Analyzing Land Cover Change to Predict Regulation Changes Using LiDAR Derived Data

Submitted as partial fulfilment of a Master's of Science in Geospatial Technologies

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Abstract

Throughout the late 2000s and early 2010s, the City of Mercer Island, WA experienced a building boom exemplified by the construction of large houses that included high roofs, tall walls, and the removal of most trees on development sites. As a result, the City of Mercer Island adopted a new set of development regulations for its single-family residential zones in 2017 intended to limit the impact of development on nearby trees and property owners. There is little research on whether property- or neighborhood-level changes can be identified using remote sensing; research has largely focused on large-scale, region wide analyses to demonstrate broad changes in land use and land coverage (for instance, from agricultural to urban uses) in response to changing demographics and governmental policies. Using the City of Mercer Island as a test case, this paper analyses changes in land cover change identified using LiDAR (Light Detection and Ranging) derived digital surface models (DSMs) to determine if detecting land cover change can predict change in a region's land use regulations. The results of this analysis show that two of the five cities experiencing the greatest changes to their land cover change patterns underwent wholesale land use regulation changes, indicating that there may be a relationship between land cover change and updates to land use regulations.

1. Introduction

Since 2000, the region surrounding Seattle, WA has experienced significant population growth (United States Census Bureau 2021). In many areas around Seattle, property was redeveloped to accommodate the influx of new residents. The result was increased density in central neighborhoods and near future transit stops planned for the expansion of Sound Transit, the regional transportation authority. Other neighborhoods experienced redevelopment of single-family residential lots that resulted in an existing house being demolished and replaced by a new, larger house.

The City of Mercer Island, WA is a suburban city that falls into the latter category described above. Mercer Island experienced significant redevelopment within its single-family residential areas characterized by existing houses being demolished and replaced with new larger houses. The redevelopment was usually accompanied by increases to impervious surfaces and building height and the removal of many large trees. In an effort to reduce the impacts of new construction, the City of Mercer Island adopted two sets of new regulations in the mid-2010s:

- In 2016, a town center development ordinance was adopted adding restrictions to building form and requirements for affordable housing for residential projects.
- In 2017, a single-family residential development ordinance was adopted that increased impervious surface, building height, and setback restrictions. This ordinance also included new provisions requiring additional trees to be retained on development sites.

The case study of Mercer Island and its attempt to mitigate the impacts of redevelopment raises two several research questions. Firstly, did the regulations adopted by the City of Mercer Island have an effect on land cover within the city? If so, did the regulations have the desired effect for new development (reduction of impervious surface, retention of additional trees, etc.)? Next, can changes to land cover patterns be identified in other jurisdictions in the Seattle metropolitan area? Finally, can land cover changes identified through remote sensing analysis be used to predict where land use regulations have changed? This paper endeavors to answer this last question. In doing so, the other research questions listed above will also be answered.

2. Literature Review

For this project, I explored the connections between land coverage changes and changes in governmental regulations. I will begin this literature review with a brief overview of the history of research in remote sensing and how it has evolved in the last several decades. I will then move on to show that some studies show that governmental regulations and policy have caused changes in land use cover, at least in part (Wu *et al.* 2006, Houet *et al.* 2010, Fichera *et al.* 2012, Li *et al.* 2020, Qacami *et al.* 2022). Finally, I will review research on how tree coverage and tree protection regulations can be detected using remote sensing (Nowak *et al.* 1996, Parmehr *et al.* 2016, Lee *et al.* 2017, Guo *et al.* 2019, Hilbert *et al.* 2019, Timilsina *et al.* 2020) since changes to tree coverage can be indicative of other land cover changes (Lee *et al.* 2017).

2.1 History of Remote Sensing and Change Detection

Over the past several decades, remote sensing technology has advanced as imagery available from satellite platforms has improved (Jensen and Cowen 1999, Rogan and Chen 2004, Weng 2012). The increase in image resolution has driven new methods to analyze data obtained through remote sensing including pixel-based algorithms, sub-pixel-based algorithms, object-oriented algorithms, and artificial neural networks (Weng 2012). Advancement of remote sensing technology has also led to its application to various fields, including: land use and land cover; building, property line, transportation, and utility infrastructure; digital elevation model creation; socio-economic characteristics; energy demand and production potential; critical environmental area assessment;

meteorological data; and disaster emergency response (Jensen and Cowen 1999). LiDAR (Light Detection and Ranging) has also been a proven method to study land cover and urban morphology (Yan *et al.* 2015). LiDAR can also penetrate tree cover to detect buildings and other impervious surfaces are often blocked from satellite and aerial photography (Yan *et al.* 2015).

Remote sensing has long been used to study changes in land cover (Jensen and Cowen 1999, Rogan and Chen 2004). Jensen and Cowen (1999) discussed a study using Landsat MSS data taken in between 1979 and 1981 to show how urban and non-urban land cover changed near Charleston, SC, although at a low resolution (79m by 79m). Green *et al.* (1994) also provided an early example of using remote sensing to find land cover changes in the Portland, OR area, while providing a statement that acknowledges that a change has occurred is relatively uninformative unless the change can be linked to its impacts. More recently, remote sensing has been used to study how land coverage has changed in both urban (Wu *et al.* 2006, Fichera *et al.* 2012, Li *et al.* 2020, Das and Angadi 2022) and rural (Houet *et al.* 2010, Qacami *et al.* 2022) settings. Additionally, remote sensing has been used to show how land and tree coverage patterns have changed due to reconstruction following natural disasters (Fichera *et al.* 2012, Guo *et al.* 2019).

2.2 Impact of Government Policy and Regulations

Government policies and regulations can have a profound effect on land cover in a region. Research shows that changes to economic policy (Wu *et al.* 2006, Houet *et al.* 2010, Li *et al.* 2020), building and land use regulations (Fichera *et al.* 2012), conservation policy (Wu *et al.* 2006, Li *et al.* 2020, Qacami *et al.* 2022), and tree protection regulations (Hilbert *et al.* 2019) have all affected patterns of regional land cover change.

2.2.1 Economic Policy and Development Regulations

As the result of economic reforms in the late 1970s, urban areas in China have experienced rapid growth (Wu *et al.* 2006, Li *et al.* 2020). Wu *et al.* (2006) and Li *et al.* (2020) note that built-up urban area increased in the Municipality of Beijing and in Gansu Province, respectively, due to these economic reforms. In the case of both cities, built up areas largely replaced farmland and unused land.

Research has also shown that other types of government policy can affect detectible land cover, including agricultural policy (Houet *et al.* 2010) and changes to building and land use regulations (Fichera *et al.* 2012). Houet *et al.* (2010) found that land cover changed in the U.S. state of South Dakota and in the Brittany region of France because regulations by the United States Department of Agriculture and the European Union, respectively, caused farmers to change the crops they grew, which in turn caused changes in the regions' landscapes. Fichera *et al.* (2012) found that building and land use regulation changes in the Campania region of Italy in response to a major earthquake in 1980 caused urban development to be refocused to areas that were previously used as farmland rather than in the established urban areas.

