John Sullivan

How have the spatial patterns of wildfire perimeters and the Wildland Urban Interface (WUI) in Oregon and Washington State shifted through time?

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Contents

1.0 Study Purpose

There is not a good system, or organization of datasets, to educate people spatially and statistically about the dangers of moving into regions more prone to wildfire. Persons living in the Western United States are starting to see the impacts to daily life as wildfires begin to burn longer, hotter, and affect populations that move deeper into their destructive path. I aim to organize datasets that aid in the spatial and temporal analysis of vulnerable regions for people moving into the Wildland-Urban Interface (WUI) of Washington and Oregon, U.S. By identifying vulnerable areas, we can help residents allocate time, resources, and techniques available to fight a wildfire nearest to them. This topic is of interest to me because I live in Olympia, WA and have developed an appreciation for the forests and people that surround me. I would also like to draw attention to the risks associated with people moving into these regions given the increasing vulnerabilities of communities to wildfire.

2.0 Background

Climate change is causing the Earth to warm faster than we anticipated and has brought larger and more frequent fires to our forested ecosystems of western North America. This trend continues today with increases in a fire's severity and areas burned (Cansler, 2014). The WUI is a regional classification, categorized using U.S. Census and USGS National Land Cover Data (NLCD), used to determine where people are living in relation to wildland vegetation. The fact that more and more people are building houses in these regions is cause for environmental concern. The main concern is that people are the number one cause for wildland fires, as well as habitat fragmentation, invasive species introduction, and biodiversity decline (Martinuzzi et al, 2020). For this study's purpose I focus on wildland fire and how, through time, people are becoming more vulnerable to its destruction by living in the WUI. This study will:

- Compare areas where houses meet or intermingle with undeveloped wildland vegetation (WUI).
- Calculate focal areas for human-environment conflicts since the year 1990, which contained the most accurate census numbers and fire perimeters.
- Decennial census data from 1990, 2000, and 2010 will demonstrate how hundreds of thousands of people are moving into vulnerable regions.
- Compare how this study's method of statically determining the number of people at risk and compare that with the WUI dataset.

According to the Department of Natural Resources (DNR), a forest fire is any non-structure fire in the wild that is either unplanned ignitions or planned ignitions that are declared wildfires. Large fires are defined as any wildland fire in timber 100 acres or greater and 300 acres or greater in grasslands/rangelands. This study has eliminated any reported wildfire that burned less than 100 acres (DNR, 2014). During 2020, Washington had the second worst year on record for wildfires, second to only 2015 for most acres burned in a single season this decade (Goodwin, 2020). Also, alarming is that the DNR Division for Wildfire reported that in 2020 they responded to 1,800 fires, and 40 percent of those were in the historically wetter Western Washington, and near some of the largest temperate rainforests in North America (Farley, 2020).

3.0 Project Scope and Approach

I will use a WUI polygon, provided by SILVIS LAB, to recategorized which populations are in vulnerable areas. Within the WUI layer, data is organized with Census results from 1990, 2000, and 2010. The attribution fields I will use to categorized which Census Blocks are at risk is based on what the WUI determines as low to high risk, the exact criteria are stated within the methodology section. I used this method because I would like to take into consideration low to high housing densities that are either intermixed or within a short distance to wildland vegetation. It is safe to assume that communities within 2.5 km of a large wildfire will either be forced to evacuate or face damage from being near a fire.

For the wildfire perimeter I will merge two polygons. One provided by the National Interagency Fire Center (NIFC) for Washington and the other by the Bureau of Land Management (BLM) for Oregon. These layers are crucial to this analysis because it will enable me to identify spatial patterns in how and why people in nearby WUI are vulnerable. Another source of my information comes from the U.S. Census Bureau, who produces a layer that is a unique number assigned to Census Blocks. A Block is the smallest geographic area for which the Census Bureau collects and tabulates Census data, and are formed by streets, roads, railroads, streams and other bodies of water, other visible and cultural features, and the legal boundaries (US Census Bureau, 2020). U.S. Census TIGER 2010 Block polygons are associated with housing and population density, while the WUI dataset incorporated spatial joins with these 1990, 2000, and 2010 Census Block housing densities.

4.0 Objectives

1. Identify areas where large populations and previous large forest fires merge.
2. Calculate the area and quantify over time how more people are moving into the WUI and previously burned fire perimeters.
3. Create temporal and thematic graphics depicting regions with heavy WUI populations near large forest fires.
4. Incorporate census data into the analysis to establish, through time, how many people are impacted.
5. Develop a robust ArcGIS Storymap detailing how these datasets correlate and have changed over time. This Storymap will give people something to use and share for educational purposes.
6. Organize all datasets into a 24 x 36-inch thematic map.

5.0 Methodology

I started by merging the two fire perimeter datasets in ArcPRO then used Microsoft Access to make some of the fields more manageable, such as the Year field being in Text format in one and numeric in another. I then combined this dataset with another provided by NIFC that had the more recent 2020 events. **Figure 1** demonstrates how I exported the polygon to shapefile for use in Access. After merging fire perimeter polygons in ArcPRO, I imported the .dbf file into Access and converted the year's text field to short integer. After I cleaned up some of the other fields I then reexported the .dbf to the same naming convention as the shapefile for incorporation and visualization in ArcPRO.

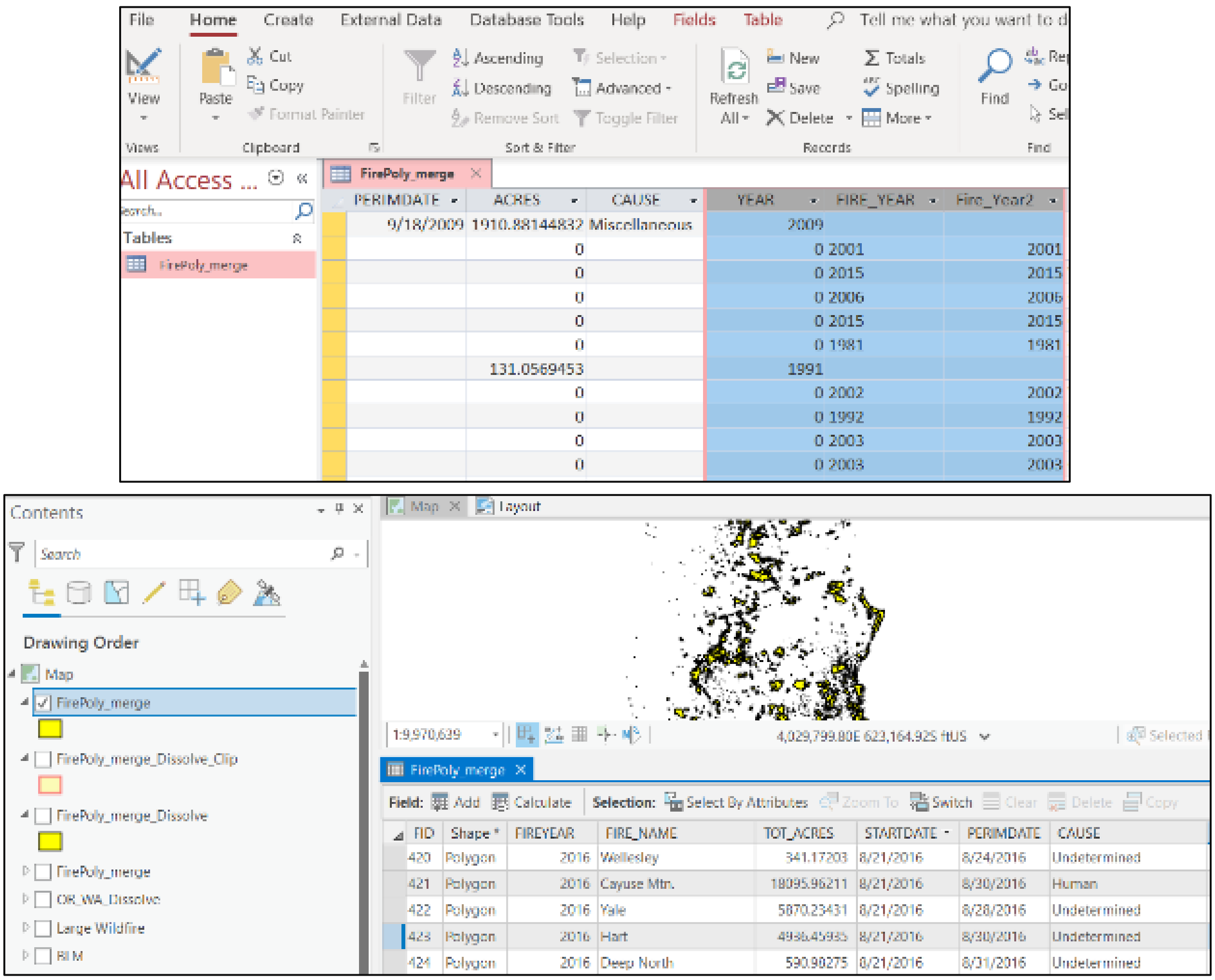


Figure 1

Figure 2 demonstrates how I was able to use structured query (SQL) functions to break up the fire polygon into five categories, four of which are a decade long. I left the year 2020 as its own layer because it helps demonstrate how bad that twelve-month period was. I left the

1980 fire incident perimeters strictly for visualization but removed them later when merging and dissolving the perimeters for comparison with Census numbers and WUI dataset.

