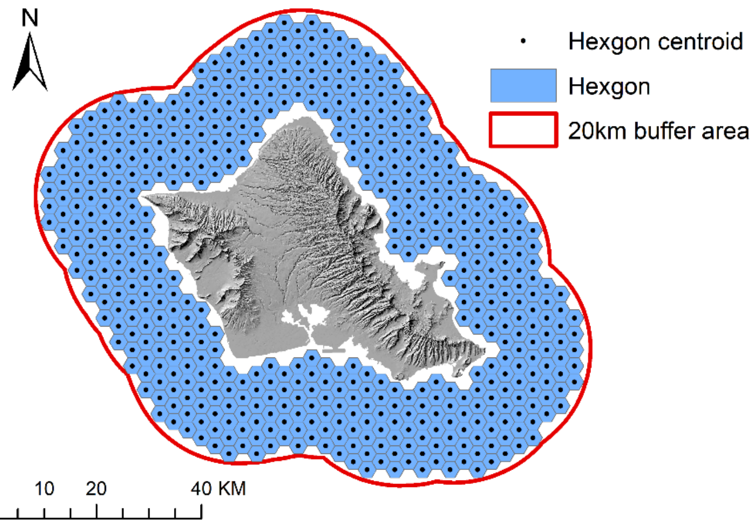

Figure 3: Generalizing ocean surface to a lattice of points

3.3 Ocean Visibility Calculation

The assessment approach is based on an aggregation of weighted viewsheds of a lattice of representative points in the ocean. The procedure includes the three general steps. First, using viewshed analysis, a binary viewshed raster (0 = invisible, 1 = visible) was computed for a point in the lattice. Second, a visibility raster covering the island was computed by multiplying the binary viewshed by visual significance of the point at all pixels in the DEM. Finally, iterating the previous two steps for all representative points in the ocean and summing up the visibility rasters of the points, a raster of the overall ocean visibility can be obtained.

In this approach, visual magnitude of a point is quantified by the visual angle occupied by the hexagon in a human observer’s vision. Imagine that an increment of distance in the ocean decreases as it moves away from the observer due to the decreasing vertical aspect (Figure 4 (a)).

In other words, an area in the ocean occupies a smaller view angle when it is further away from the observer (Figure 4 (b)). As demonstrated in Figure 4 (c), given the elevation of an observer (*h*), horizontal distance from the observer to a point (*d*), and mean diameter of the hexagon ($\emptyset = 3.027km$), the view angle (*a*) to the hexagon can be calculated using the law of cosines:

$$\boldsymbol{a} = \mathbf{arccos}(\frac{\boldsymbol{e^2 + f^2 - \emptyset^2}}{\boldsymbol{2ef}}) \qquad \text{Equation 1}$$

Because $e = \sqrt{h^2 + (d - \frac{\emptyset}{2})^2}$ and $f = \sqrt{h^2 + (d + \frac{\emptyset}{2})^2}$, Equation 1 can be transformed to:

$$\boldsymbol{a} = \mathbf{arccos}(\frac{\boldsymbol{h^2 + d^2 - \left(\frac{\emptyset}{2}\right)^2}}{\boldsymbol{ef}}) \qquad \text{Equation 2}$$

Finally, the ocean visibility (*I*) at an observing point is defined as the sum of view angles of all visible points:

$$\boldsymbol{I} = \frac{\boldsymbol{\sum_{i=0}^{n} a_i * V_i}}{\boldsymbol{n}} \qquad \text{Equation 3}$$

where V_i is the binary viewshed of Point i, a_i is the visual angle of the hexagon centered at Point i, and n is the total number of points (hexagons).

The elevations (h) were obtained from the DEMs. The horizontal distances (d) were derived from rasters of Euclidean distances from the points in the ocean. Using map algebra, a viewshed raster weighted by the view angle (a) was computed for every point in the lattice. Finally, all 530 weighted viewsheds were summed, creating a 5m-resolution raster of ocean visibility. The ocean visibility at each pixel in the DEM is dependent on the elevation of the pixel, the number of visible points, and the distances from the visible points to the pixel. Three rasters of ocean visibility (I_{DTM}, I_{DSM} and $I_{DTM<50}$) were computed using the DTM, the DSM, and the DSM with no higher-than-50m buildings respectively.

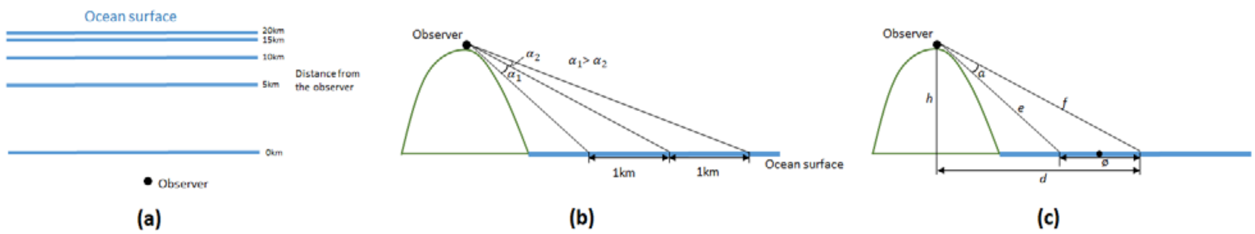

Figure 4: Computing the view angle to an ocean area. (a) 5-km distance increments at different distances from an observer. (b) View angles of the same ocean area at different distances. (c) Computing the view angle (a) to an ocean area using the law of cosine.

3.4 Implementation

The visibility analysis approach introduced in this study implements an area-to-area visibility analysis by representing the target area as a point lattice. The result is an aggregation of all visibility rasters computed from the points, weighted by visual magnitude at different locations. This study utilizes the viewshed function in ArcGIS® for Desktop v10.3 based on the direct algorithm (R3 algorithm) due to its accuracy and reliability. The density of the point lattice can be adjusted according to different accuracy requirements and computation budget. The computation of the ocean indices is completed in a desktop computer with Intel(R) Xeon(R) E5-1660 v4 3.20GHz CPU. Using one computing instance, the average processing time of ocean visibility for one point is ~680 seconds, which includes 600 seconds for viewshed analysis, 45 seconds for computing Euclidean distance, and 35 seconds for adding the weighted viewsheds into the overall visibility raster. Theoretically, the entire computation for all the 530 points in the lattice would take ~100 hours (4.2 days) using a sequential program in one computing instance. However, the algorithm consists of independent processes and can be parallelized into multiple computing instances. In the test of employing eight parallel instances, the processing time of the entire program was reduced to ~12 hours, which is approximately 1/8 of the processing time in a sequential program.