2.2.2 Conservation Policy

There is also evidence showing that enacting conservation policy has been effective at causing or preventing land cover change. Wu *et al.* (2006) found that a 1994 ordinance intended to protect agricultural areas in the Municipality of Beijing slowed the conversion of the area's cropland to urban uses. They also found that existing conservation policy, such as nature preserves and parks, prevented land cover changes elsewhere in the Municipality of Beijing. Li *et al.* (2020) also found that conservation policies intended to protect natural lands and agricultural lands resulted in different areas being converted to built-up urban areas. Conservation policies were found to be effective in preserving forest land in the High Atlas region of Morocco as well (Qacami *et al.* 2022).

2.3 Tree Cover

There has likewise been significant research in identifying urban tree cover using remote sensing. Being able to identify areas where urban tree coverage has changed is important because changes to tree coverage can correspond to other land cover changes, such as changes to impervious surface coverage (Lee *et al.* 2017). Early remote sensing efforts in studying tree cover involved studying aerial photography. Nowak *et al.* (1996) used several methods (crown cover scale, transect method, dot method, scanning method) to study aerial photography of cities across the United States and found that tree coverage varies from city to city based on the physical characteristics of the region. Building on this work, Parmehr *et al.* (2016) compared a random point sample analysis of aerial imagery to an analysis of LiDAR and found that both methods have at least 95% accuracy.

Remote sensing has been used to detect changes to tree coverage over many geographies, including Christchurch, New Zealand (Guo *et al.* 2019), Hobart, Australia (Timilsina *et al.* 2020), and Los Angeles County, CA (Lee *et al.* 2017). Each of these studies found that tree coverage decreased over their study periods for various reasons, such as the removal of hazardous trees and reconstruction of property following a major earthquake (Guo *et al.* 2019) and the increase of impervious surface associated with property redevelopment (Lee *et al.* 2017).

Several papers also were able to show that government policies and regulations have affected tree coverage. Hilbert *et al.* (2019) performed a study of 43 cities in Florida and found that increased housing density resulted in a lower percentage of tree coverage. This study also found that cities with tree protection ordinances had higher urban tree cover, and that cities with protections to heritage trees (particularly old and large trees) had even higher tree coverage. Pike *et al.* (2021) built on this study and showed that tree protection regulations are effective at preserving trees after residential construction, reducing tree canopy loss and increases in impervious surface area. However, the ability of government policies and regulations to protect and expand tree coverage is limited. Lee *et al.* (2017) found that tree canopy coverage in Los Angeles County, CA decreased, and impervious surface coverage increased, on single-family residentially zoned lots between 2000 and 2009 even though Los Angeles County adopted a policy to promote planting new trees. Any gains in tree coverage from the newly planted trees were offset by the removal of trees on residentially-zoned lots.

3. Methods

3.1 Study Area

My study focused on land cover changes in King County, WA between 2003 and 2021. King County is located in the Puget Sound region of Washington, bounded by Puget Sound to the west and the Cascade Mountains to the east. According to the United States Census Bureau (2021), the population of King County increased from 1,931,249 in 2010 to 2,269,675 in 2020. The need to accommodate this increase in population resulted in an increase in building density in the largest cities in the county (Seattle and Bellevue), as well as along planned light rail lines in several other suburbs.

In general, the built-up urban area in King County is focused around the City of Seattle, near Puget Sound and Lake Washington in the western half of the county. The geography of the county becomes more mountainous further east in the county, supporting more rural land uses and resource-based industry, such as mining and forestry. Eastern King County is mountainous and sparsely developed, so it is unlikely to have experienced significant land cover changes (aside from timber harvesting for forest industries) over the study period. Therefore, my study area excluded the easternmost portions of King County and instead focused on the areas of King County between Puget Sound to the west and the Snoqualmie Valley to the east. My study area similarly excluded Vashon Island, located in Puget Sound to the southwest of Seattle, due to its relative lack of intense development.

3.2 Data Sources

As stated in the introduction above, the City of Mercer Island, WA implemented changes to its single-family residential development regulations in 2017. To test whether this regulation change caused land cover changes in Mercer Island, three sets of remote sensing data taken at three different dates were required. The data set for the middle date needed to be close to the enactment date of Mercer Island's regulations in 2017. The data sets also needed to cover more of Western King County in order to explore whether land cover change could be used to predict land use regulation changes in other jurisdictions.

For this analysis, I used LiDAR derived digital surface models (DSMs) obtained from the Washington State Department of Natural Resources' Washington LiDAR Portal. The DSMs I obtained cover Western King County and were created in 2003, 2016, and 2021. The spatial extent of the three DSMs differ, but their common extent covers most of the main population centers in King County, as well as much of the outlying areas west of the Snoqualmie River and the foothills of the Cascade Mountains. Figure 1 shows the extents of each of the DSMs, as well as the common coverage area used for the study area of this analysis. I also obtained political boundary data for King County and cities within King County from the King County GIS Data Hub for use in my analysis.

Figure 1. DSM extents and common study area.

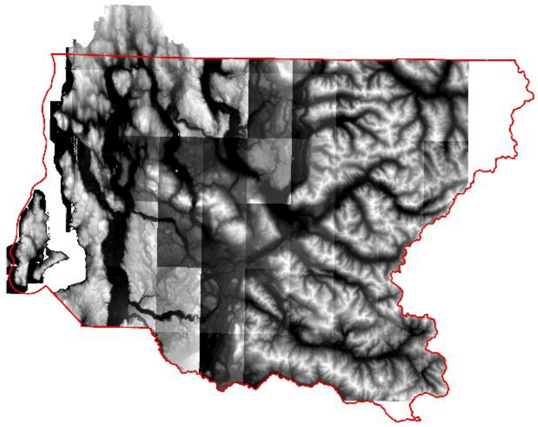


Figure 1a. Extent of the 2003 DSM within King County.

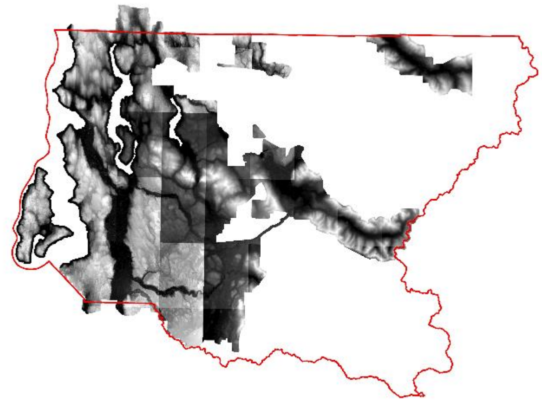


Figure 1b. Extent of the 2016 DSM within King County.

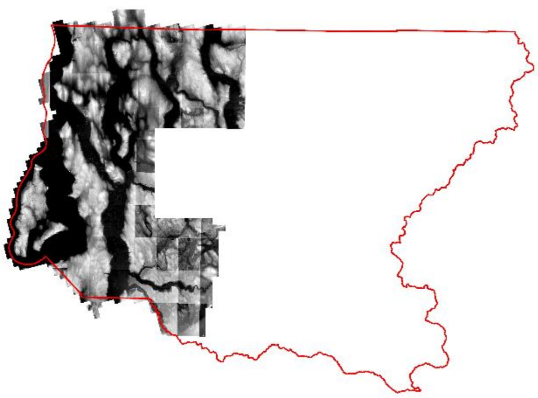


Figure 1c. Extent of the 2021 DSM within King County.