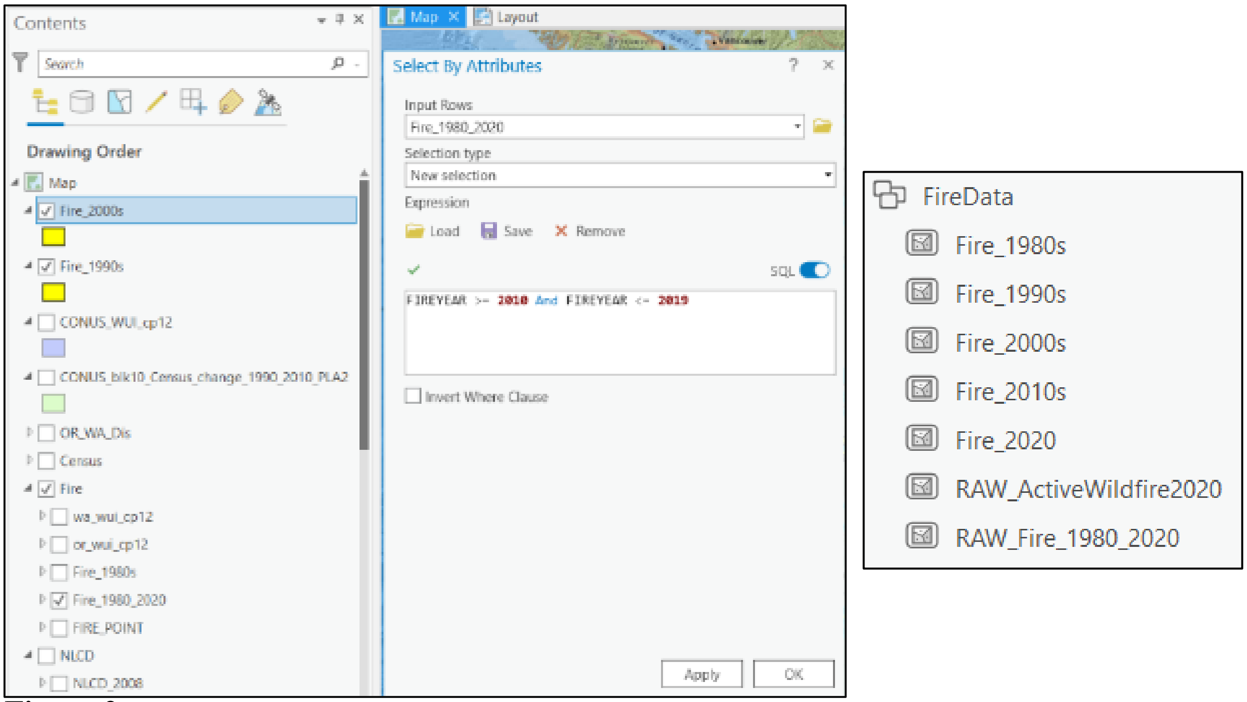


Figure 2

Figure 3 is an example of how I spatially went through the datasets to delete redundant records of fires. Since a fire can cover the same region over the span of the 40-year time frame, I first used the select by location tool then manually by scrolling around the study area and toggling on and off layers to determine which perimeters overlapped.

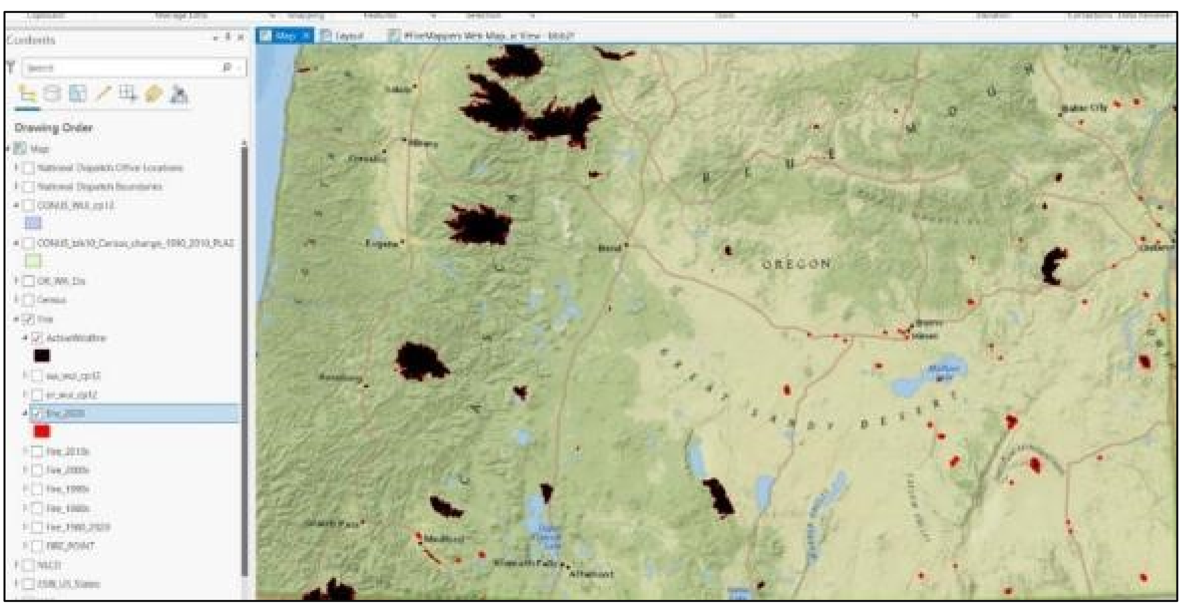


Figure 3

All datasets used in this analysis were then clipped to the Census provided Washington and Oregon State polygon and use the NAD 1983 HARN StatePlane Washington South FIPS 4602 (US Feet) projection. I choose this projection because of its central location to the firepolygon_merge layer. The NLCD came from seven separate years and was clipped to a Washington / Oregon merged polygon. From these raster layers I will be able to demonstrate how the four categories of urban development are infringing on the same regions as previous wildfires, as seen in **Figure 4**.

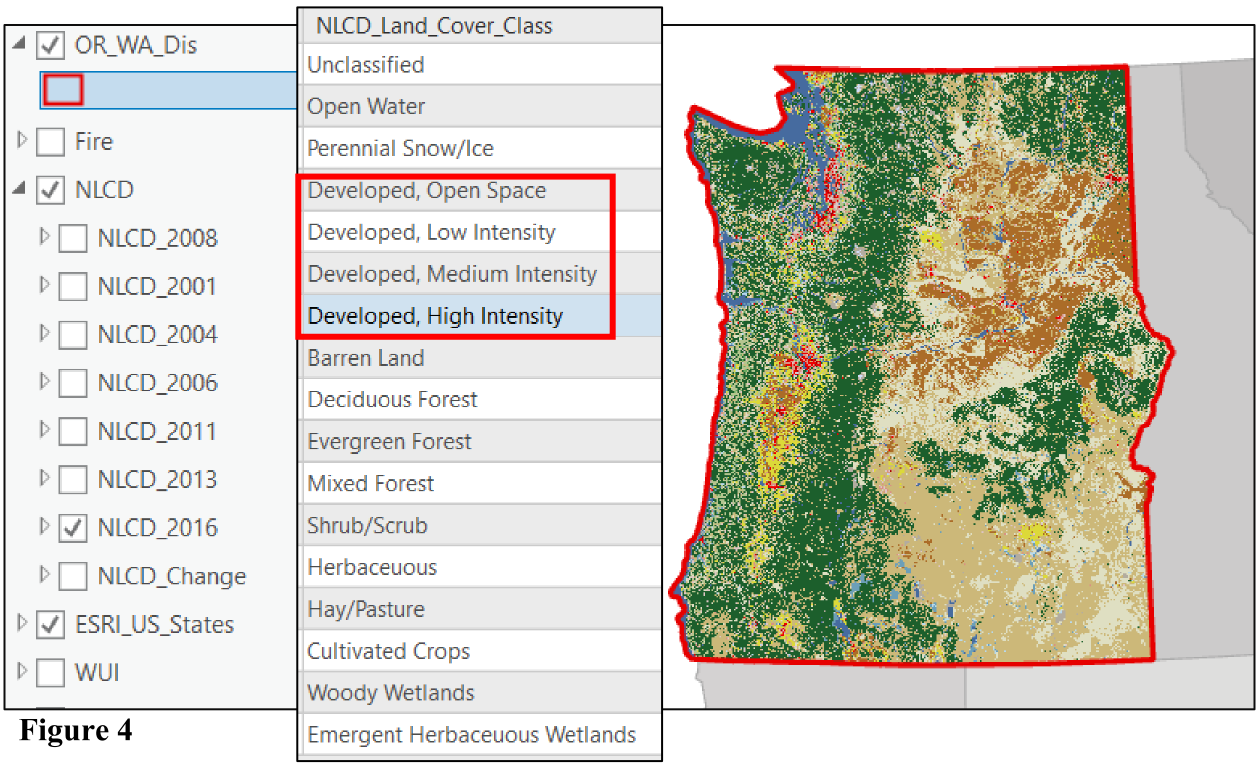


Figure 4

For visual aesthetics I downloaded NaturalVue, SRTM2, and DTED1 image/elevation tiles from USGS EarthExplorer and used mosaic dataset processing methods such as building pyramids and calculating statistics. These will be useful when I put together thematic maps of the areas more prone to wildfire. Applying image tiles and using ArcPRO raster functions such as shaded relief maps can aid in not only the visual affects but also slope analysis of a fire's destructive path. **Figure 5** demonstrates how some of the mosaic dataset and raster processing functions were applied to this dataset.