3.5 Statistical Analyses

Finally, the relations between ocean visibility and a number of socio-economic and health variables are examined by overlaying the raster of ocean visibility and spatial data in different spatial units. The boundaries and prices of land parcels are acquired from the Hawaii Open Data Portal maintained by the Office of Planning (http://geoportal.hawaii.gov/), based on the 2017 assessment. The socio-economic variables (including income, age and race composition) are derived from 2015 U.S. Census data at a block group level. The mental health variables (including ratio of depressive order and number of mental bad days in past 30 days) were acquired from Hawaii Health Data Warehouse (2015) at a community level (http://hhdw.org/health-reports-data/category/mental-health/). The descriptions of the mental health variables are documented in (State of Hawaii, 2015). In the analyses with socio-economic and health variables, average ocean visibility was calculated only in developed areas (impervious area) which represent most residential areas. Ocean visibility in undeveloped land, parks and green space were excluded in the computation. The student's *t*-test is used to compare the prices of residential land parcels with and without an oceanview. Regression analyses between ocean visibility and the individual variables are conducted and the results are reported in Table 1. Scatter plots and regression lines are illustrated in Figure 8.

4 Analysis Results

4.1 Spatial Distribution of Ocean Visibility

Figure 5 shows ocean visibility raster calculated using the DSM model (i.e. I_{DTM}), which represents the real condition with buildings. Not surprisingly, areas with high ocean visibility are located along the mountain ridges at high elevations, for example, Koʻolau Range extending from the south-east corner of O’ahu to the north and Waiʻanae Range in parallel at the western side of O’ahu. These areas are well-known for extensive oceanview to multiple directions. The highest ocean visibility is located at 21.32310° N, 157.73710° E at 765m elevation. From Google Earth we can see this location has an extensive oceanview to both the south and northwest side of the ocean (Figure 6).

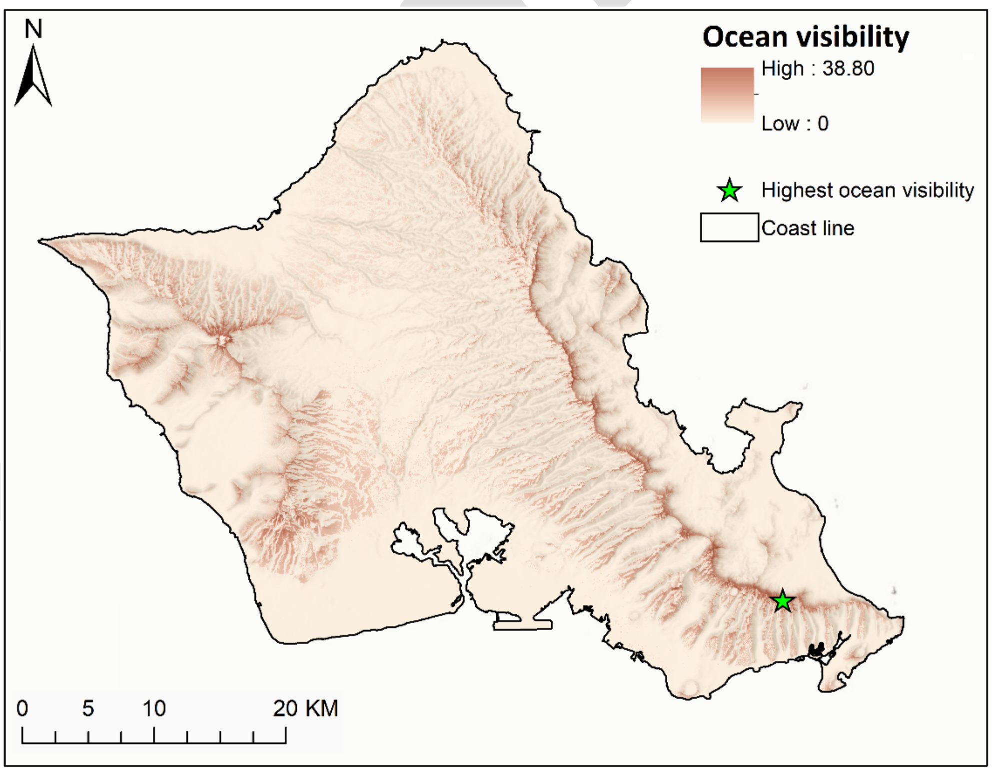

Figure 5: Ocean visibility in O’ahu (a semi-transparent overlay on a hillshade background).

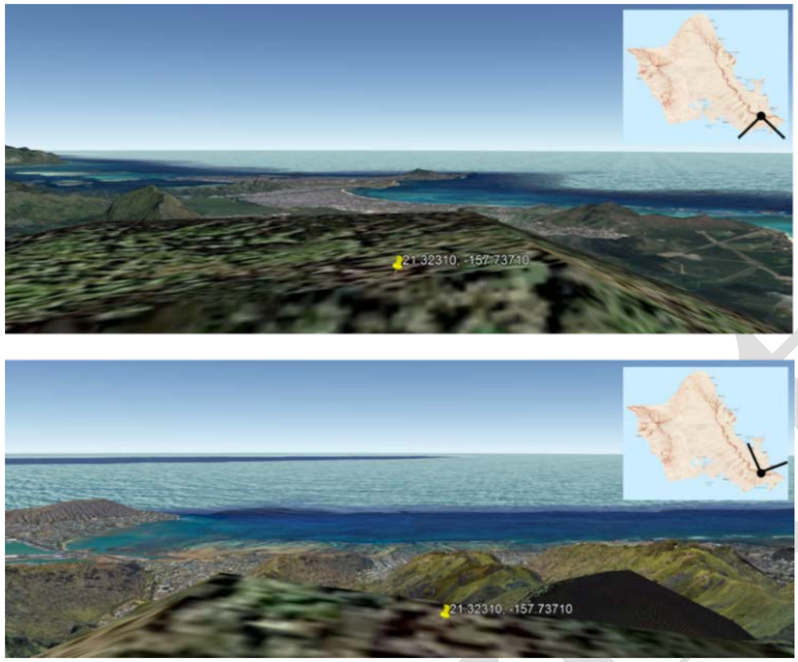

Figure 6: Google Earth view at the location with highest ocean visibility (21.32310° N, 157.73710° E).

Averaging ocean visibility within land parcels, it is known that 751,482 (57.3%) residential land parcels in O'ahu have an oceanview (i.e. $I_{DSM} > 0$). According to the most recent land price data from County and City of Honolulu (2017 September), the average price of land parcels with an oceanview is \$1,009,756, which is significantly (p<0.001) higher that without an oceanview (\$786,584). Figure 7 shows the distribution ocean visibility averaged in land parcels of the whole island, zoomed-in view to in the Waikiki area (a tourist attraction with ocean-front hotels and apartments), and the contrast between the Waialae Iki (a well-known up-scale residential community) and the Wailupe area (an community with more affordable homes).