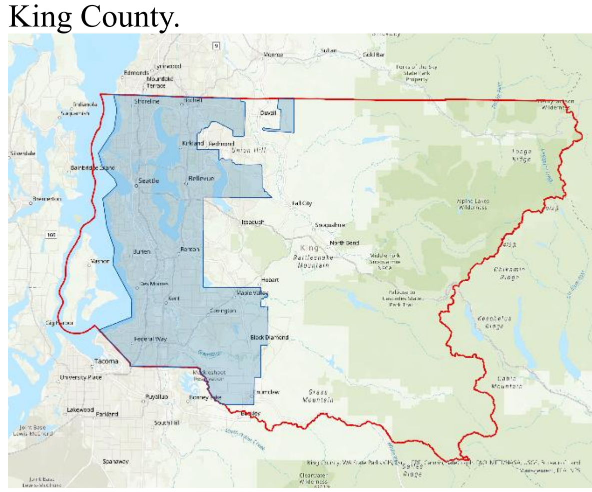
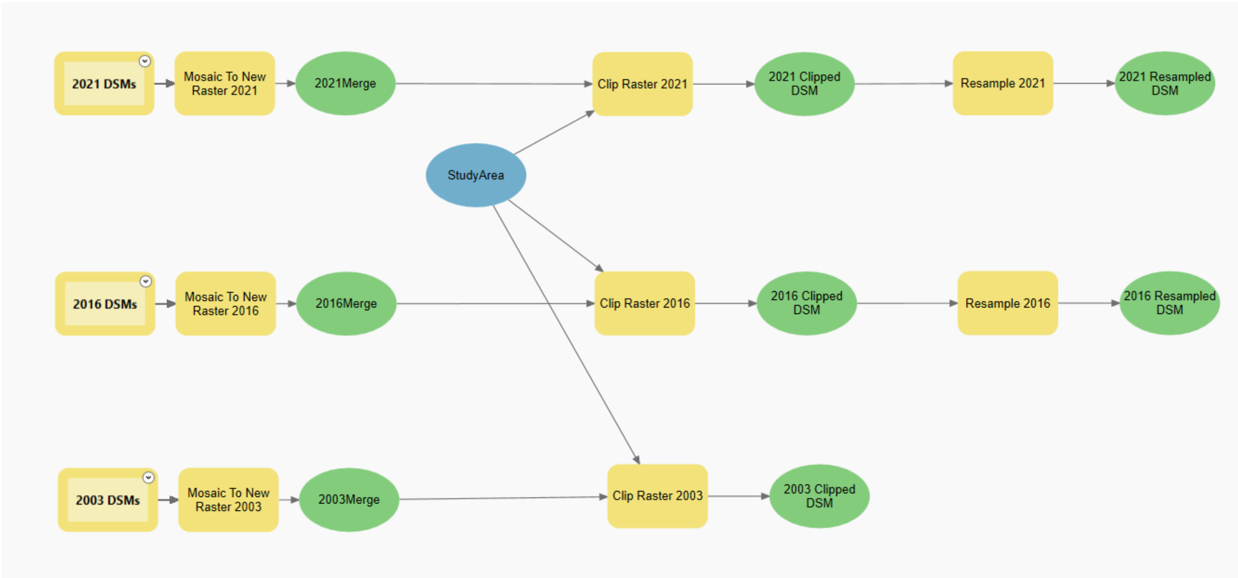


Figure 1d. Common extent of all three DSMs within King County.

3.3 Data Preparation and Analysis

Due to the way the DSMs were prepared and differences in the DSMs' resolutions, data preparation was required before they could be used for my analysis. I used several tools in ArcGIS Pro to both prepare the data for analysis and to conduct the land cover change analysis. Figure 2 shows the workflow for how the data were prepared for analysis.

Figure 2. Data preparation workflow



This figure shows the workflow for how data was prepared for my analysis.

Each of the DSMs was provided by the Washington LiDAR Portal as a set of many smaller DSMs: the dataset from 2003 contained 62 DSMs, the dataset from 2016 contained 47 DSMs, and the dataset from 2021 contained 94 DSMs. To prepare these datasets for analysis over the entire study area, I used the Mosaic To New Raster tool to combine each of the sets of DSMs into a single DSM for each year in my study period. I then clipped each of the rasters to their common extent using a masking polygon.

As shown in the metadata, the resolution of the 2016 and 2021 DSM rasters is 1.5 feet (Quantum Spatial 2017, NV5 Geospatial 2021). However, the DSM raster for the 2003 dataset has a resolution of 3 feet. As a result, I was required to use the Reclassify tool on the 2016 and 2021 DSMs to create new DSM rasters for each date that also have a raster resolution of 3 feet. This step was required to ensure that all three rasters had the same resolution so the analysis would be accurate.

Figure 3 shows the workflow for the technical portion of my analysis. Once the three DSMs had the same spatial extent and resolution, I used the Minus tool to find differences in the DSMs over time. To create two rasters that showed land cover change for two time periods, I used the Minus tool to subtract the 2003 DSM from the 2016 DSM and to subtract the 2016 DSM from the 2021 DSM. The resulting change rasters can be seen in Figures 4 and 5. These rasters show changes in elevation throughout the study area between 2003 and 2016 and between 2016 and 2021.