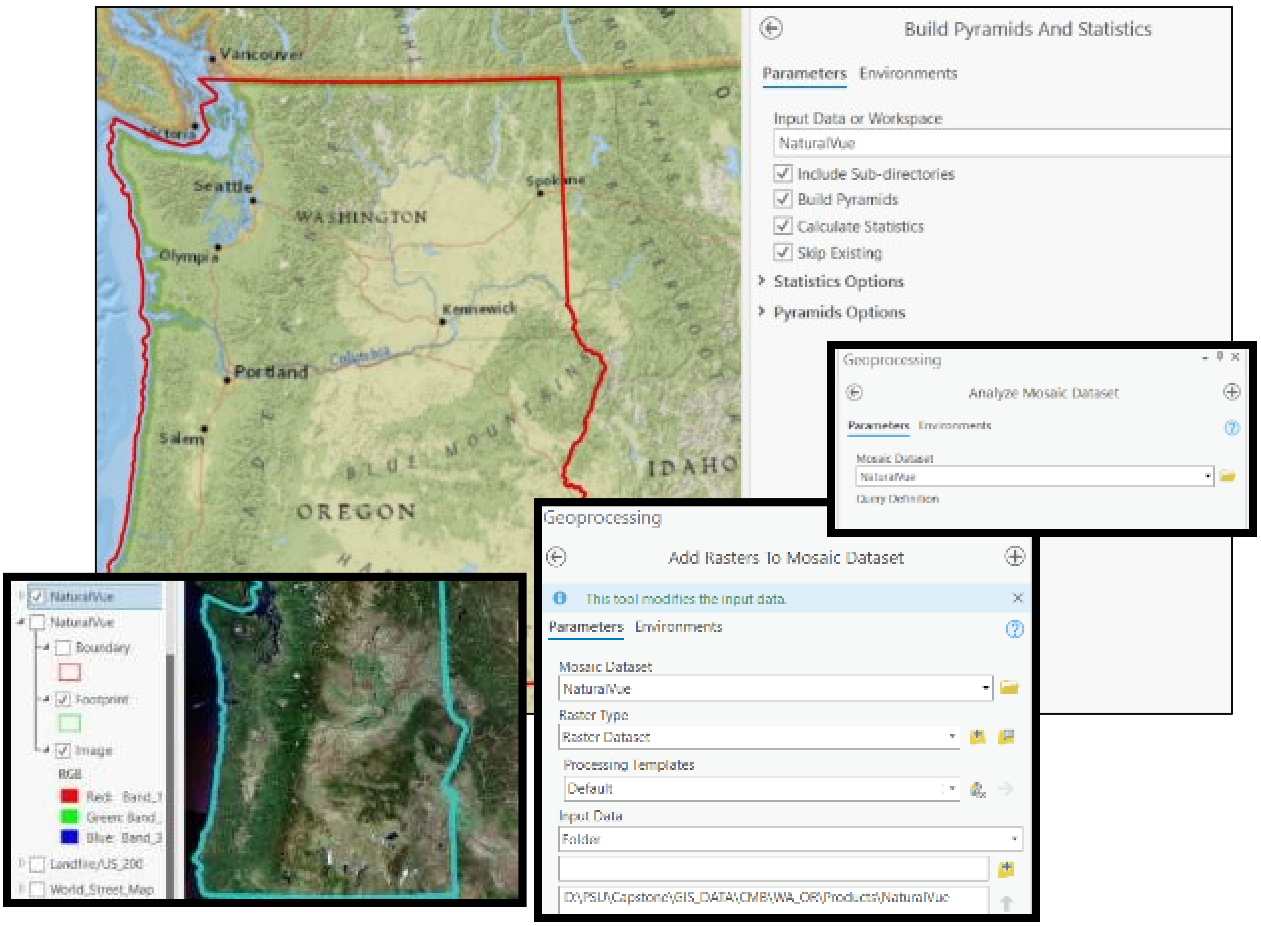


Figure 5

The datasets I am organizing also contain a WUI polygon to recategorized which populations are in vulnerable areas. I restructured the data within my own database to apply coded domains to certain fields. This is going to make adding or updating areas I identify as more vulnerable from more current landcover / LANDSAT8 images with band combinations for urban analysis. The attribution fields can be used to categorized which census blocks are at risk. **Figure 6** is an example where I took into consideration low to high housing densities that are either intermixed or within a short distance to wildland vegetation.

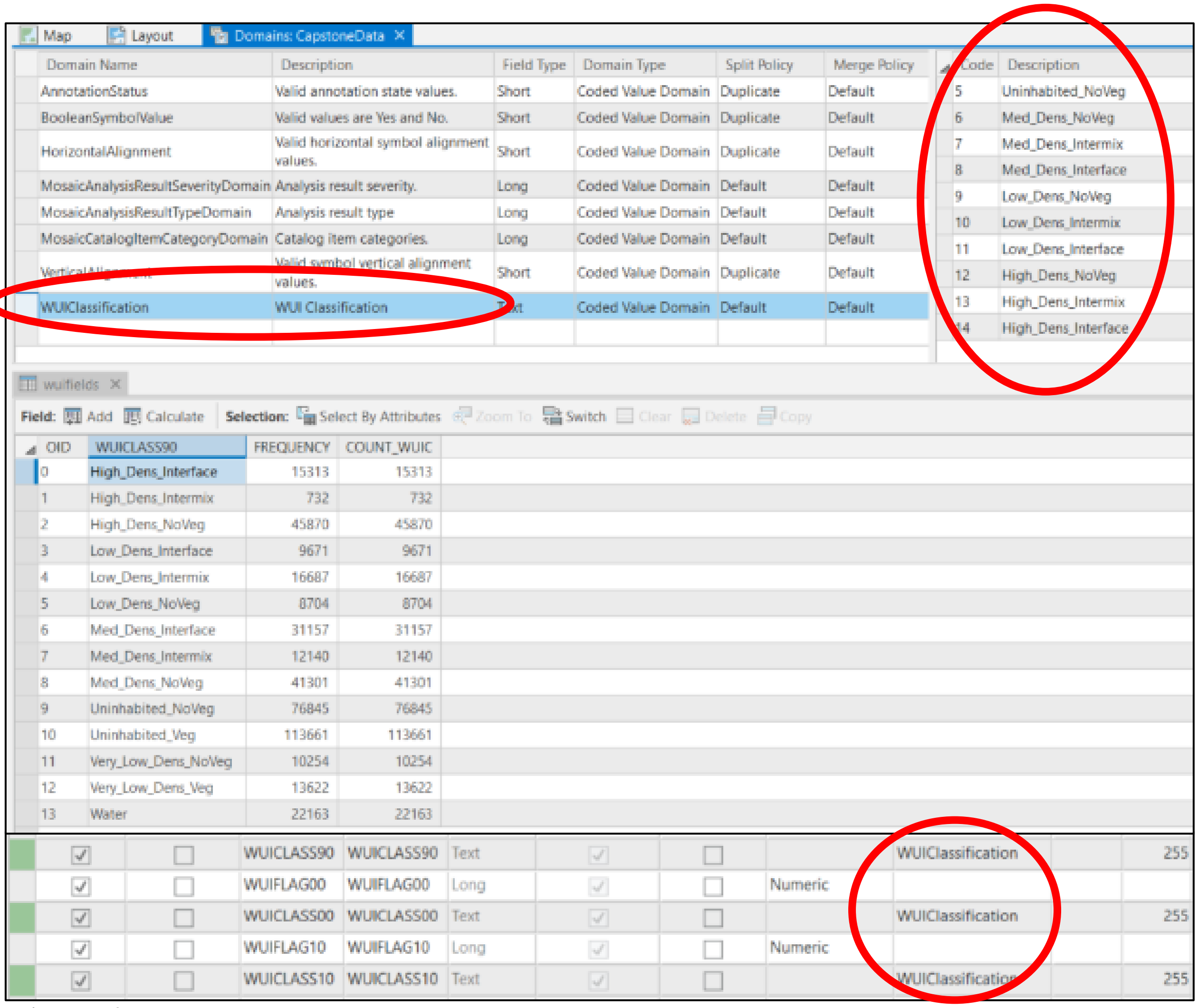


Figure 6

Figure 7 utilizes the previously organized fire polygon perimeters to help visualize how these wildfires are burning more area as the decades progress. I left the most recent events underneath the older ones to demonstrate how wildfires are encroaching on areas previously untouched. These are a few of the layers I will load into ArcPortal and create a set of interactive storymaps to help educate viewers. After this I removed the 1980 incidents, then merged and dissolved the remaining perimeters into one final wildfire polygon encompassing all events from 1990 to 2020.