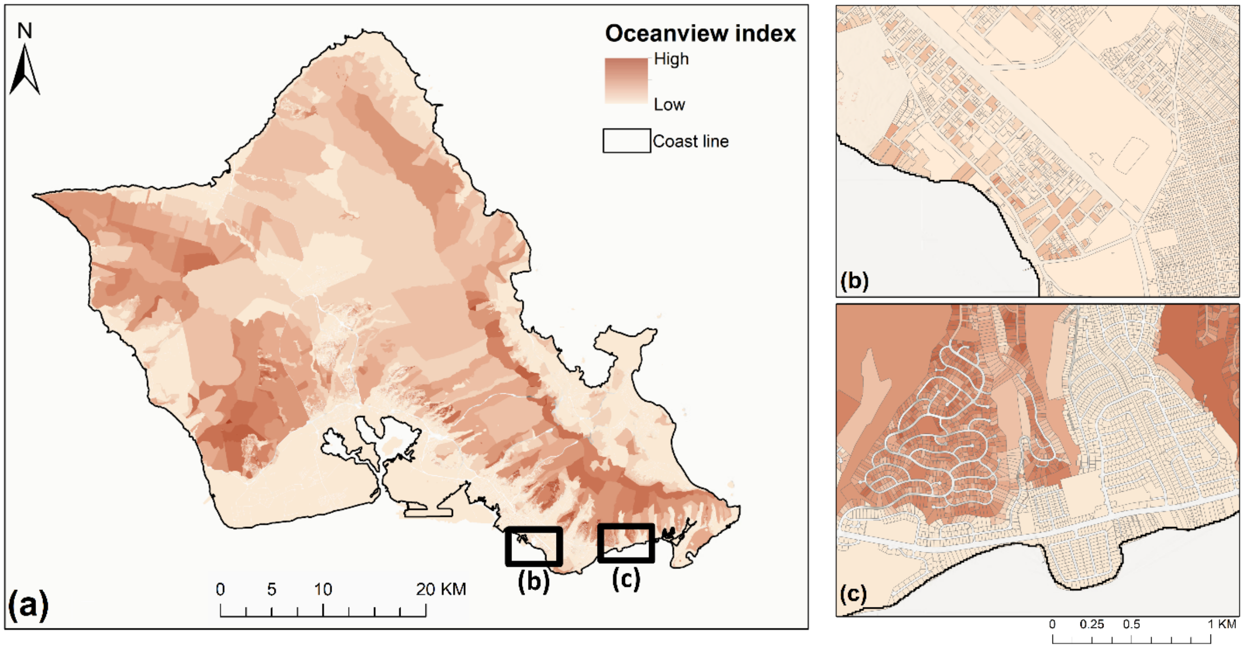

Figure 7: (a) Average ocean visibility in land parcels. (b) The Waikiki area. (c) The Waialae Iki area in the ridge at the left side and Wailupe Valley at the right side.

4.2 Socio-Economic and Health Conditions

4.2.1 <u>Income and House Value</u>

As expected, census block groups with a higher ocean visibility generally have a higher income and housing price (Figure 8(b)). Although the linear relations are significant, the low adjusted *R*-square values indicates that ocean visibility only explains a small portion of the variance of income and housing price (Table 1). Ranking the block groups into four quartiles by ocean visibility, it becomes evident that the average median household income in Q4 block groups (the highest ocean visibility) is much higher than that in Q1-Q3 block groups (Figure 9 left).

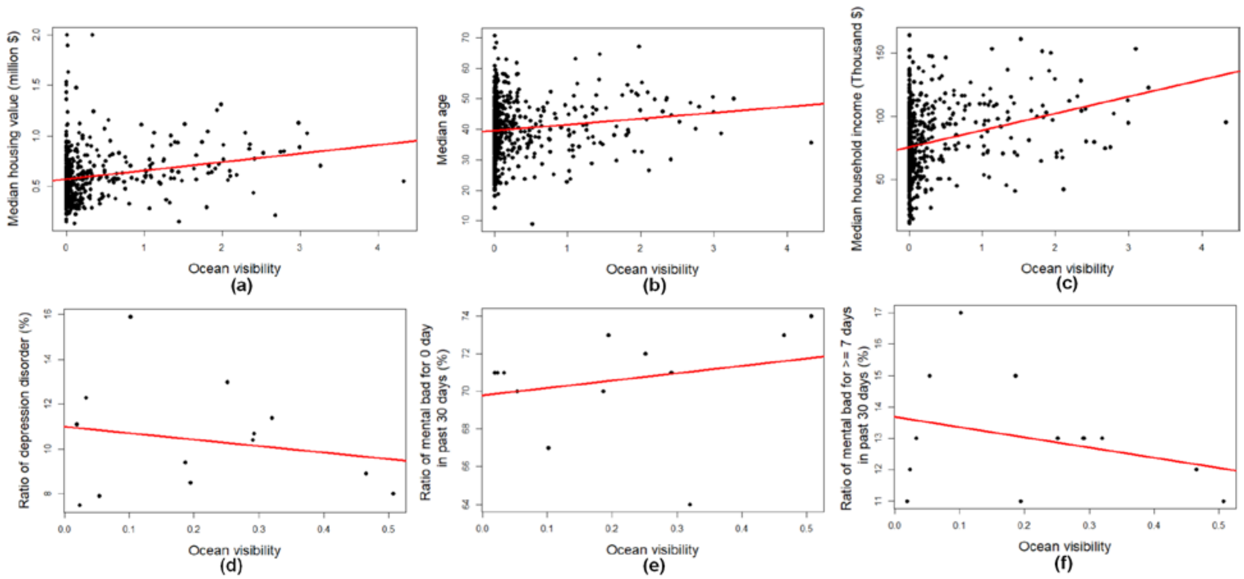

Figure 8: Scatter plots and regression lines between ocean visibility and socio-economic and health variables: (a) median house value (million \$), (b) median age, (c) median household income (thousand \$), (d) Ratio of depression disorder, (e) ratio of no mental bad in past 30 days. (f) ratio of mental bad for equal or more than 7 days in past 30 days.

Table 1: Results of regression analyses between ocean visibility and socio-economic and health variables. Significant relations ($p<0.01$) are highlighted in the bold font.

Dependent variables	β	p	Adjusted R^2	DF
Median housing value (million $)	**0.08484**	**<0.001**	**0.0412**	**511**
Median household income (thousand $)	**13.34800**	**<0.001**	**0.0759**	**556**
Median age	**1.9462**	**0.0024**	**0.0141**	**575**
Ratio of depressive disorder	-2.903	0.5177	-0.0483	11
Ratio of mental bad for < 7 days in past 30 days	69.792	0.4228	-0.0262	11
Ratio of mental bad for >= 7 days in past 30 days	-3.2472	0.3215	0.0064	11

4.2.2 Age

The linear relation between ocean visibility and median age is also significant, indicating the median age of a block group increases as ocean visibility increases (Figure 8 (c)). This trend is also reflected in the ratios of older adults (>65 years old) and children (<18 years old) in the four quartiles of ocean visibility. The ratio of older adults is increasing from 12.5% in the Q1 block groups (least ocean visibility) to 17.1% in the Q4 block groups (highest ocean visibility). In contrast, the ratio of children presents a nearly reversed trend: the ratio of children decreases from 24.1% in Q1 to 19.2% in Q3, and slightly bounced back in Q4 to 20.9%. Figure 10 (left) illustrates the proportions of different age groups living in the four quartiles of ocean visibility, indicating that older adults have the largest proportion (27.7%) living in the Q4 block groups, while children have the largest proportion (29.5%) living in the Q1 block groups.