Figure 3. Workflow for technical analysis

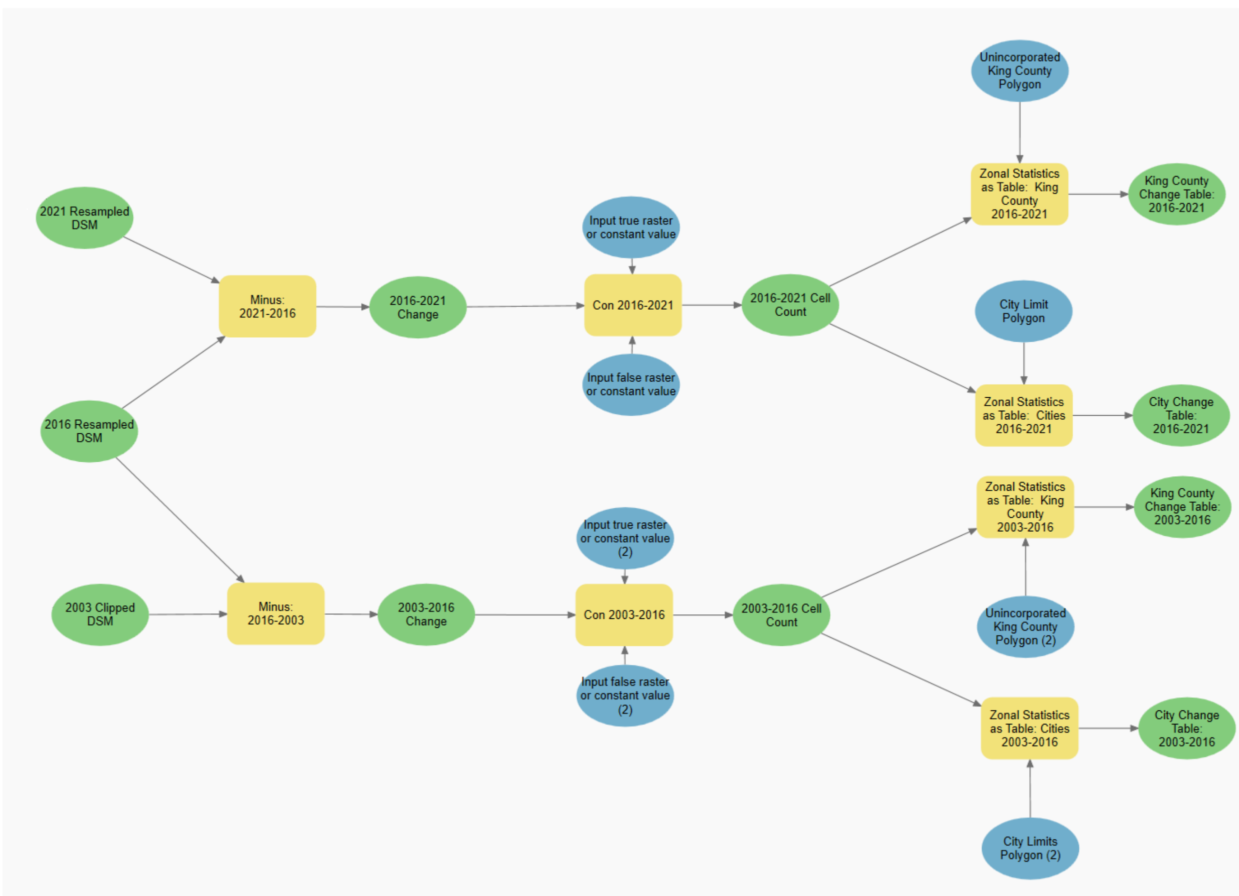


Figure 4. Change raster from 2003 to 2016

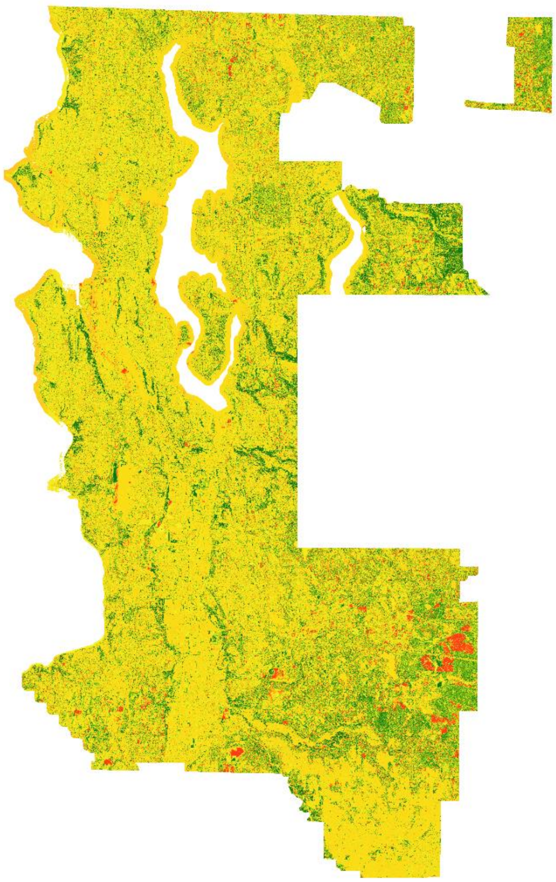
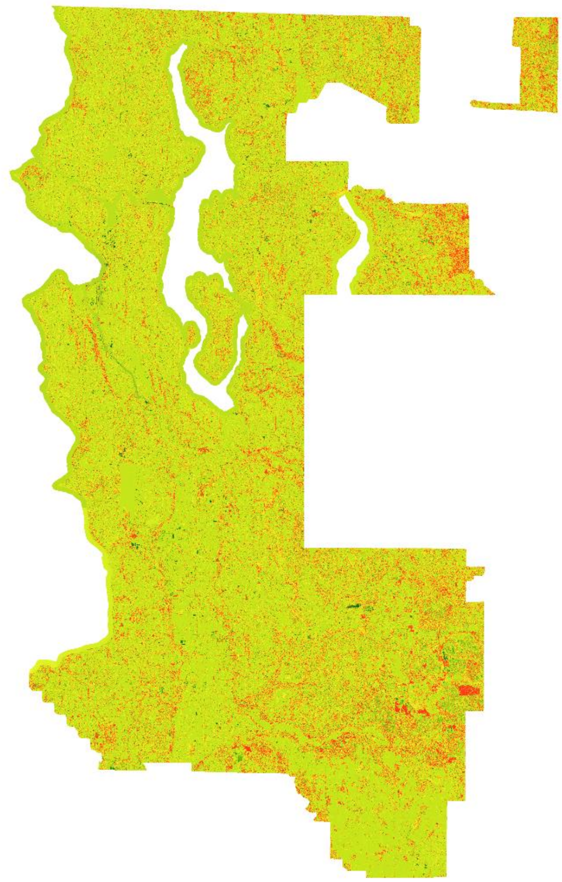


Figure 5. Change raster from 2016-2021



Both figures show elevation changes over the course of the first (2003 to 2016) and second (2016 to 2021) subperiods of the study period. Areas shown in dark green had significant positive elevation change. Areas shown in dark red had significant negative elevation change.

The main purpose of my analysis was to determine where land cover change patterns changed the most between the two study subperiods. To achieve this, I used the Con tool to filter all the pixels in the change rasters based on how much the elevation changed using a conditional expression. The output of the Con tool is a raster with true or false values based on whether the conditional expression was met. I chose to set the true value to capture any pixels where the elevation changed by at least 10 feet. I chose to filter out anything that changed by less than 10 feet since it would exclude most changes to ground cover while still identifying pixels where buildings were constructed or demolished or where trees were removed. The rasters created using Con can be seen in Figures 5 and 6.