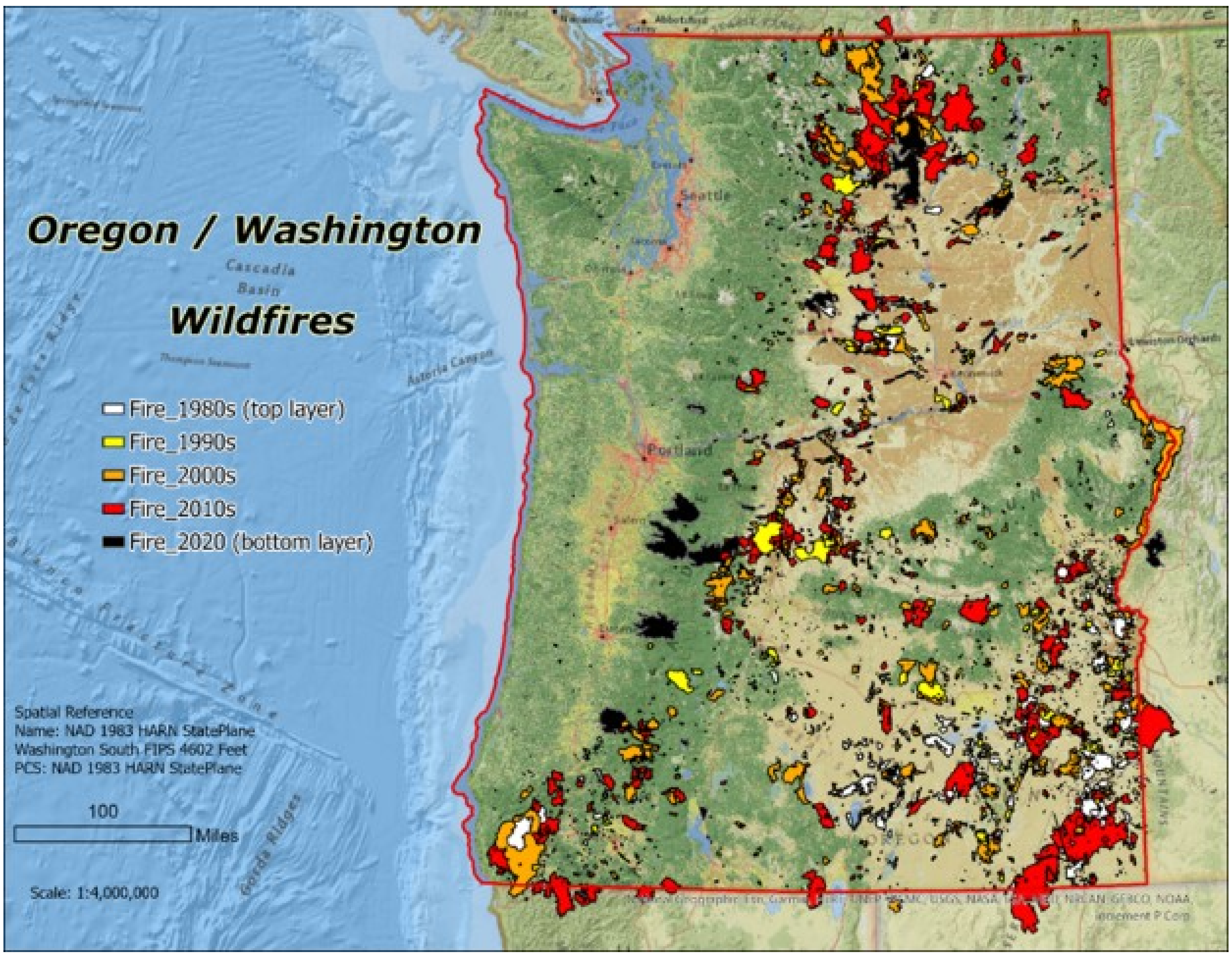


Figure 7

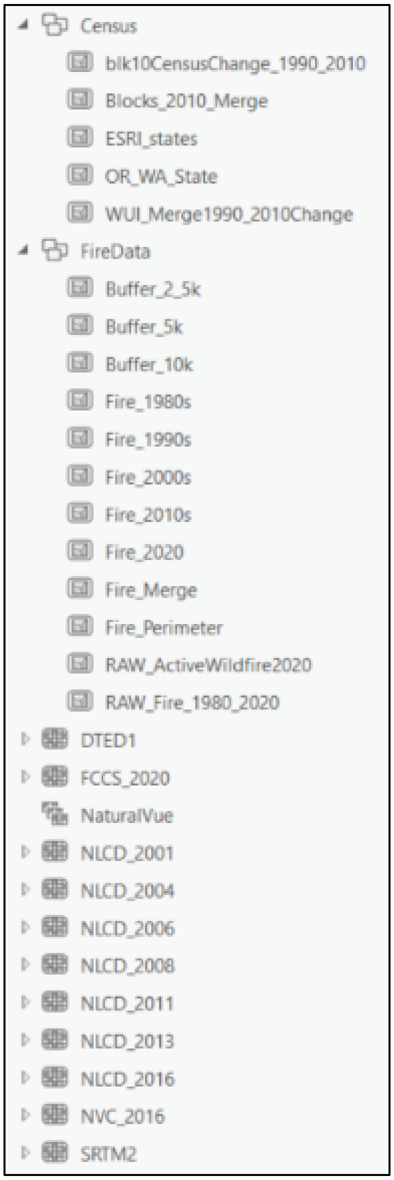
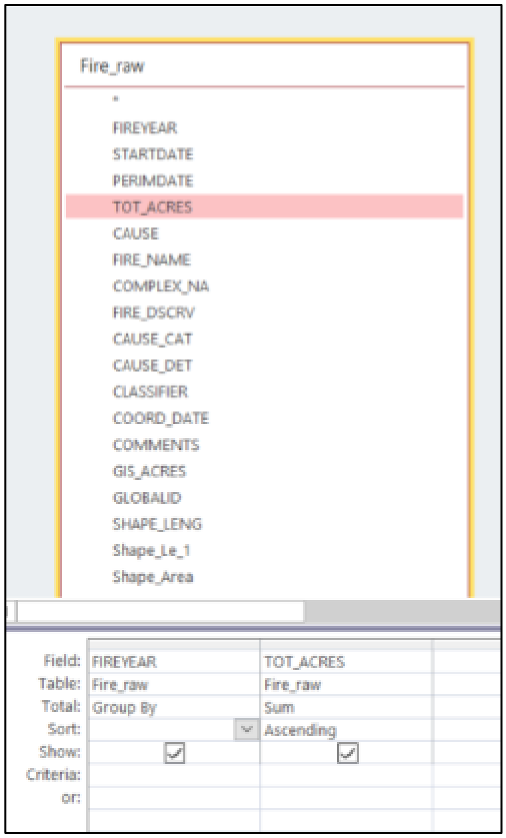


Figure 8

Figure 8 is a list of the final datasets; I clipped everything to the OR_WA_State polygon perimeter. The data can now be compiled for map production and analysis. I did a few queries in Access to demonstrate the types of information users will be able to find out now that the information is structured in a meaningful way. I first exported the tables for Blocks_2010_Merge, WUI_Merge1990_2010Change, and RAW_Fire_1980_2020 layers out of the geodatabase. Then I imported the .dbf into Access.



Query1

FIREYEAR	SumOfTOT_ACRES
1993	3093
1995	10025
1989	10125
1980	10661
1988	13018
1997	14051
1999	18816
1986	41347
1992	41753
1982	43373
1998	45792
1984	46629
1991	47842
1981	55034
1983	55464
1996	89631
1987	93294
2019	117451
1990	125489
2009	140488
2000	141459
2005	147216
1985	189943
1994	192870
2008	252669
2010	270875
2020	313117
2004	330888
2011	411606
2001	470751
2003	514965
2013	600836
2016	668324
2007	766537
2017	864272
2002	871017
2006	995337
2012	1525608
2014	2318795
2015	2387789
2018	2540768

Figure 9

Figure 9 is an example of a query that can now be done on the raw fire data. Here I wanted to find the total amount of acres burned for the given year. I also changed the property sheet to format as fixed with zero decimal places for ease of viewing. Right away I can see that more acres are burning from wildfires in the 2000s.

Figure 10 depicts the Reclassify parameters I used and below is the Loop python script I developed to recode all rasters into a folder I called 'Rasters'.

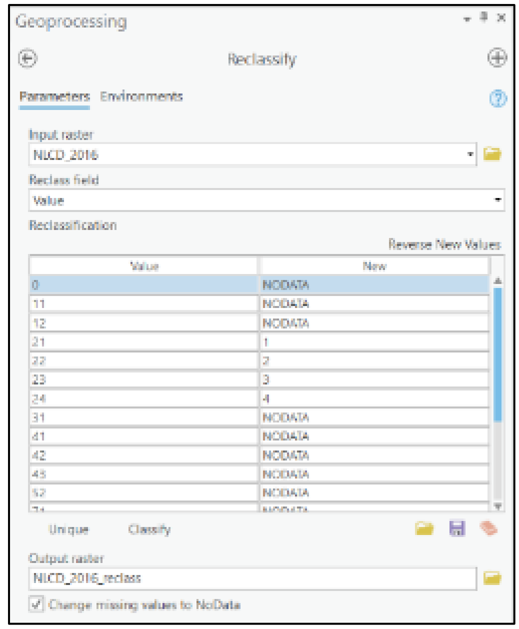


Figure 10

```
# Import system modules
import arcpyfrom arcpy
import envfrom arcpy.sa
import *
# Set environment settings
env.workspace =
r"D:\PSU\Capstone\CapstoneData\CapstoneData.gdb"
# Set local variables
outFolder = r"D:\PSU\Capstone\CapstoneData\Rasters"
# Check out the ArcGIS Spatial Analyst extension license
arcpy.CheckOutExtension("Spatial")
# Get a list of the rasters in the workspace
rasters = arcpy.ListRasters()

# Loop through the list of rasters
for inRaster in rasters:
# Set the outputname for each output to be the same as the input
    outRaster = outFolder + "\\" + inRaster
# Process: recode
    out_raster = arcpy.sa.Reclassify(inRaster, "Value", "0 NODATA;11 NODATA;12 NODATA;21 1;22
2;23 3;24 4;31 NODATA;41 NODATA;42 NODATA;43 NODATA;52 NODATA;71 NODATA;81 NODATA;82 NODATA;90
NODATA;95 NODATA", "DATA");     out_raster.save(outRaster)
print('Done Processing')
```

Next I exported the four perimeter files (**Figure 11**) I will be using to mask my coded rasters to .shapefiles for incorporation into the below python Loop and Masking python script.

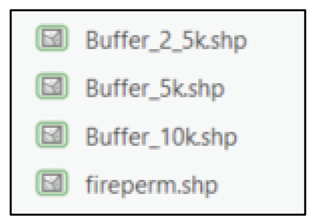


Figure 11

```
# Import system modules
import arcpy
from arcpy import env
from arcpy.sa
import *
# Set environment setting
senv.workspace = r"D:\PSU\Capstone\CapstoneData\Rasters"
# Set local variables
inMaskData = r"D:\PSU\Capstone\CapstoneData\fireperm.shp"
inMaskData2 = r"D:\PSU\Capstone\CapstoneData\Buffer_2_5k.shp"
inMaskData3 = r"D:\PSU\Capstone\CapstoneData\Buffer_5k.shp"
inMaskData4 = r"D:\PSU\Capstone\CapstoneData\Buffer_10k.shp"
outFolder = r"D:\PSU\Capstone\CapstoneData\CapstoneData.gdb"
# Check out the ArcGIS Spatial Analyst extension license
arcpy.CheckOutExtension("Spatial")
# Get a list of the rasters in the workspace
rasters = arcpy.ListRasters()

# Loop through the list of rasters
for inRaster in rasters:
# Set the outputname for each output to be the same as the input
    outRaster = outFolder + "\\" + inRaster + "_p"
# Process: Extract by Mask
```

```
    arcpy.gp.ExtractByMask_sa(inRaster, inMaskData, outRaster)
print('Done Processing Perimeter')

# Loop through the list of rasters
for inRaster in rasters:
# Set the outputname for each output to be the same as the input
    outRaster = outFolder + "\\" + inRaster + "_2_5"
# Process: Extract by Mask
    arcpy.gp.ExtractByMask_sa(inRaster, inMaskData2, outRaster)
print('Done Processing 2.5km buffer')

# Loop through the list of rastersfor inRaster in rasters:
# Set the outputname for each output to be the same as the input
    outRaster = outFolder + "\\" + inRaster + "_5"
# Process: Extract by Mask
    arcpy.gp.ExtractByMask_sa(inRaster, inMaskData3, outRaster)
print('Done Processing 5km buffer')

# Loop through the list of rasters
for inRaster in rasters:
# Set the outputname for each output to be the same as the input
    outRaster = outFolder + "\\" + inRaster + "_10"
# Process: Extract by Mask
    arcpy.gp.ExtractByMask_sa(inRaster, inMaskData4, outRaster)
print('Done Processing 10km buffer')
```

Below is a list and description of the developed categories I reclassified from the NLCD. Impervious surfaces include roads, driveways, rooftops, and other compact surfaces that do not allow rain to infiltrate into the soil and groundwater.