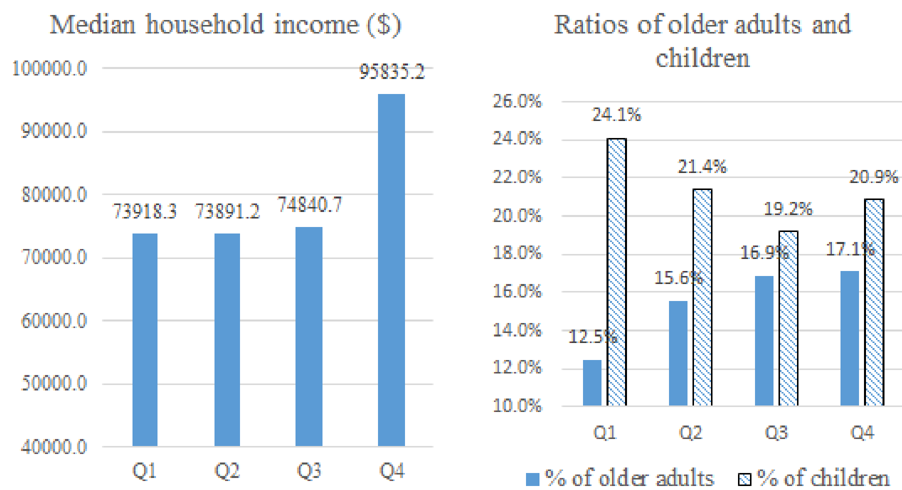

Figure 9: Average median household income (left) and ratios of older adults (>65) and children (<18) (right) in the quartiles of block groups.

4.2.3 <u>Race</u>

As shown in Figure 10 (right), 36.3% of American Indians and Alaska Native are living in Q1 block groups, which is the highest ratio among all race groups, followed by Black and African Americans (31.7%). Asian people have the lowest percentage living in Q1 (i.e. 23.6). In Q4 block groups, families with two or more races have the highest percentage (27.6%), followed by Native Hawaiians and Pacific Islanders (25.4%) and White (25.0%). Only 19.7% Black and 20.6%

American Indians and Alaska Natives reside in Q4 block groups, which are the lowest among all the race groups.

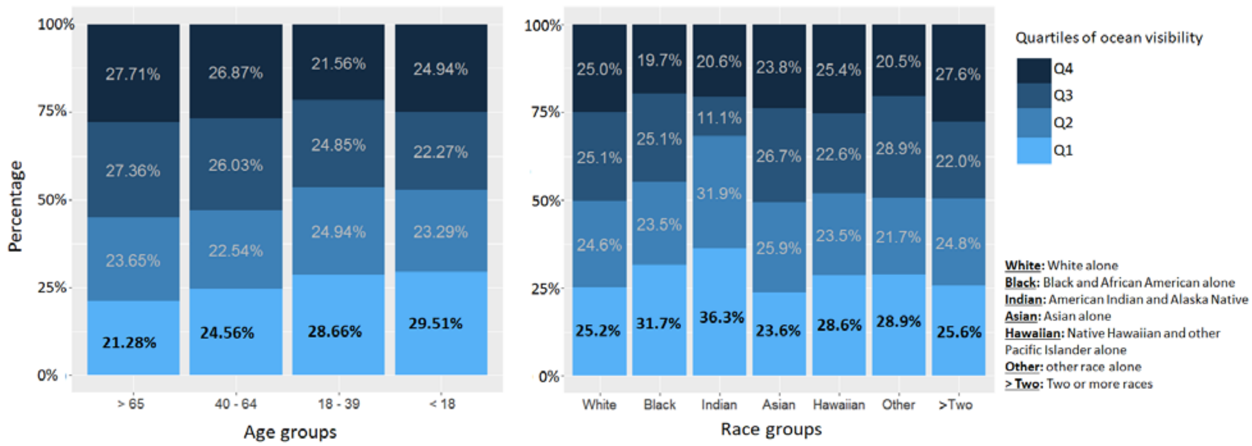

Figure 10: Proportions of different age and race groups in quartiles of ocean visibility

4.2.4 Mental Health

The regression analysis between ocean visibility and the health variables are not significant, possibly due to the small sample size (13 samples). The best fit regression lines in Figure 8 (d-f) generally reflect that an increase in ocean visibility would lead to (1) lower ratio of depressive disorder, (2) lower ratio of mental bad for more than 7 days in past 30 days, and (3) higher ratio of no mental bad in past 30 days. However, these trends need to be confirmed in analysis with a larger sample size before solid conclusions can be drawn.

4.3 Building Impact

The impact of buildings to the ocean visibility in O'ahu was analyzed by comparing ocean visibility rasters computed using the different DEMs (i.e. I_{DTM}, I_{DSM}, and $I_{DSM<50}$). In the I_{DTM} (without buildings), 824.8km^2 (53.3% of the total area) in O'ahu has an oceanview (i.e. $I_{DTM} > 0$). In I_{DSM}, which represents the current situation with buildings, area with an oceanview decreases to 691.7km^2 (44.7% of the total area). The contrast between I_{DTM} and I_{DSM} suggests that area with an oceanview has shrunk 133.1km^2 (16.1%) due to man-made buildings. As shown in Figure 11, most oceanview shrink occurred in foothill areas of mountains at a distance from the coast. Additionally, there are 419.2 km^2 (27.1% of the total area) with a decreased ocean visibility (where $I_{DSM} < I_{DTM}$) where the oceanview is partially blocked by buildings. The spatial distribution of the change (loss and gain) of ocean visibility is displayed in Figure 12 (a).

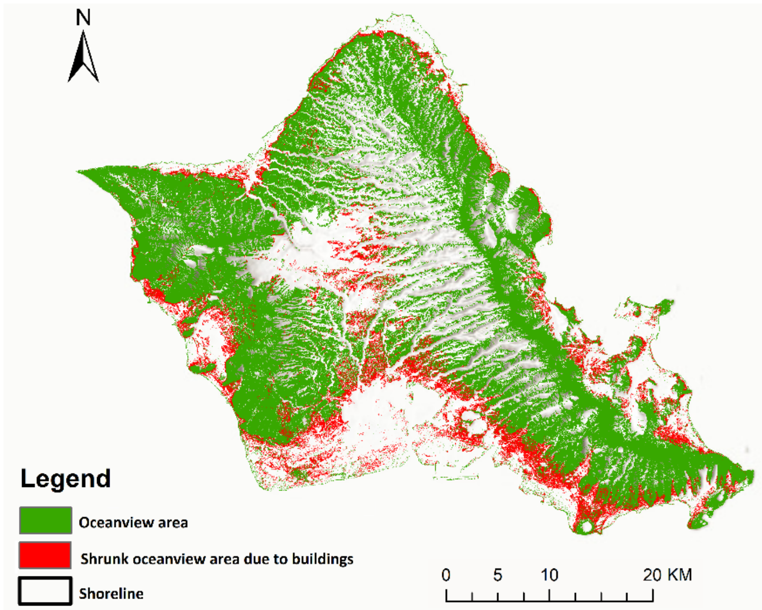

Figure 11: Shrunk oceanview in O’ahu.