Figure 6. Change detection raster 2003-2016

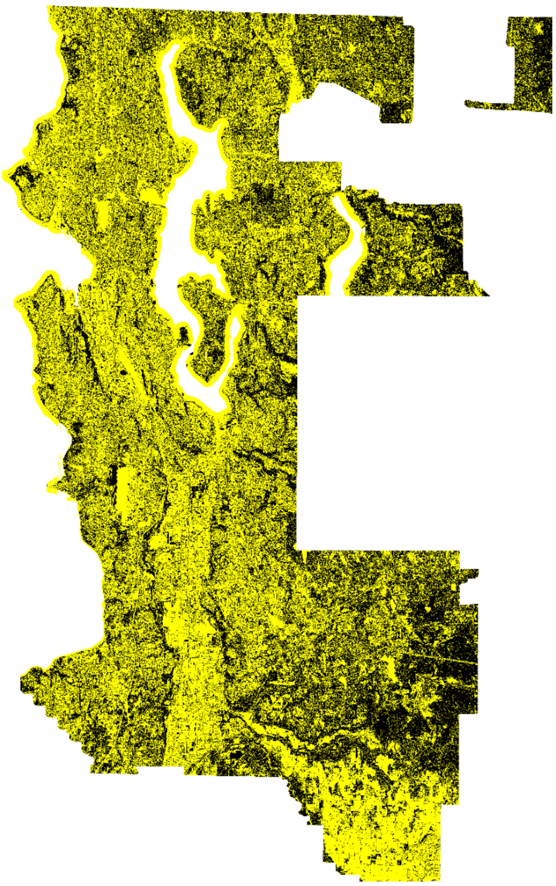
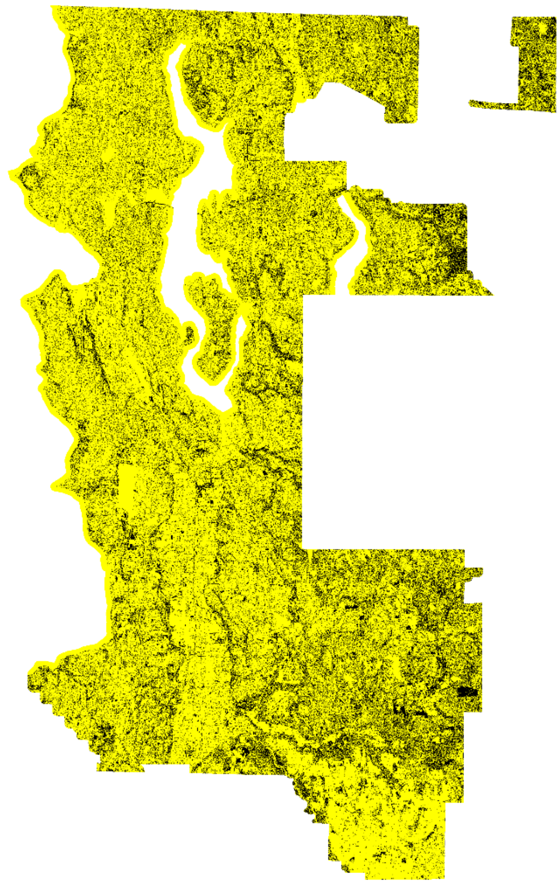


Figure 7. Change detection raster 2016-2021.



In both change detection rasters, the areas where change was detected are shown in black. Unchanged pixels are shown in yellow.

The next step of my analysis was to determine which jurisdictions in King County experienced the greatest changes to their land cover patterns. I used the Zonal Statistics as Table tool to count how many total pixels and how many pixels had a detected elevation change in each city and the portion of unincorporated King County in my study area for both subperiods. This step of the analysis created four tables:

- Change detected in cities between 2003 and 2016.
- Change detected in cities between 2016 and 2021.
- Change detected in Unincorporated King County between 2003 and 2016.
- Change detected in Unincorporated King County between 2016 and 2021.

I consolidated the information in the tables created using the Zonal Statistics as Table tool into a single table so I could compare the land cover change observed in the jurisdictions against each other. I further processed the data by performing the following calculations for each jurisdiction:

1. I divided the number of pixels that indicated elevation change between 2003 and 2016 in each jurisdiction by the total number of pixels in that jurisdiction.
2. I divided the result of step 1 by 13, which is the number of years in the first study subperiod. This provides a rough annual rate of change for the first subperiod of the study.
3. I divided the number of pixels that indicated elevation change between 2016 and 2021 in each jurisdiction by the total number of pixels in that jurisdiction.
4. I divided the result of step 3 by 5, the number of years in the second study subperiod. This provides a rough annual rate of change for the second subperiod of the study.
5. I subtracted the values of step 4 by the values of step 2 to find the change of land cover change patterns.

3.4 Regulatory Analysis

Once the I found the changes in land cover change patterns, I identified the five jurisdictions with the greatest land cover change and performed an analysis of their land use regulations to see whether they were changed in ways that would affect land cover change. For this regulatory analysis, I viewed publicly available land use regulations on the websites of the five jurisdictions identified in my technical analysis as having the most change.

During this analysis, I counted all ordinances that amended land use regulations between 2008 and 2019. I chose this time period because it covers the time where regulations would be most likely to affect land cover change over my study period. Ordinances adopted before 2008 would likely have affected land cover change over the entire study period, making it difficult to tell if they had any effect on land cover patterns. Due to lag times between adoption of ordinances and when land is developed, ordinances adopted after 2019 would not likely have had an effect on land cover change until after 2021 and would not have been detected in my analysis. When reviewing the ordinances that amended land use regulations during my study period, I also reviewed the content of the ordinances to ensure that they were relevant to my analysis. I excluded any ordinances that addressed issues unrelated to land use and land cover, that affected only permit review procedure, or amended development regulations in ways that would not have had a significant effect on land cover change.

4. Results

Table 1 shows the results of the technical portion of my analysis, sorted with the jurisdictions experiencing the most changes on top. My analysis found that of the 34 jurisdictions within my study area (33 cities and unincorporated King County), the rate of land cover change in 33 increased in the period between 2016 and 2021 as compared to the period between 2003 and 2016. Most of the jurisdictions experienced changes in their land cover change between approximately .5% and 1.5% per year. However, there were five jurisdictions that had land cover pattern changes of less than .5% per year (all five jurisdictions are small, mostly single-family residential towns along the eastern shore of Lake Washington).