21 - Developed, Open Space- areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20% of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes.

22 - Developed, Low Intensity- areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 20% to 49% percent of total cover. These areas most commonly include single-family housing units.

23 - Developed, Medium Intensity -areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 50% to 79% of the total cover. These areas most commonly include single-family housing units.

24 - Developed High Intensity-highly developed areas where people reside or work in high numbers. Examples include apartment complexes, row houses and commercial/industrial. Impervious surfaces account for 80% to 100% of the total cover.

After doing some preliminary analysis on my raster mask output I discovered, for whatever reason, there was no change to the four develop NLCD categories between the years 2006 and 2008, then again between 2011 and 2013. Because of this, I chose to remove 2006 and 2011 from describing the change to urban development the NLCDs represent. I then calculated the acres – each X, Y cell size is 166.234375149578 feet, which equals 27633.87 feet squared and equates to 0.63438636364 acres per pixel. I then created another field to calculate the number of acres based on the count of pixels (see **Figure 12**).

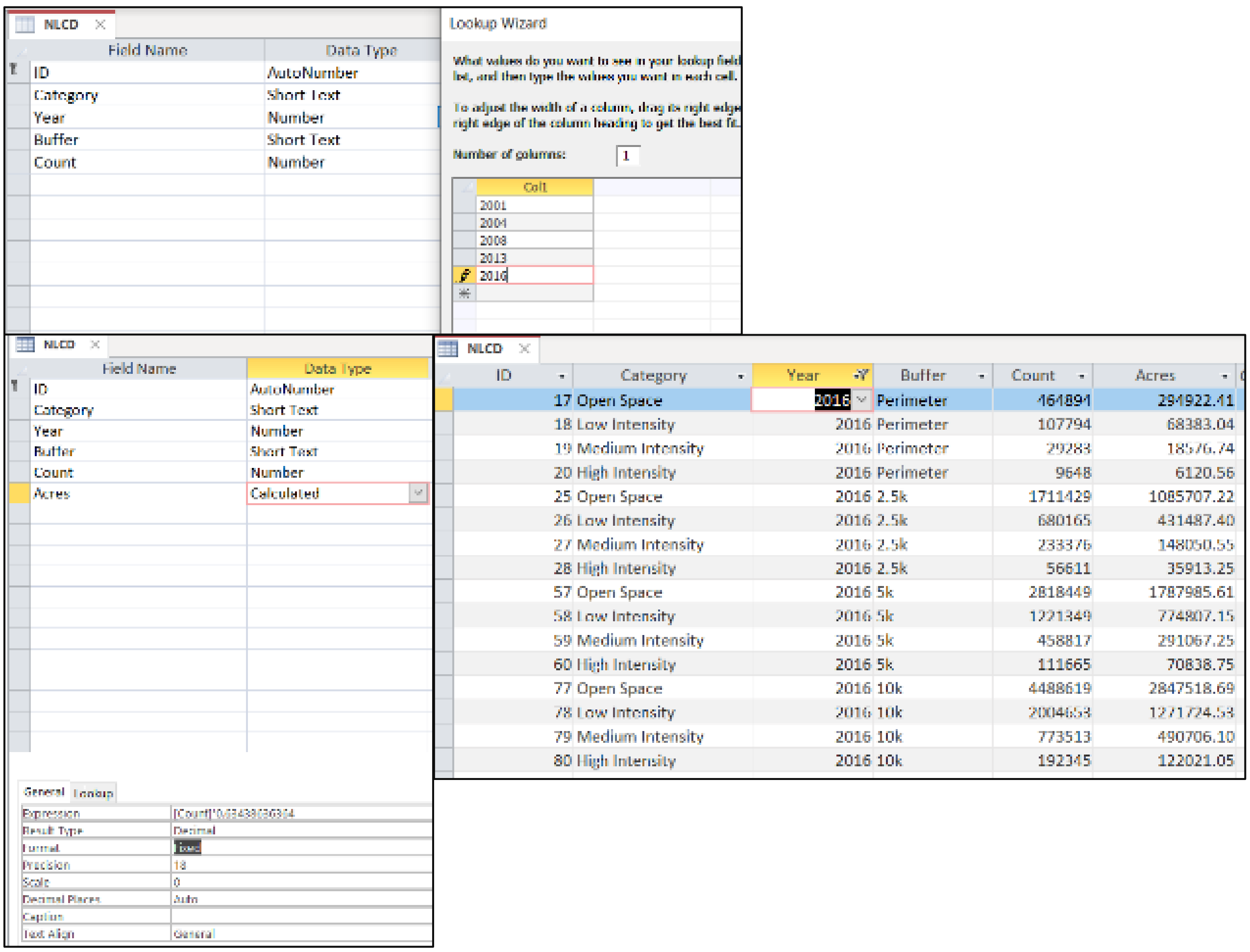


Figure 12

I then created a new layer (**Figure 13**) by selecting the WUI_merge layer that intersect with the fire perimeter, and one that intersects with each fire perimeter buffer. The criteria for the WUI classes I took into consideration are as follows. **Figure 14** depicts a merger of the following WUI categories by decade.

- **High_Dens:** Housing density >= 741.3162 houses per square km
- **Med_Dens:** Housing density between 49.42108 and 741.3162
- **Low_Dens:** Housing density between 6.177635 and 49.42108
- **Intermix:** wildland vegetation > 50%
- **Interface:** wildland vegetation <= 50% and within 2.414 km of area with >= 75% wildland vegetation

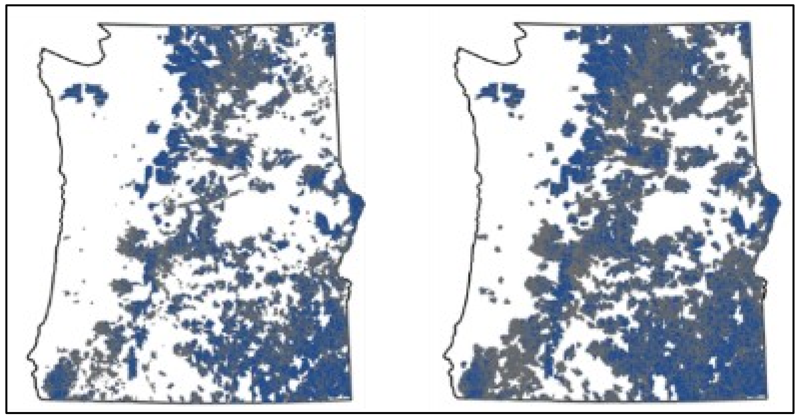


Figure 13

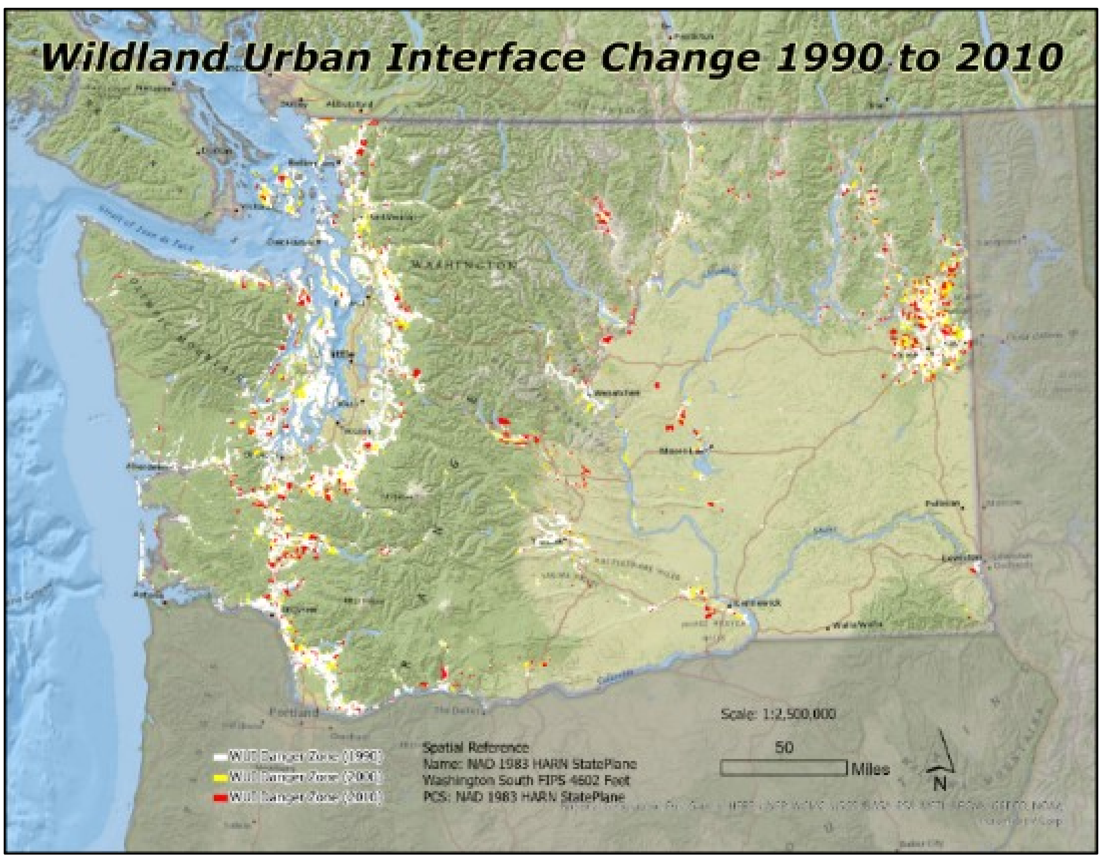
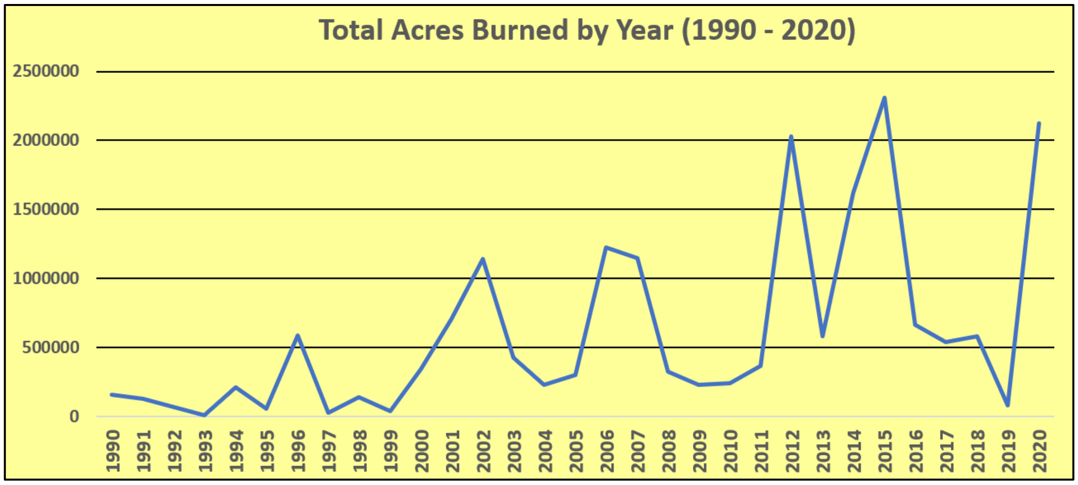