Gain of ocean visibility mostly occurs in ocean-front areas with tall buildings. For instance, in Figure 12 (c), spots of ocean visibility gain are in the downtown area of Honolulu where high-rise buildings are concentrated. Meanwhile, these high-rise buildings have casted a ‘shadow’ (area with decreased ocean visibility) in the foothill areas behind them where ocean visibility has declined or vanished. Figure 13 is a picture taken at a location in the ‘shadow’, where the view of the ocean is mostly blocked by the buildings in the ocean front.

Particularly, buildings higher than 50m have a greater impact to ocean visibility than lower buildings. In O’ahu, every m^2 of developed area lead to 0.15 m^2 of completely vanished oceanview and 0.43 m^2 of decreased oceanview. Every m^2 of 50m-high building causes 3.51 m^2 of vanished oceanview and 180.3 m^2 of decreased oceanview. Comparing Figure 12 (c) and (d), many shadow areas are diminished when buildings higher than 50m are removed.

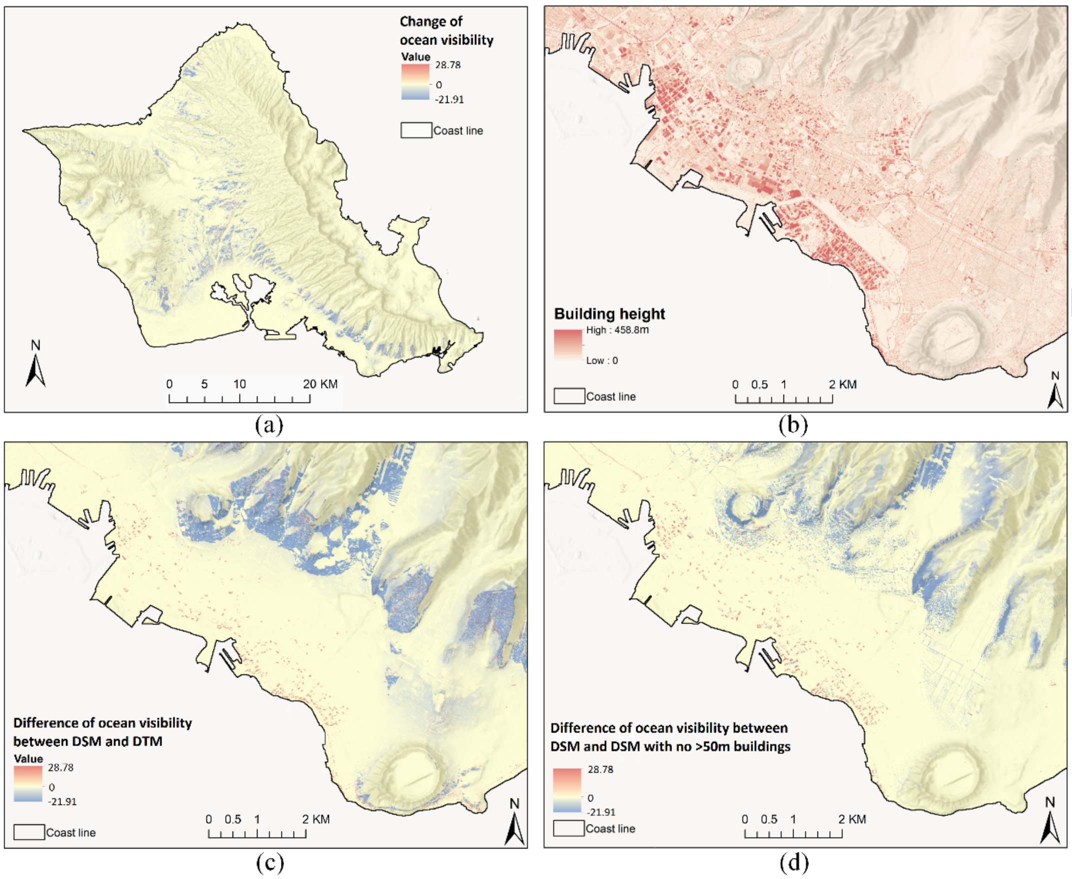

Figure 12: Impact of buildings to ocean visibility. (a) Difference between I_{DSM} and I_{DTM} (i.e. $I_{DSM} - I_{DTM}$) in the island of Oahu. (b) Building heights in downtown Honolulu. (c) Difference between I_{DSM} and I_{DTM} (i.e. $I_{DSM} - I_{DTM}$) in downtown Honolulu; (d) Difference between $I_{DSM<50}$ and I_{DTM} (i.e. $I_{DSM<50} - I_{DTM}$) in downtown Honolulu;

Figure 13: The view at a location with reduced ocean visibility towards the ocean.

5 Discussion

This study introduced a quantitative assessment approach for the visibility of blue space, which is a vague concept usually stored in textual materials and people's mind. In the case study in the island of O'ahu, the assessment results showed that the variation of ocean visibility is largely dependent on the terrain variation and man-made buildings. Areas with high ocean visibility are mostly located on mountain ridges which have extensive oceanview to multiple sides of the ocean. The identified areas of high ocean visibility can be validated from local experience and tourist guides. For instance, the position with the highest oceanview index is located near the top of the Wiliwilinui Ridge trail and the Kuliouou Ridge trail, which are featured as top scenic trails for panoramic oceanview in tourist guides (e.g. Journey Era 2017; TripAdvisor 2017).

The spatial assessment of ocean visibility was related with socio-economic and health variables. The result quantified the desirability of oceanview in the real property market: land parcels with an ocean view are 28.4% more expensive than those without an oceanview. The linear relation between housing price and ocean visibility is significant at the block group level: the median housing value increases with the increase of ocean visibility (Figure 8 (a)). The analysis results show that wealthier and older adults tend to live in communities with higher ocean visibility.

This finding could be explained by the accumulation of wealth as age increases so that older adualts are more likely to afford the higher price of properties with an oceanview. However, it is worth noting that children in the island have a lower share of oceanview (the highest proportion of children live in Q1 communities, as shown in Figure 10). We acknowledge that visual exposure to blue space is only one of the numerous factors that influence children’s physical and mental development. However, since the literature suggests that the visual perception to landscape has profound influence to children’s long-term memory (Yamashita 2002, Sebba 1991), place attachment (Morgan 2010) and social identities (Robertson et al. 2003, Bonaiuto et al. 1996), more efforts are needed to understand how the variation of visible blue space (as well as the loss of visible blue space) in this island is associated with children’s long-term mental and personality development, especially for the Hawaiian natives who have cultural connections with ocean but now increasingly live behind concrete forests. Moreover, the unequal shares of ocean visibility among different age, income and ethnic groups may constitute issues of environmental injustice, which has been discussed for green space in (Wolch et al. 2014, Kabisch and Haase 2013). In future studies, the introduce approach can be integrated with relevant data to further examine these issues.