Table 1. Results of techincal analysis

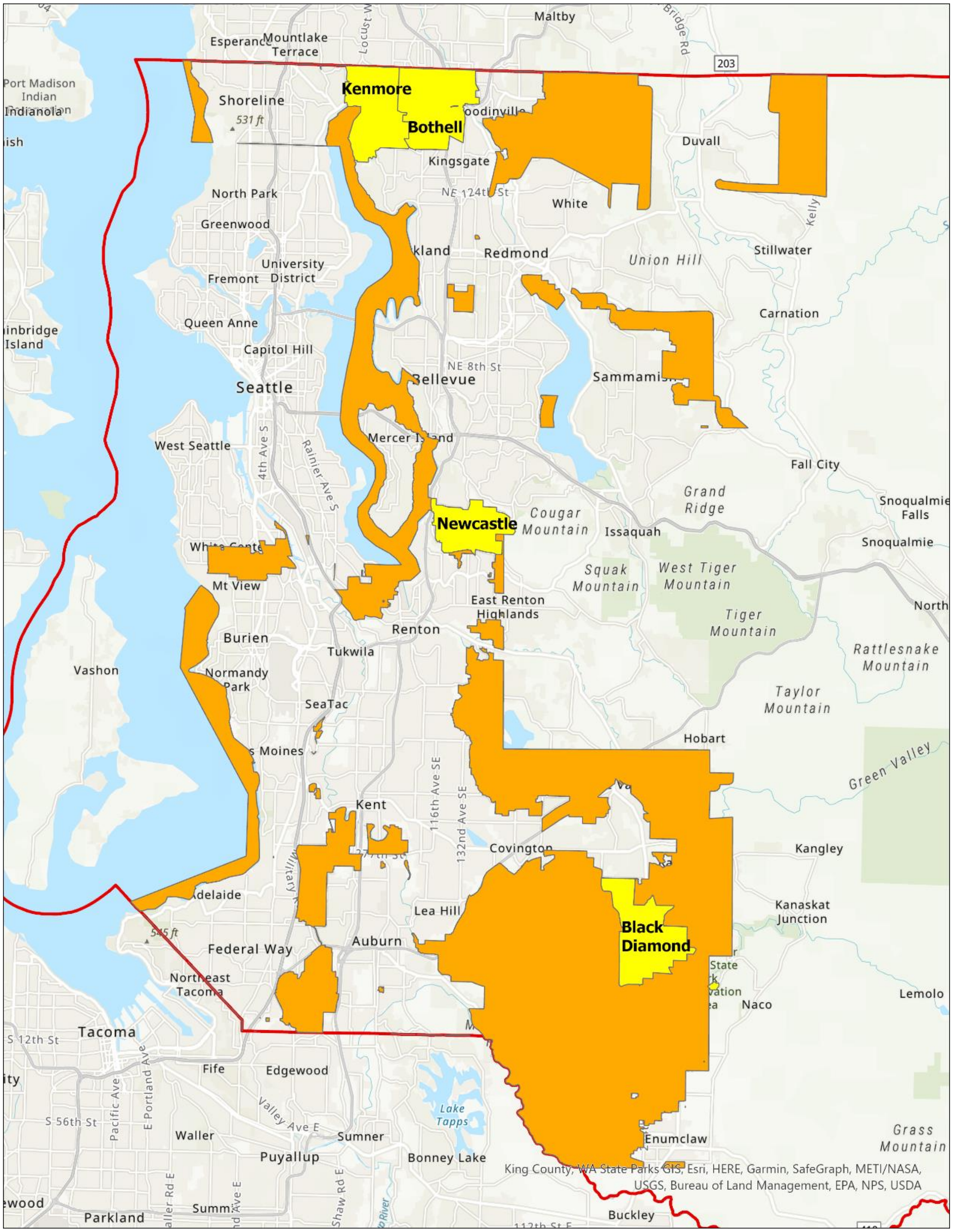
City Name	Total Pixels within Jurisdiction	Changed Pixels 2003-2016	Percent Changed Pixels 2003-2016	Percent Changed Pixels/Year 2003-2016	Changed Pixels 2016-2021	Percent Changed Pixels 2016-2021	Percent Change Pixels/Year 2016-2021	Difference in Change Rate
Black Diamond	5511782	3232272	0.586429579	0.045109968	1837971	0.333462209	0.066692442	0.021582474
Kenmore	4865261	1996042	0.410264115	0.031558778	1188272	0.244236024	0.048847205	0.017288427
Unincorporated King County	138670338	65490745	0.472276522	0.036328963	36877665	0.265937659	0.053187532	0.016858568
Newcastle	3286880	1711831	0.52080727	0.040062098	909452	0.276691574	0.055338315	0.015276217
Bothell	5610412	2375020	0.423323635	0.032563357	1339028	0.23866839	0.047733678	0.015170322
Auburn	21828347	7911844	0.362457313	0.027881332	4584609	0.210030059	0.042006012	0.01412468
Woodinville	4382976	1843418	0.420585922	0.032352763	1016173	0.23184544	0.046369088	0.014016325
Des Moines	5058540	1819281	0.359645471	0.027665036	1033709	0.204349279	0.040869856	0.01320482
Covington	4682396	1861199	0.397488593	0.030576046	1018604	0.217539055	0.043507811	0.012931765
Pacific	987028	246135	0.249369825	0.019182294	158098	0.1601758	0.03203516	0.012852866
Normandy Park	1967190	915657	0.465464444	0.035804957	471187	0.239522873	0.047904575	0.012099617
Renton	17880748	6606315	0.369465248	0.028420404	3612424	0.202028685	0.040405737	0.011985333
Lake Forest Park	2784798	1353258	0.485944762	0.037380366	683864	0.245570415	0.049114083	0.011733717
Algona	1011315	218451	0.216006882	0.016615914	142984	0.141384237	0.028276847	0.011660933
Federal Way	16706988	6631869	0.396951802	0.030534754	3495701	0.20923586	0.041847172	0.011312418
Redmond	6260488	2699805	0.431245136	0.033172703	1388901	0.221851875	0.044370375	0.011197672
Kent	26635305	8122958	0.304969588	0.023459199	4581571	0.172011208	0.034402242	0.010943043
Kirkland	14063678	5551973	0.394773899	0.030367223	2900438	0.206236093	0.041247219	0.010879996
Bellevue	22477136	9008833	0.400799862	0.030830759	4627003	0.205853762	0.041170752	0.010339994
Burien	7753884	2844099	0.366796692	0.02821513	1474649	0.190181978	0.038036396	0.009821266
Tukwila	7451870	2162023	0.290131605	0.022317816	1170485	0.157072654	0.031414531	0.009096715
Mercer Island	4898711	2263876	0.462137081	0.035549006	1084292	0.221342308	0.044268462	0.008719455
Maple Valley	4783918	1981924	0.414288874	0.031868375	964468	0.201606298	0.04032126	0.008452885
Seattle	74699678	20981480	0.280877784	0.021605983	11127523	0.148963467	0.029792693	0.00818671

Enumclaw	2395845	391182	0.16327517	0.012559628	246373	0.102833447	0.020566689	0.008007061
Milton	492980	229939	0.46642663	0.035878972	107010	0.21706763	0.043413526	0.007534554
Samammish	12272786	6267652	0.510695127	0.039284241	2868590	0.233735844	0.046747169	0.007462928
SeaTac	7962839	2551644	0.320444002	0.024649539	1261503	0.158423773	0.031684755	0.007035216
Shoreline	8974291	3369823	0.375497407	0.028884416	1577707	0.175802969	0.035160594	0.006276178
Medina	1344728	418354	0.311106781	0.023931291	192425	0.143095853	0.028619171	0.00468788
Yarrow Point	367066	109103	0.297229926	0.02286384	48651	0.132540197	0.026508039	0.003644199
Beaux Arts Village	63199	37277	0.589835282	0.045371945	15292	0.241965854	0.048393171	0.003021226
Clyde Hill	819103	252529	0.308299445	0.023715342	107741	0.13153535	0.02630707	0.002591728
Hunts Point	349414	107976	0.309020245	0.023770788	41426	0.118558501	0.0237117	-5.90879E-05

There were also five jurisdictions that had changes to their land cover patterns that exceeded 1.5% per year: the cities of Black Diamond, Kenmore, Newcastle, and Bothell, as well as Unincorporated King County. The locations of these jurisdictions within my study area can be seen in Figure 8. Since these five jurisdictions experienced the most change to their land cover change patterns, I used them as the subject jurisdictions for my regulatory analysis.

The results and details of the regulatory analysis are shown in Table 2. Upon review of the land use regulations in the five identified jurisdictions between 2008 and 2019, I found that a total of 249 ordinances changed the land use regulations: 26 in Black Diamond, 30 in Kenmore, 101 in Unincorporated King County, 40 in Newcastle, and 52 in Bothell. Of the ordinances amending the land use regulations in the study jurisdictions, most were not relevant to my analysis because they amended permit processing procedure, made minor changes to definitions, or made changes to regulations that were so minor as to not affect land cover change. As a result, only two ordinances in Black Diamond, three ordinances in Kenmore, three ordinances in Unincorporated King County, two ordinances in Newcastle, and four ordinances in Bothell were relevant to land cover change. A full list of the relevant land use regulation amendments can be seen in Table 3. Additionally, two of the jurisdictions reviewed as a part of the regulatory analysis enacted wholesale changes to their zoning codes: Black Diamond in 2009 and Kenmore in 2011.