Figure 14

6.0 Results

Of the 4,696 wildfire incidents I calculated from the merged Washington and Oregon BLM and NIFC datasets, 2,447 burned 100 or more acres. The year 2020 was particularly bad for the study area, though 2015 closely equaled it. The numbers demonstrate an alarming upward trend for incidents reported and acres burned. What the charts also show is that the worst years tend to come in waves, possibly equating to some type of cycle trending upward.

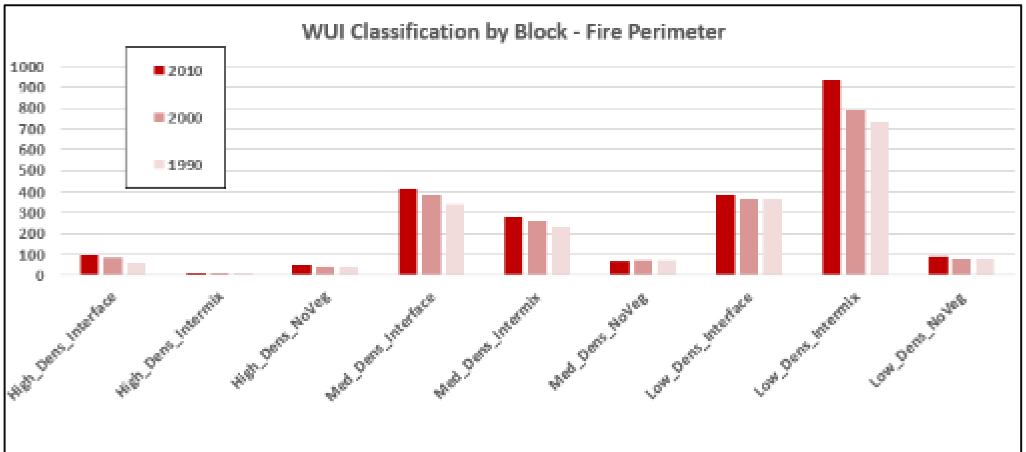


Year	Total Acres Burned	Number of Incidents (All)	Number of Incidents (>=100 Acres Burned)
1990	159162	96	31
1991	130765	104	39
1992	69859	130	45
1993	9273	32	13
1994	210270	91	43
1995	56852	64	21
1996	588473	171	91
1997	30162	72	24
1998	141076	88	38
1999	41676	107	44
2000	346542	115	54
2001	704152	250	122
2002	1144288	203	99
2003	427933	129	74
2004	228526	151	74
2005	300667	158	94
2006	1224437	306	143
2007	1144937	263	157
2008	323307	151	91
2009	229650	164	86
2010	244869	140	71
2011	370273	173	95
2012	2029280	217	155
2013	580593	156	91
2014	1615981	210	125
2015	2308078	182	145
2016	665518	123	81
2017	537510	112	60
2018	584439	155	76
2019	83927	59	24
2020	2127752	324	141

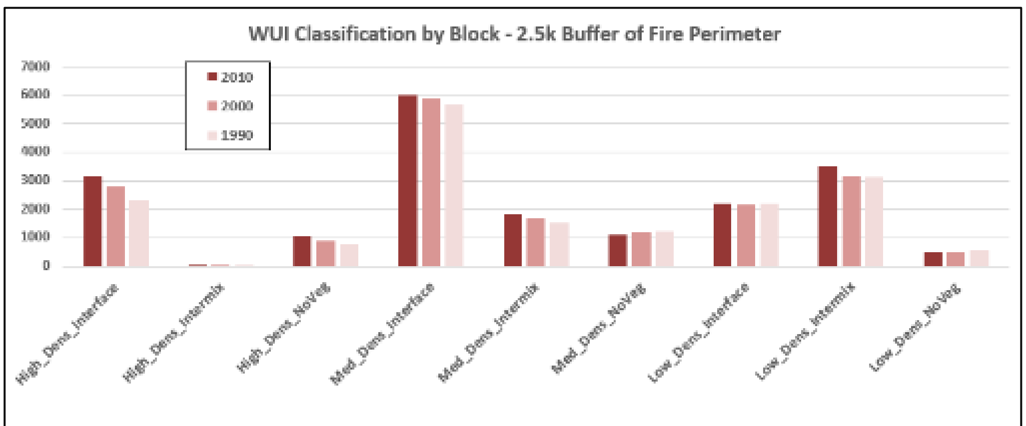
The table below was used to summarize the total amount of acres based on the four Developed Landcover Classifications from the NLCD for each buffer zone and year. The numbers illustrate how hundreds of acres are being developed in areas prone to wildfire. The large jump from 2001 to 2004 is likely equated to either a large population expansion or a change in how the landcover data was collected.

Fire Perimeter				
Year	**High Intensity**	**Medium Intensity**	**Low Intensity**	**Open Space**
2001	2,069	6,232	23,985	103,217
2004	5,902	17,807	67,853	294,312
2008	5,997	18,152	68,011	294,453
2013	6,039	18,315	68,165	294,733
2016	6,121	18,577	68,383	294,922
2.5 Kilometer Buffer				
2001	10,929	46,101	148,862	379,356
2004	31,104	131,839	423,896	1,081,619
2008	33,368	139,886	426,743	1,084,259
2013	34,933	144,310	428,915	1,085,806
2016	35,913	148,051	431,487	1,085,707
5 Kilometer Buffer				
2001	20,856	89,955	266,407	623,651
2004	59,625	257,249	758,798	1,778,629
2008	64,625	273,914	764,826	1,784,464
2013	68,612	283,721	769,646	1,787,937
2016	70,839	291,067	774,807	1,787,986
10 Kilometer Buffer				
2001	36,010	151,768	436,979	993,106
2004	102,837	433,572	1,244,796	2,831,784
2008	111,535	461,460	1,255,685	2,842,499
2013	118,241	478,337	1,263,243	2,847,592
2016	122,021	490,706	1,271,725	2,847,519

According to the WUI dataset, numbers have steadily increased in all vulnerable categories, especially in the low-density intermixed category. Low density is usually the beginning stages that lead to medium to high density, so it is safe to assume thousands of people are moving into areas prone to wildfire more and more over the past three decades. The tables below reflect the number of BlockIDs that intersect the given perimeter category. Note the large jump in numbers when we incorporate the 2.5k buffer.

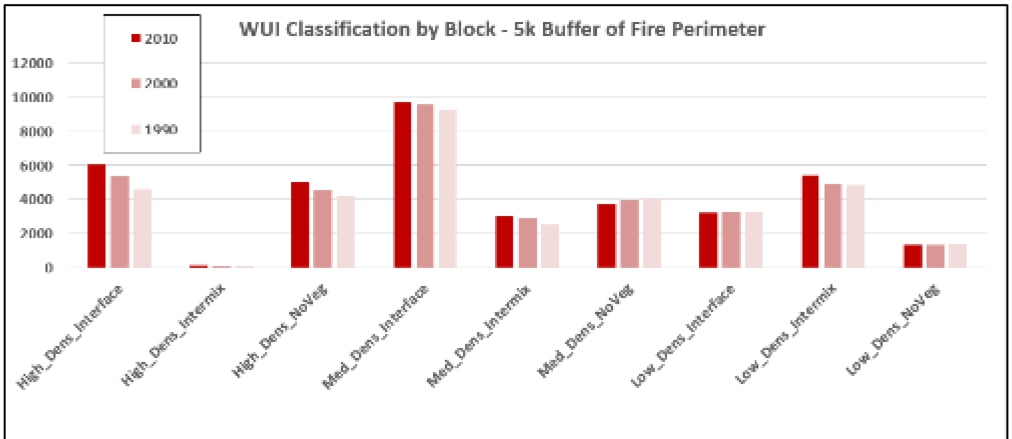


WUI Classification	2010	2000	1990
High_Dens_Interface	98	86	59
High_Dens_Intermix	9	12	11
High_Dens_NoVeg	48	41	39
Med_Dens_Interface	417	385	342
Med_Dens_Intermix	282	263	233
Med_Dens_NoVeg	67	71	73
Low_Dens_Interface	384	365	367
Low_Dens_Intermix	937	792	732
Low_Dens_NoVeg	88	78	78

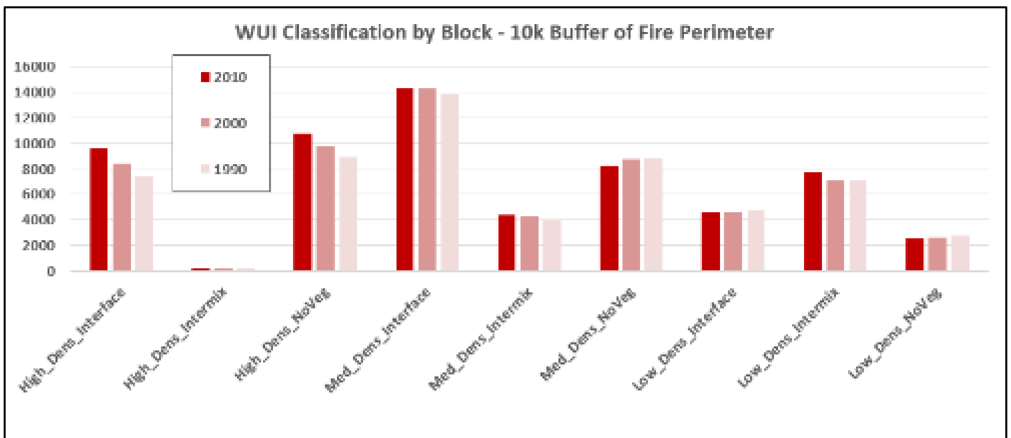


WUI Classification	2010	2000	1990
High_Dens_Interface	3195	2798	2322
High_Dens_Intermix	58	59	60
High_Dens_NoVeg	1080	901	760
Med_Dens_Interface	6018	5885	5688
Med_Dens_Intermix	1815	1711	1508
Med_Dens_NoVeg	1102	1168	1222
Low_Dens_Interface	2184	2170	2183
Low_Dens_Intermix	3500	3175	3112
Low_Dens_NoVeg	505	517	540

After looking at the number of Blocks that intersect the study areas fire perimeter, we can see that medium to high housing densities begin to take over low density as the perimeter buffer is expanded. This is another alarming example of how, within only a short distance, more people will be vulnerable to wildfires should they spread or massive amounts of people are forced to evacuate.