The preliminary results in this study did not show a statistically significant relation between ocean visibility and mental health variables, which is possibly due to the small sample size used in the analysis (13 samples). In the next phase, we plan to extend our analysis to other islands in Hawaii to create a larger sample size to further test the hypotheses. Alternatively, ocean visibility maps can be produced for other regions where final-scale mental health data are available. Most of the psychological studies about the health benefits of visible blue space are based on experiments or interviews with human participants viewing photos and videos including different scenes (e.g. Ulrich 1981, Laumann 2001, Karmanov and Hamel, 2008). These methods are usually limited to a small sample of participants and can be biased due to miscommunication, biased sample of participants, or unrealistic experiment settings (e.g. viewing photos is different from viewing the real scene). Instead, the ocean visibility map derived in this study quantify visible blue space in people's living environment, which can be overlaid with mental health data recorded in different spatial scales to investigate the long-term influence for a much larger population. We acknowledge the strength of viewpoint-based approaches in assessing blue space visibility at specific locations (e.g. households). However, due to the issues related to data confidentiality (such as mentioned in Nutsford et al. 2016), mental health household level data are often reported within spatial boundaries. The visibility assessment conducted at a point (e.g. centroid) cannot completely represent the visibility within the entire boundary. In contrast, raster output of the introduced approach can be easily aggregated in different spatial units to be associated with other datasets.

The impact of man-made buildings to ocean visibility became apparent by contrasting the assessments from the DTM (bare ground elevation) and the DSM (elevation with building heights). In O'ahu, man-made buildings have blocked the oceanview in 8.6% of the entire island and decreased the ocean visibility in 27.1% of the island. The loss of ocean visibility is mostly distributed in low elevation areas in the foothills, while the gain is concentrated at the oceanfront urban area. The high-rise buildings in the oceanfront have particularly higher impact to ocean visibility. Other than the neighborhood communities, the buildings can impact ocean visibility in communities several kilometers away. Given the positive relation between ocean visibility and the economic condition (income and property value) reflected in previous studies (e.g. Luttik 2000, Jim et al. 2009) and further confirmed in this study, the casted "shadows" behind the coastal development can potentially devalue properties, defer gentrification, and lead to growth of slums and poverty. Additionally, considering the numerous restorative and health effects of visible blue space documented in literature (Völker and Kistemann 2013), the low share of oceanviews in the 'shadows' may increase the likelihood of mental stress, depression, and even behavioral disorders. The redistribution of ocean visibility caused by urban development can potentially intensify environmental injustice associated with visible blue space. This study suggests that improved urban planning, policy-making and legislation are needed to minimize the impact of urban development to visible blue space and mitigate the inequality of visible blue space in different population groups.

Currently, environmental policy regarding building impact to ocean visibility is still partial and fragmented. At the national scale, the National Environmental Policy Act 1969 (NEPA) requires a detailed statement and mitigation recommendation for major federal actions (e.g. policies, plans, programs, and projects) significantly affecting the quality of the human environment (Wood 2003). Non-economic goals such as aesthetic and scenic quality, visibility and air quality, and noise has been included in environmental impact statements institutionally, especially for the impacts of energy technologies on scenic quality (Covello et al. 2013). Psychological assessment research and techniques have been applied to support such assessment from an observer-based perspective (Covello et al. 2013). However, the NEPA policies are rather limited to major federal actions and do not apply to state actions or most private projects unless a federal permit is required (Wood 2003).

At the state level, the environmental assessment policies practiced in Hawaii has identified scenic view as a type of significant impact on the environment, however the applicability of the law is still limited. The Hawaii Environmental Policy Act (HEPA) have identified administrative criteria to determining "significant impact on environment", including "substantially affects scenic vistas and view planes identified in county or state plans or studies" (Office of Environmental Quality Control 2012). However, in HEPA, only a few instances are considered as statutory trigger conditions in which an environmental assessment process becomes mandatory (Office of Environmental Quality Control 2012). These trigger conditions are limited to development in State and County lands, conservation district, historic site, and protected shorelines. Despite the Hawaii Ocean Resources Management Plan (Hawaii State Office of Planning 2013) recognizes the protection, preserving, and possibly restoring scenic and open space resources as one of their policy objective, they also acknowledge that scenic and open space resource conservation has not receive top priority in past planning decisions partially due to the lack of standard analytical methods to assess the impact perception. The proposed method can be used to evaluate the impact of new buildings to oceanviews in a larger area to support the county or state plans to minimize the cumulative long term impacts. In addition to oceanview, the most attractive landscape element in the study area, a comprehensive assessment including other scenic elements (e.g. greenspace) and unsightly elements (e.g. wind turbines) should be conducted to fully understand the impact of buildings to the overall scenery in the island.

The proposed method of calculating blue space visibility is based on a cumulative viewshed analysis to calculate the amount of blue space that can be seen at different locations in a digital elevation model (DEM). Different from existing methods, this method applies reverse viewshed analysis to calculating the amount of blue space (represented by a point lattice) that can be viewed in a terrain. The output of the proposed method is a 5m resolution raster with quantitative visibility scores. Compared to other methods that calculate visibility at pre-determined point locations, the high-resolution raster can capture the variation of blue space visibility in a complex terrain or urban environment, which is important for evaluating building impacts to the blue space visibility.

The viewshed analyses of the representative points are calculated using the built-in function in ArcGIS® based on a direct viewshed algorithm. The efficiency of the method can be improved by employing more efficient viewshed algorithms such as XDraw and R2 (Franklin and Ray 1994). Additionally, non-uniform sampling lattice (such as points with changing density or TIN) can be considered. The next phase of research will include a systematical assessment that compares the accuracy and efficiency of the different algorithms and sampling methods in different types of terrain. Alternatively, the computing time of the method can be shortened by employing more computing instances in a parallel computing system. A preliminary report of the performance and scalability of the approach was provided in this study. With the development of CyberGIS (i.e. GIS built on cyberinfrastructure) (Wang et al. 2013, Shook et al., 2016), the proposed assessment method has the potential to scale up for more precise assessments with a denser point lattice or extended assessment for a larger area.