Figure 8. Jurisdictions selected for regulatory analysis



The jurisdictions identified as having the most land cover pattern change are shown on this map. The cities of Black Diamond, Bothell, Kenmore, and Newcastle are shown in yellow. The portion of unincorporated King County within my study area is shown in orange.

Table 2. Regulatory analysis results

Jurisdiction	Land use regulations reviewed	Total ordinances	Relevant ordinances	Wholesale zoning change?
Black Diamond	Titles 16-20 of the Black Diamond Municipal Code[1]	26	2	Yes
Kenmore	Titles 16-20 of the Kenmore Municipal Code	30	3	Yes
Unincorporated King County	Titles 18-21A, 24, and 25 of the King County Code	101	3	No
Newcastle	Titles 14 and 17-20 of the Newcastle Municipal Code	40	2	No
Bothell	Titles 11-15 and 22 of the Bothell Municipal Code	52	4	No

[1] Due to limitations to public records access in Black Diamond, only ordinances between 2009 and 2017 were reviewed for my analysis. Ordinances from 2018 and 2019 were not available, so they could not be reviewed.

Table 3. List of land use ordinances affecting land cover change

Jurisdiction	Year	Ordinance number	Description
Black Diamond	2009	09-897	Increased densities in the city's master planned developments.
Black Diamond	2009	09-909	Wholesale update to the city's zoning regulations.
Kenmore	2011	11-0329	Wholesale updates to the city's zoning regulations.
Kenmore	2014	14-0391	Created new zones that allowed more intense development than the previous zones.
Kenmore	2019	19-0481	Created zoning standards to protect existing manufactured home developments from more intense development.
Unincorporated King County	2008	16263	Zoning changes throughout the county that resulted in some areas being zoned to allow more intense development.

Unincorporated King County	2009	16601	Created an inventory of areas to conserve in open space. My analysis shows that these areas remained undeveloped throughout the study period.
Unincorporated King County	2016	18427	Zoning changes throughout the county that resulted in some areas being zoned to allow more intense development.
Newcastle	2008	2008-380	Allowed greater impervious surface coverage in portions of the city, which could have led to more vegetation removal.
Newcastle	2015	2015-515	Increased residential density to several zones.
Bothell	2009	2025	Created new subareas and revised development standards that were stricter in some places, but looser in others.
Bothell	2010	2053	Created new standards for portions of the city that were planned to be annexed (and have since been annexed) to the city.
Bothell	2013	2123	Encouraged condominium development by allowing additional land division.
Bothell	2016	2215	Rezoned a portion of the city to allow more development.

5. Conclusions

The findings shown in Tables 2 and 3 indicate that changes in land cover change patterns could be related to changes in land use regulations. All five jurisdictions studied in the regulatory analysis had changes to their land use regulations that affected or could have affected land cover change patterns. Most of the regulation amendments identified as relevant in the regulatory analysis increased development potential by promoting intense development or increasing residential densities. This is in line with the increases in land cover change in the period between 2016 and 2021 as compared to the period between 2003 and 2016, as seen in Figures 4 and 5 and Table 1.

Additionally, two of the five jurisdictions studied in the regulatory analysis had wholesale zoning changes during the study period. This indicates that there may be a relationship between changes in land use cover change and the adoption of new land use regulations. However, the City of Mercer Island, which enacted wholesale zoning regulations to both its Town Center and single-family zones during the study period, ranked 22nd out of the 34 jurisdictions in my study area. This indicates that more study is required to determine if land cover changes are predicative of changes in land use regulations.

5.1 Topics for further study

While this analysis indicates that there could be a relationship between changes to land cover change patterns and changes to land use regulations, there are several factors for which further research may yield more definitive results.

1. The regulatory analysis could be expanded to include all jurisdictions within the study area. This would provide more information about whether land use regulation changes occurred in other cities within the study area that affected land cover change. This would also allow statistical analysis to be performed across the whole study area to see if there is a correlation between changing land use regulations and other factors within the jurisdictions (this is discussed in more detail below).
2. This analysis focused on using LiDAR derived data to analyze land cover changes. LiDAR data is expensive to create, so it is not created very often. This led to my analysis using three data sets spanning 18 years that did not have a uniform time interval. Other types of remote sensing data, such as LANDSAT aerial imagery, can be used to analyze land cover changes and is available for almost any time interval desired for analysis.

   This would also be a useful way to check the findings of my analysis. The DSM from 2016 used in my analysis appears to have some discrepancies related to the heights of trees. While it is unlikely that these discrepancies would have greatly affected my analysis (the discrepancies would have been identified as changed pixels in both the 2003-2016 and

2016-2021 change rasters), it would be beneficial to verify this assumption using other types of data.

3. Statistical analysis could be performed on the results of both the technical and regulatory analysis to see if there are spatial patterns in where land cover changes and regulatory changes are distributed throughout the study area. This analysis could be expanded to include other factors that may affect land cover or regulation changes, such as distance to an urban core (the downtown areas of Seattle and Bellevue), average commute times, access to public transit, income levels, property values, and housing availability.
4. This analysis focused on how much land cover change was present in each jurisdiction rather than whether the land cover change was positive or negative. I also focused on whether land use regulations in the top five jurisdictions adopted land use regulations that could have had an effect on land cover change but did not do a deep dive into the legislative intent behind the regulation changes. Further research could be conducted to see whether the identified land use regulations were intended to increase or decrease development intensity and whether the intent was reflected in positive or negative land cover change.
5. My analysis primarily focused on identifying land cover change based on detected changes in elevation. Further research could be conducted to see other methods of change detection using remote sensing data could be predicative of land use regulation changes. For example, analysis of aerial photography or reclassification of LiDAR point clouds could be used to determine if impervious surface has changed within the study area.

References

1. City of Black Diamond, 2009, Amending Master Planned Development Code 18.98 (Ordinance No. 09-897). Retrieved from http://www.oldblackdiamondwebsite.com/Depts/Clerk/Ordinances/2009/09-897.pdf.

2. City of Black Diamond, 2009, New Title 19 Zoning Code (Ordinance No. 09-909). Retrieved from http://www.oldblackdiamondwebsite.com/Depts/Clerk/Ordinances/2009/09-909.pdf.
3. City of Black Diamond, 2023, Black Diamond Municipal Code. Retrieved from https://library.municode.com/wa/black_diamond/codes/code_of_ordinances?nodeId=BLACK_DIAMOND_MUNICIPAL_CODE.
4. City of Bothell, 2009, Bothell Downtown Subarea Plan and Regulations (Ordinance No. 2025). Retrieved from https://portal.laserfiche.com/Portal/DocView.aspx?id=59075&repo=r-5b25af1e.
5. City of Bothell, 2010, City of Bothell 2010 Comprehensive Plan Amendments and Associated Code Amendments (Ordinance No. 2053). Retrieved from https://portal.laserfiche.com/Portal/DocView.aspx?id=59103&repo=r-5b25af1e.
6. City of Bothell, 2013, Amending Bothell Municipal Code Chapters 11.02 Definitions, 11.04 Types of Project Permit Applications, 12.14 Area Dimensions and Design, 15.08 Preliminary Plats, 15.12 Binding Site Plans, and 15.16 General Requirements for Subdivision Approval, to Facilitate the Creation of Fee Simple Lots Within Attached Residential Zoning Classifications. Retrieved from https://portal.laserfiche.com/Portal/DocView.aspx?id=93774&repo=r-5b25af1e.
7. City of Bothell, 2016, 2016 Campus Master Planning Process Plan and Code Amendments (Ordinance No. 2215). Retrieved from https://portal.laserfiche.com/Portal/DocView.aspx?id=201143&repo=r-5b25af1e.
8. City of Bothell, 2023, Bothell Municipal Code. Retrieved from https://bothell.municipal.codes/.
9. City of Kenmore, 2011, Untitled Ordinance (Ordinance No. 11-0329). Retrieved from https://kenmore.civicweb.net/filepro/documents/27521/?preview=30663.
10. City of Kenmore, 2014, Zoning Code Amendments (Ordinance No. 14-0391). Retrieved from https://kenmore.civicweb.net/filepro/documents/45265/?preview=55547.
11. City of Kenmore, 2019, Manufactured Housing Communities Code Amendments (Ordinance No. 19-0481). Retrieved from https://kenmore.civicweb.net/filepro/documents/95980/?preview=97047.
12. City of Kenmore, 2023, Kenmore Municipal Code. Retrieved from https://www.codepublishing.com/WA/Kenmore/.
13. City of Newcastle, 2008, Impervious Surfaces (Ordinance No. 2008-0380). Retrieved from https://newcastle.civicweb.net/filepro/documents/2821/?preview=1743.