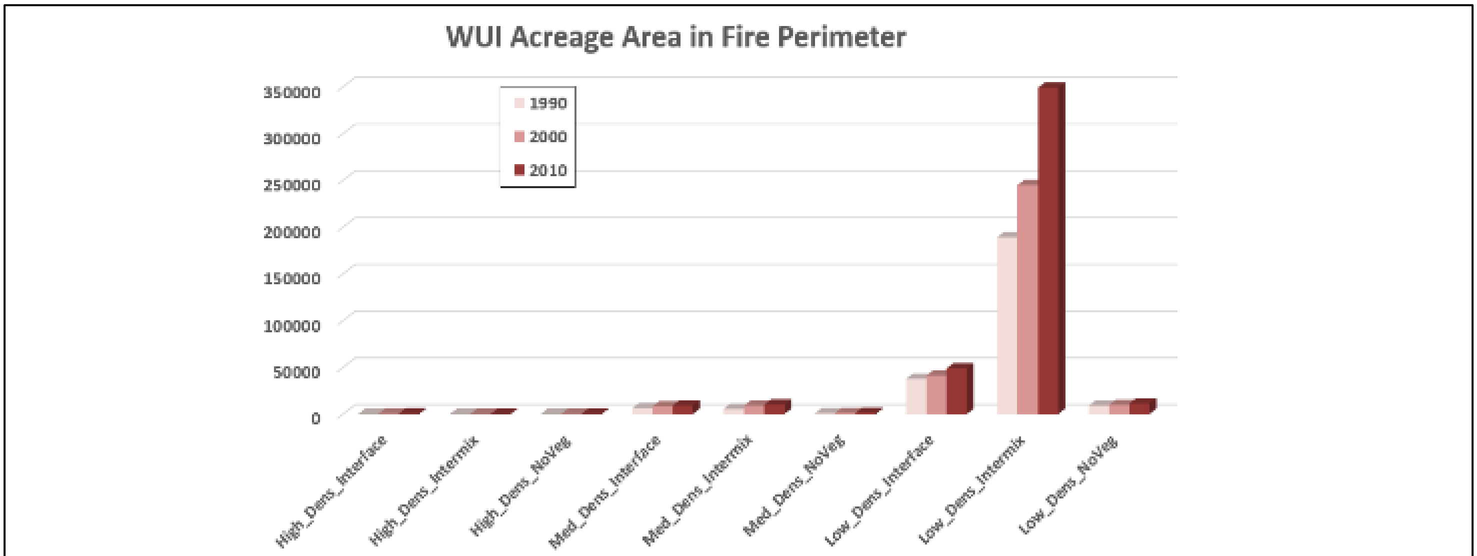


WUI Classification	2010	2000	1990
High_Dens_Interface	6055	5355	4604
High_Dens_Intermix	99	94	91
High_Dens_NoVeg	5059	4560	4239
Med_Dens_Interface	9695	9554	9286
Med_Dens_Intermix	3040	2885	2542
Med_Dens_NoVeg	3739	3982	4068
Low_Dens_Interface	3222	3258	3302
Low_Dens_Intermix	5396	4931	4866
Low_Dens_NoVeg	1301	1339	1417

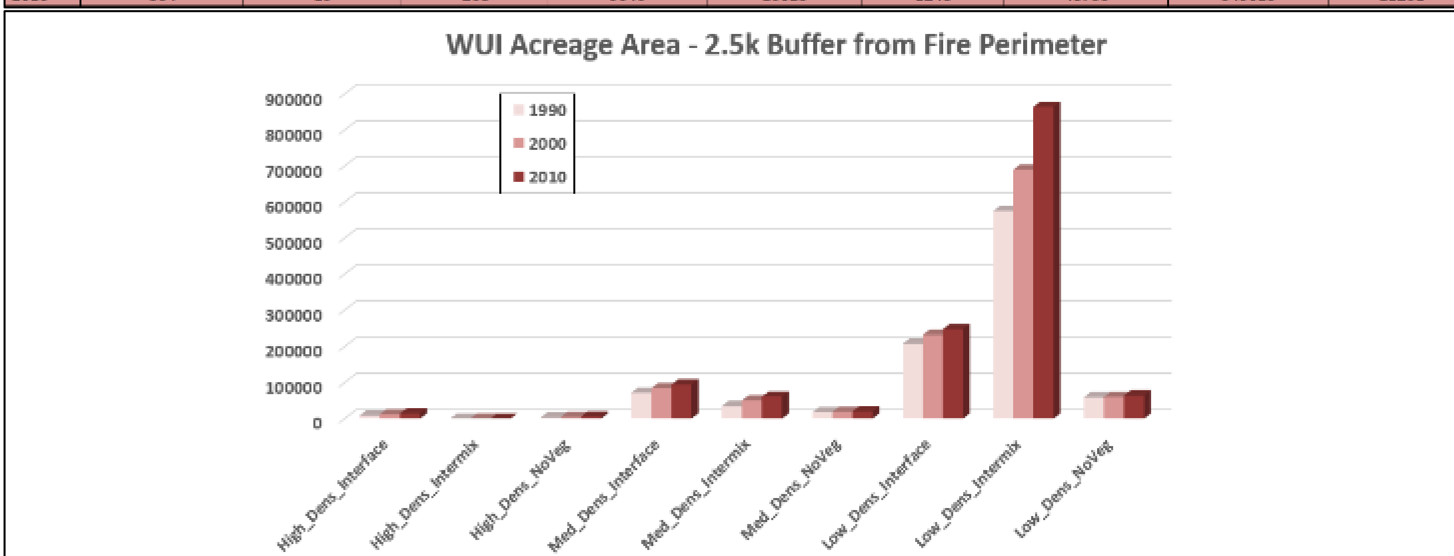


WUI Classification	2010	2000	1990
High_Dens_Interface	9580	8420	7385
High_Dens_Intermix	163	178	163
High_Dens_NoVeg	10744	9737	8948
Med_Dens_Interface	14313	14312	13856
Med_Dens_Intermix	4414	4256	3994
Med_Dens_NoVeg	8251	8750	8811
Low_Dens_Interface	4650	4633	4680
Low_Dens_Intermix	7705	7082	7034
Low_Dens_NoVeg	2545	2630	2757

Next, I calculated the total acreage of WUI categories used in this analysis to see how that correlates with the four Developed Landcover acreage we clipped in the NLCD. Low Density Intermix is the dominate category within the fire perimeter, though Medium Density begins to show substantial risk looking at the 2.5k buffer.

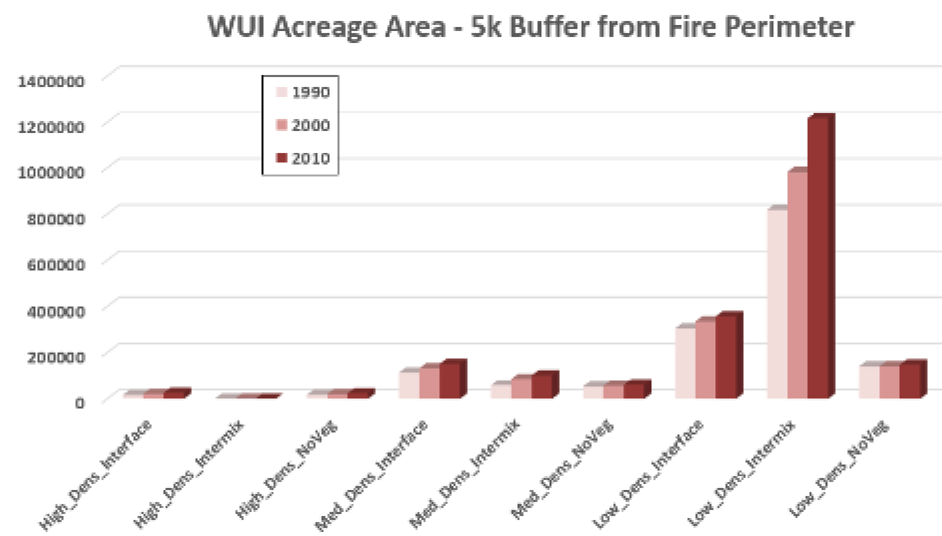


	High_Dens_Interface	High_Dens_Intermix	High_Dens_NoVeg	Med_Dens_Interface	Med_Dens_Intermix	Med_Dens_NoVeg	Low_Dens_Interface	Low_Dens_Intermix	Low_Dens_NoVeg
1990	213	16	240	6152	5332	762	37564	189016	8935
2000	475	23	256	8108	9077	975	41035	244774	9614
2010	534	15	268	9040	10023	1248	48735	349025	11201