6 Conclusion

This study introduced a quantitative approach to assess visible blue space and analyze building impact to visible blue space using digital elevation models (DEM). Using this approach, visibility of blue space, which used to be a vague concept stored in people's mind and textual materials, can be quantified as numerical scores over space. Compared with traditional visibility analyses based on viewpoints, the introduced approach takes a reverse sampling approach to generate a continuous raster of blue space visibility at a fine spatial resolution. The output raster covers a large spatial area and can be associated with data recorded at different spatial units to study the health and socio-economic issues (e.g. environmental justice) associated with blue space visibility. Further, this approach enables spatial assessments of building impact to blue space visibility by comparing visibility rasters computed using different DEMs (DTM, DSM and DSM without high buildings). The algorithm of this assessment approach can be easily scale-up by parallelization in a multi-core computing system, and thus has the potential to be applied by planning and policy practitioners as a standard assessment tool. The utility of this approach was demonstrated in a case study in the island of O’ahu, in which several major findings have been derived: (1) The oceanview is a kind of desirable natural resource that is unequally shared by people with different incomes, ages and races. Specifically, wealthier and older people tend to possess higher share of ocean visibility in O’ahu. (2) Man-made buildings have caused large area shrink and redistribution of ocean visibility. In total, 16.1% of the area in the island has completely lost oceanview and 27.1% has a decreased oceanview, most of which is in the foothill areas away from the coast. Most gain is in oceanfront urban areas where high-rise buildings are concentrated. (3) High-rise buildings have particularly higher impact to ocean visibility in the space. In O’ahu, every m^2 of 50m-high building causes lost oceanview in 3.51 m^2 and decreased oceanview in 180.3 m^2. The findings suggest that improved environmental assessment processes and planning policies are needed to mitigate the impact of urban development to the scenic oceanviews. More attention should be paid to the unequal shares of oceanviews in different population groups and the associations with public mental health, social disparities and environmental injustice. In the future, the workflow of this assessment approach will be developed into a more automated and scalable software tool, which can be easily reused and applied in other and/or larger areas for comparative studies about and effects of different planning modes in preserving visible blue space.

References

1. Andrade, Marcus V. A., Salles V. G. Magalhães, Mirella A. Magalhães, W. Randolph Franklin, and Barbara M. Cutler. 2011. "Efficient Viewshed Computation on Terrain in External Memory." *GeoInformatica* 15 (2): 381–97. https://doi.org/10.1007/s10707-009-0100-9.
2. Dong, Pinliang, and Qi Chen. 2017. *LiDAR Remote Sensing and Applications*. CRC Press.
3. Bonaiuto, Marino, Glynis M. Breakwell, and Ignacio Cano. 1996. "Identity Processes and Environmental Threat: The Effects of Nationalism and Local Identity upon Perception of Beach Pollution." *Journal of Community & Applied Social Psychology* 6 (3): 157–75. https://doi.org/10.1002/(SICI)1099-1298(199608)6:3<157::AID-CASP367>3.0.CO;2-W.
4. Chamberlain, Brent C., and Michael J. Meitner. 2013. "A Route-Based Visibility Analysis for Landscape Management." *Landscape and Urban Planning* 111 (March): 13–24. https://doi.org/10.1016/j.landurbplan.2012.12.004.
5. County and City of Honolulu. 2017. "Real Property Assessment." http://geoportal.hawaii.gov /datasets/cchnl::ownall-table.
6. Covello, Vincent T., Jeryl L. Mumpower, Pieter Jan M. Stallen, and V. R. R. Uppuluri. 2013. *Environmental Impact Assessment, Technology Assessment, and Risk Analysis: Contributions from the Psychological and Decision Sciences*. Vol. 4. Springer Science & Business Media.
7. Domingo-Santos, Juan M., Rubén Fernández de Villarán, Ígor Rapp-Arrarás, and Eva Corral-Pazos de Provens. 2011. "The Visual Exposure in Forest and Rural Landscapes: An Algorithm and a GIS Tool." *Landscape and Urban Planning* 101 (1): 52–58. https://doi.org/10.1016/j.landurbplan.2010.11.018.

8. Feng, Wang, Wang Gang, Pan Deji, Liu Yuan, Yang Liuzhong, and Wang Hongbo. 2015. "A Parallel Algorithm for Viewshed Analysis in Three-Dimensional Digital Earth." *Computers & Geosciences* 75 (February): 57–65. https://doi.org/10.1016/j.cageo.2014.10.012.
9. Franklin, Wm Randolph, and Clark Ray. 1994. "Higher Isn't Necessarily Better: Visibility Algorithms and Experiments." In *Advances in GIS Research: Sixth International Symposium on Spatial Data Handling*, 2:751–770. Taylor & Francis Edinburgh.
10. Fisher, Peter F. 1994. "Probable and Fuzzy Models of the Viewshed Operation." *Innovations in GIS* 1:161–175.
11. Floriani, Leila De, Paola Marzano, and Enrico Puppo. 1994. "Line-of-Sight Communication on Terrain Models." *International Journal of Geographical Information Systems* 8 (4): 329–42. https://doi.org/10.1080/02693799408902004.
12. Hawaii State Office of Planning. 2013. "Hawai'i Ocean Resources Management Plan July 2013". http://files.hawaii.gov/dbedt/op/czm/ormp/ormp_update_reports/final_ormp_2013.pdf
13. Iverson, Wayne D. 1985. "And That's About the Size of It: Visual Magnitude as a Measurement of the Physical Landscape." *Landscape Journal* 4 (1): 14–22. https://doi.org/10.3368/lj.4.1.14.
14. Izraelevitz, David. 2003. "A Fast Algorithm for Approximate Viewshed Computation." *Photogrammetric Engineering & Remote Sensing* 69 (7): 767–774.
15. Jim, C. Y., and Wendy Y. Chen. 2009. "Value of Scenic Views: Hedonic Assessment of Private Housing in Hong Kong." *Landscape and Urban Planning* 91 (4): 226–34. https://doi.org/10.1016/j.landurbplan.2009.01.009.
16. Journey Era. 2017. "10 Best Hikes on Oahu." https://www.journeyera.com/10-best-hikes-on-oahu/.

17. Karmanov, Dmitri, and Ronald Hamel. 2008. “Assessing the Restorative Potential of Contemporary Urban Environment(s): Beyond the Nature versus Urban Dichotomy.” *Landscape and Urban Planning* 86 (2):115–25. https://doi.org/10.1016/j.landurbplan.2008.01.004.

18. Kaučič, Branko, and Borut Zalik. 2002. “Comparison of Viewshed Algorithms on Regular Spaced Points.” In *Proceedings of the 18th Spring Conference on Computer Graphics*, 177–183. SCCG ’02. New York, NY, USA: ACM. https://doi.org/10.1145/584458.584487.

19. Nadja, K. and Haase, D. 2014. Green Justice or Just Green? Provision of Urban Green Spaces in Berlin, Germany. *Landscape and Urban Planning* 122: 129–39. https://doi.org/10.1016/j.landurbplan.2013.11.016.

20. Krischke, George. 2017. “*Guide to Honolulu Ocean View Homes and Neighborhoods*.” https://www.hawaiiliving.com/blog/honolulu-ocean-view-homes-neighborhoods/.

21. Kumsap, C., Frédéric Borne, and D. Moss. 2005. “The Technique of Distance Decayed Visibility for Forest Landscape Visualization.” *International Journal of Geographical Information Science* 19 (6):723–744.

22. Lange, Eckart, and Peter V. Schaeffer. 2001. “A Comment on the Market Value of a Room with a View.” *Landscape and Urban Planning* 55 (2):113–20. https://doi.org/10.1016/S0169-2046(01)00148-7.

23. Laumann, KARIN, TOMMY Gärling, and KJELL MORTEN Stormark. 2001. “Rating Scale Measures of Restorative Components of Environments.” *Journal of Environmental Psychology* 21 (1):31–44. https://doi.org/10.1006/jevp.2000.0179.