14. City of Newcastle, 2015, Establishing Minimum Residential Density CBC (Ordinance No. 2015-515). Retrieved from https://newcastle.civicweb.net/filepro/documents/5340/?preview=5853.
15. City of Newcastle, 2023, Newcastle Municipal Code. Retrieved from https://www.codepublishing.com/WA/Newcastle/.
16. Das, S. and Angadi, D, 2022, Land use land cover change detection and monitoring of urban growth using remote sensing and GIS techniques: a micro-level study. *GeoJournal*, 87: 2101-2123.
17. Fichera, C., Modica, G. and Pollino, M., 2012, Land cover classification and change-detection analysis using multi-temporal remote sensed imagery and landscape metrics. *European Journal of Remote Sensing*, 45(1): 1-18.
18. Green, K., Kempka, D., and Lackey, L., 1994, Using Remote Sensing to Detect and Monitor Land-Cover and Land-Use Change. *Photogrammetric Engineering & Remote Sensing*, 60(3): 331-337.
19. Guo, T., Morgenroth, J., Conway, T., and Xu, C., 2019, City-wide canopy decline due to residential property redevelopment in Christchurch, New Zealand. *Science of The Total Envoronment*, 681: 202-210.
20. Hilbert, D., Koeser, A., Roman, L., Hamilton, K., Landry, S., Hauer, R., Campanella, H., Andreu, M., and Perez, H., 2019 Development practices and ordinances predict inter-city variation in Florida urban tree canopy coverage. *Landscape and Urban Planning*, 190: 103603.
21. Houet, T., Loveland, T., Hubert-Moy, L., Gaucherel, C., Napton, D., Barns, C., and Sayler, K., 2010, Exploring subtle land use and land cover changes: a framework for future landscape studies. *Landscape Ecology*, 25: 249-266.
22. Jensen, J. and Cowen, D., 1999, Remote Sensing of Urban/Suburban Infrastructure and Socio-Economic Attributes. *Photogrammetric Engineering & Remote Sensing*, 65(3): 611-622.
23. King County, 2008, An ordinance relating to comprehensive planning and permitting (Ordinance 16263). Retrieved from https://aqua.kingcounty.gov/Council/Clerk/OldOrdsMotions/Ordinance%2016263.pdf.
24. King County, 2009, An ordinance adopting an inventory of high conservation value properties and specifying the manner in which an inventory of high conservation value properties will be periodically updated (Ordinance 16601). Retrieved from https://aqua.kingcounty.gov/Council/Clerk/OldOrdsMotions/Ordinance%2016601.pdf.
25. King County, 2016, An ordinance relating to comprehensive planning and permitting (Ordinance 18427). Retrieved from https://aqua.kingcounty.gov/Council/Clerk/OldOrdsMotions/Ordinance%2018427.pdf.
26. King County, 2023, King County Code. Retrieved from https://kingcounty.gov/council/legislation/kc_code.aspx.

27. Lee, S., Longcore, T., Rich, C., and Wilson, J., 2017, Increased home size and hardscape decreases urban forest cover in Los Angeles County's single-family residential neighborhoods. *Urban Forestry & Urban Greening*, 24: 222-235.

28. Li, K., Feng, M., Biswas, A., Su, H., Niu, Y., and Cao, J., 2020, Driving Factors and Future Prediction of Land Use and Land Cover Change Based on Satellite Remote Sensing Data by the LCM Model: A Case Study from Gansu Province, China. *Sensors*, 20, 2757.

29. Nowak, D., Rowntree, R., McPherson, E., Sisinni, S., Kerkmann, E., and Stevens, J., 1996, Measuring and analyzing urban tree cover. *Landscape and Urban Planning* 36(1): 49-57.

30. NV5 Geospatial, 2021, USGS 3DEP King County, Washington Delivery 1 Lidar Technical Data Report. Retrieved from https://lidarportal.dnr.wa.gov.

31. Parmehr, E., Amati, M., Taylor, E., and Livesley, J., 2016, Estimation of urban tree canopy cover using random point sampling and remote sensing methods. *Urban Forestry & Urban Greening*, 20: 160-171.

32. Pike, K., O'Herrin, K., Klimas, C., and Vogt, J., 2021, Tree preservation during construction: An evaluation of a comprehensive municipal tree ordinance. *Urban Forestry & Urban Greening*, 57: 126914.

33. Qacami, M., Khattabi, A., Lahssini, S., Rifai, N., and Meliho, M., 2022, Land-cover/land-use dynamics modeling based on land change modeler. *The Annals of Regional Science*, https://doi.org/10.1007/s00168-022-01169-z.

34. Quantum Spatial, 2017, PSLC King County 2016-2017 LiDAR Final Technical Data Report. Retrieved from https://lidarportal.dnr.wa.gov.

35. Rogan, J. and Chen, D.M., 2004, Remote sensing technology for mapping and monitoring land-cover and land-use change. *Progress in Planning*, 61: 301-325.

36. Timilsina, S., Aryal, J., and Kirkpatrick, J., 2020, Mapping Urban Tree Cover Changes Using Object-Based Convolution Neural Network (OB-CNN). *Remote Sensing*, 12(18), 3017: https://doi.org/10.3390/rs12183017.

37. United States Census Bureau, 2021, QuickFacts for King County, Washington. Retrieved from https://www.census.gov/quickfacts/fact/table/kingcountywashington/PST045221.

38. Weng, Q., 2012, Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends. *Remote Sensing of Environment*, 117; 34-49.

39. Wu, Q., Li, H., Wang, R. Paulussen, J., He, Y., Wang, M., Wang, B., and Wang, Z., 2006, Monitoring and predicting land use change in Beijing using remote sensing and GIS. *Landscape and Urban Planning*, 78(4): 322-333.

40. Yan, W., Shaker, A., and El-Ashmawy, N., 2015, Urban land cover classification using airborne LiDAR data: A review. *Remote Sensing of Environment*, 158: 295-310.