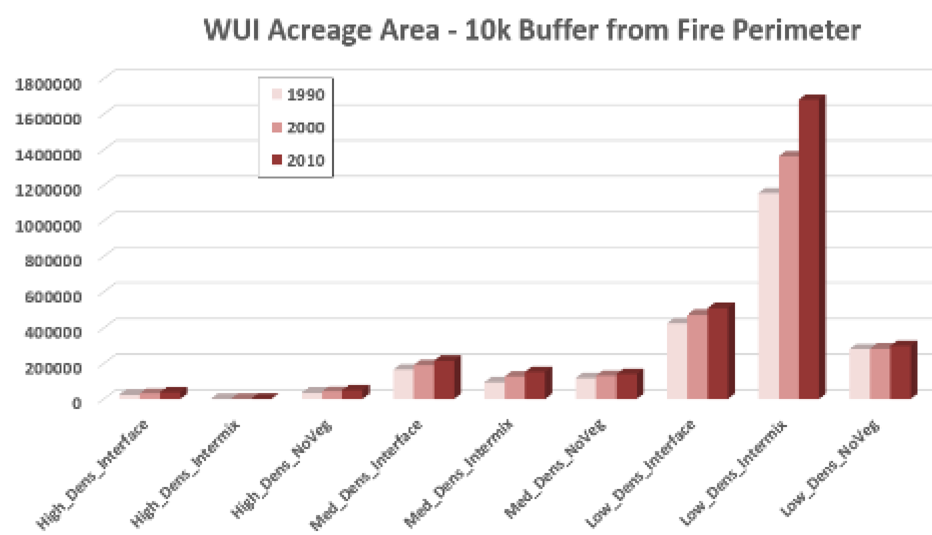


	High_Dens_Interface	High_Dens_Intermix	High_Dens_NoVeg	Med_Dens_Interface	Med_Dens_Intermix	Med_Dens_NoVeg	Low_Dens_Interface	Low_Dens_Intermix	Low_Dens_NoVeg
1990	8633	91	3289	71710	34895	17623	208164	575243	59204
2000	11735	252	4405	84735	50812	18713	231796	689964	60038
2010	14521	174	5756	94607	61054	20320	247344	864263	64312

When looking at the 5k and 10k buffer numbers we can see how High-Density housing begins to show substantial increases in acreage, while Medium and Low Density continues to climb as well.

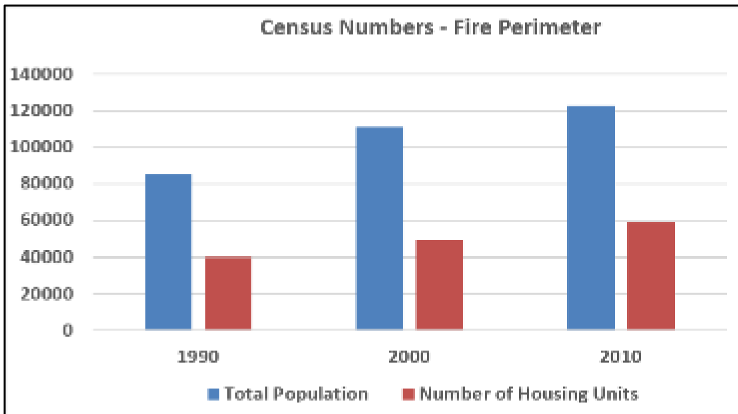


	High_Dens_Interface	High_Dens_Intermix	High_Dens_NoVeg	Med_Dens_Interface	Med_Dens_Intermix	Med_Dens_NoVeg	Low_Dens_Interface	Low_Dens_Intermix	Low_Dens_NoVeg
1990	16048	171	16909	112443	58410	53016	304013	817409	139439
2000	20722	366	20044	131608	84292	56375	334538	981606	140148
2010	25512	302	23693	150970	100840	60507	356349	1217049	147224

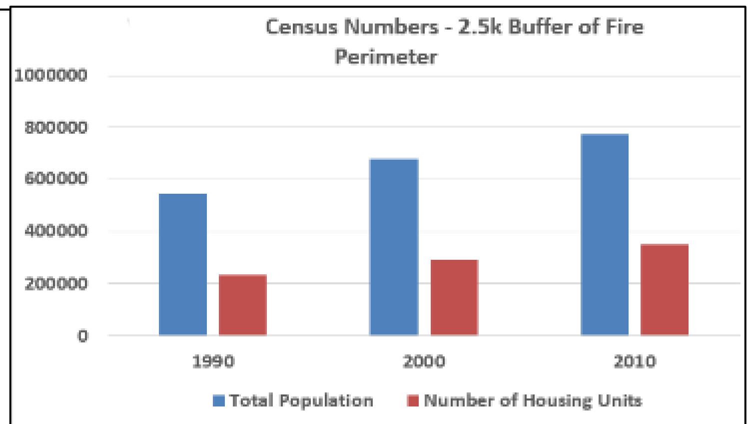


	High_Dens_Interface	High_Dens_Intermix	High_Dens_NoVeg	Med_Dens_Interface	Med_Dens_Intermix	Med_Dens_NoVeg	Low_Dens_Interface	Low_Dens_Intermix	Low_Dens_NoVeg
1990	24004	396	34862	165605	93841	117176	426004	1154877	279754
2000	30491	621	41397	190086	126694	130347	472121	1361978	283438
2010	37958	520	49148	215084	152003	140092	508592	1681391	298525

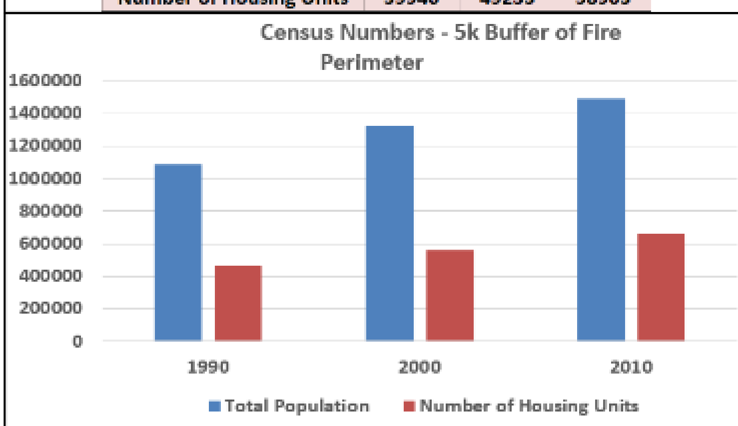
Here we look at the Census numbers of total population and number of housing units. The numbers depict the large amount of people who are within a short distance to where a wildfire has burned since 1990. According to the 2010 Census, 123,182 people and 58,903 housing units are within the fire perimeter polygon. When we look just 2.5 kilometers out from the fire perimeter the numbers jump to 773,590 people and 347,583 housing units. That is a drastic increase, and only gets bigger as we look five and ten kilometers out.



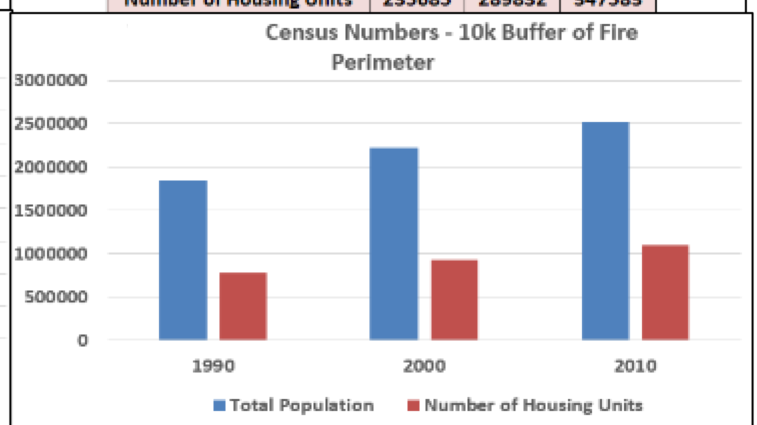
Census Data	1990	2000	2010
Total Population	85472	110945	123182
Number of Housing Units	39940	49233	58903



Census Data	1990	2000	2010
Total Population	548024	681223	773590
Number of Housing Units	235685	289832	347583



Census Data	1990	2000	2010
Total Population	1087912	1324394	1492189
Number of Housing Units	463780	559684	659032



Census Data	1990	2000	2010
Total Population	1841330	2229330	2525899
Number of Housing Units	780217	932050	1095780

7.0 Challenges / Limitations

- Census data does not entirely depict where and how people are living in the regions where human's meet nature.
- 2020 census data was not available for this analysis.
- There is not enough public knowledge or support to drastically change how and where we live. It is difficult to shift the way we live to mitigate the damage wildfires can cause.
- We are just starting to see how seasonal wildfires can damage our lives and economy. As we move into the 2021 summer months vulnerable populations need to actively embrace for contingency plans.
- This is a very complex problem with numerous variables involved to how or why a wildfire starts. Predictive models are not the solution, active education and prevention is what is needed to shift policy and the public's mindset.
- Time is always an issue when we research and challenge complex problems such as climate change. This research covers a large geographic area, which may help sway policy at the federal or state level.

Link to Storymap

Link to 24 x 36 inch Thematic Map

8.0 Conclusion

The goal of this analysis is to help educate people about the dangers regarding the high numbers of people moving into regions prone to wildfire. I was able to determine that more people are moving into regions prone to wildfire and that wildfires are getting more severe and occurring all over Oregon and Washington. This study focused on the historic locations of wildfires in Washington and Oregon, which occurred mostly in the regions east of the Cascade Mountain Range. The greatest area of concern is that there are signs of wildfires creeping on the Western Cascade (more populated) slopes, as well as more people moving into the Eastern Cascade regions.

This analysis not only helps paint a picture of what has happened in each region but can also help allocate for additional resources and funding. Fighting a fire must be done on a more micro scale, so educating these large amounts of people living in vulnerable areas on how to fight future fires will help stop future destruction. There is currently a Bill (2413) in the WA State Senate to generate $63 million dollars yearly toward fighting fires. This will provide the needed funds to employ more fire fighters, analysts, and response stations (Holappa, 2020). The data presented in this study, as well as events occurring in California, tell us the Pacific Northwest is vulnerable to wildland fire. It is up to policy makers and the people moving into the WUI to prepare for the next large incident.

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Datasets

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Oregon and Washington Geospatial Open Data Portal: http://geo.wa.gov/datasets/wadnr::Oregon and Washington-large-fires-1973-2018. Accessed January 13, 2020.

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