24. Lee, Jay. 1991. "Analyses of Visibility Sites on Topographic Surfaces." *International Journal of Geographical Information Systems* 5 (4): 413–29. https://doi.org/10.1080/02693799108927866.

25. Lubczonek, J, W Kazimierski, and M Palczyński. 2011. "Planning of Combined System of Radars and CCTV Cameras for Inland Waterways Surveillance by Using Various Methods of Visibility Analyses". *Proceedings of 2011 International Radar Symposium (IRS)*. pp. 269-274. Leipizig, Germany, 13 October 2011.

26. Luttik, Joke. 2000. "The Value of Trees, Water and Open Space as Reflected by House Prices in the Netherlands." *Landscape and Urban Planning* 48 (3):161–67. https://doi.org/10.1016/S0169-2046(00)00039-6.

27. Council on Environmental Quality. 1969. *The National Environmental Policy Act of 1969*, https://www.fws.gov/r9esnepa/RelatedLegislativeAuthorities/nepa1969.PDF

28. Marcus, Clare Cooper, and Marni Barnes. 1999. Healing Gardens: Therapeutic Benefits and Design Recommendations. John Wiley & Sons.

29. Morgan, Paul. 2010. "Towards a Developmental Theory of Place Attachment." *Journal of Environmental Psychology* 30 (1): 11–22. https://doi.org/10.1016/j.jenvp.2009.07.001.

30. Nutsford, Daniel, Amber L. Pearson, Simon Kingham, and Femke Reitsma. 2016. "Residential Exposure to Visible Blue Space (but Not Green Space) Associated with Lower Psychological Distress in a Capital City." *Health & Place* 39 (Supplement C):70–78. https://doi.org/10.1016/j.healthplace.2016.03.002.

31. Nutsford, Daniel, Femke Reitsma, Amber L Pearson, and Simon Kingham. 2015. "Personalising the Viewshed: Visibility Analysis from the Human Perspective." *Applied Geography* 62:1–7. https://doi.org/http://dx.doi.org/10.1016/j.apgeog.2015.04.004.

32. Office of Environmental Quality Control, State of Hawaii. 2012. "*Guide to the Implementation and Practice of the Hawaii Environmental Policy Act – 2012 Edition*." http://oeqc2.doh.hawaii.gov/OEQC_Guidance/2012-GUIDE-to-the-Implementation-and-Practice-of-the-HEPA.pdf.

33. Robertson, Margaret, Rex Walford, and Alison Fox. 2003. "Landscape Meanings and Personal Identities: Some Perspectives of East Anglian Children." *International Research in Geographical and Environmental Education* 12 (1): 32–48. https://doi.org/10.1080/10382040308667511.

34. Sebba, Rachel. 1991. "The Landscapes of Childhood: The Reflection of Childhood's Environment in Adult Memories and in Children's Attitudes." *Environment and Behavior* 23 (4): 395–422. https://doi.org/10.1177/0013916591234001.

35. State of Hawaii. 2015. The Hawaii Behavioral Risk Factor Surveillance System. https://health.hawaii.gov/brfss/files/2016/07/brfss15_results.pdf

36. Stucky, Jayleedan. 1998. "On Applying Viewshed Analysis for Determining Least-Cost Paths on Digital Elevation Models." *International Journal of Geographical Information Science* 12 (8):891–905. https://doi.org/10.1080/136588198241554.

37. Travis, Michael R., Gary H. Elsner, Wayne D. Iverson, and Christine G. Johnson. 1975. "VIEWIT: Computation of Seen Areas, Slope, and Aspect for Land-Use Planning." *Gen. Tech. Rep. PSW-GTR-11. Berkeley, CA: Pacific Southwest Research Station, Forest Service, U.S. Department of Agriculture: 70 P* 011. https://www.fs.usda.gov/treesearch/pubs/27276.

38. TripAdvisor. 2017. "The Top 10 Oahu Hiking Trails." https://www.tripadvisor.com/Attractions-g29222-Activities-c61-t87-Oahu_Hawaii.html.

39. Ulrich, Roger S. 1981. "Natural Versus Urban Scenes: Some Psychophysiological Effects." *Environment and Behavior* 13 (5): 523–56. https://doi.org/10.1177/0013916581135001.

40. Ulrich, Roger S. 1999. "Effects of Gardens on Health Outcomes: Theory and Research." *Healing Gardens: Therapeutic Benefits and Design Recommendations* 27: 86.

41. Velarde, M. D., G. Fry, and M. Tveit. 2007. "Health Effects of Viewing Landscapes – Landscape Types in Environmental Psychology." *Urban Forestry & Urban Greening* 6 (4): 199–212. https://doi.org/10.1016/j.ufug.2007.07.001.

42. Völker, Sebastian, and Thomas Kistemann. 2011. "The Impact of Blue Space on Human Health and Well-Being – Salutogenetic Health Effects of Inland Surface Waters: A Review." *International Journal of Hygiene and Environmental Health*, 214 (6):449–60. https://doi.org/10.1016/j.ijheh.2011.05.001.

43. Wheatley, David. 1995. "Cumulative Viewshed Analysis: A GIS-Based Method for Investigating Intervisibility, and Its Archaeological Application." *Archaeology and GIS: A European Perspective. London: Routledge*, 171–86.

44. White, Mathew, Amanda Smith, Kelly Humphryes, Sabine Pahl, Deborah Snelling, and Michael Depledge. 2010. "Blue Space: The Importance of Water for Preference, Affect, and Restorativeness Ratings of Natural and Built Scenes." *Journal of Environmental Psychology* 30 (4):482–93. https://doi.org/10.1016/j.jenvp.2010.04.004.

45. Wang, S., Anselin, L., Bhaduri, B., Crosby, C., Goodchild, M. F., Liu, Y., & Nyerges, T. L. (2013). CyberGIS software: a synthetic review and integration roadmap. *International Journal of Geographical Information Science*, *27*(11), 2122–2145. https://doi.org/10.1080/13658816.2013.776049

46. Wolch, J.R., Byrne, J., and Newell, J. P. 2014. Urban Green Space, Public Health, and Environmental Justice: The Challenge of Making Cities ‘Just Green Enough. *Landscape and Urban Planning* 125: 234–44. https://doi.org/10.1016/j.landurbplan.2014.01.017.

47. Wood, Christopher. 2003. *Environmental Impact Assessment: A Comparative Review*. Pearson Education. London, United Kingdom.

48. Yamashita, Sampei. 2002. “Perception and Evaluation of Water in Landscape: Use of Photo-Projective Method to Compare Child and Adult Residents’ Perceptions of a Japanese River Environment.” *Landscape and Urban Planning* 62 (1): 3–17. https://doi.org/10.1016/S0169-2046(02)00093-2.

49. Yan, Wai Yeung, Ahmed Shaker, and Nagwa El-Ashmawy. 2015. “Urban Land Cover Classification Using Airborne LiDAR Data: A Review.” *Remote Sensing of Environment* 158 (March): 295–310. https://doi.org/10.1016/j.rse.2014.11.001.

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