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Spatial Programming Final Project – GEOG 4303

A Tool for Mapping the Wildland-Urban Interface

Between the bustling centers of urban development and the untamed wilderness lies a boundary called the Wildland-Urban Interface (WUI). As suburban sprawl increases, so does the WUI and its risks. This interface poses an opportunity for fire to spread from one type of land to another – wildfires can enter the city and structure fires can spread to the forest [3]. Mapping this boundary and its properties allows for identification of areas which present the largest risk of a wide-spread fire and can help determine the best fire mitigation strategies for these areas.

The WUI is an area where structures are built in or near wildland vegetation [2]. The U.S. Federal Register defines the WUI as an area with at least 6.17 structures per square kilometer and one of two vegetation requirements: either 50% or more of the land is covered in vegetation, or the structures are within 2.4 kilometers of at least 5 square kilometers of 75% vegetation coverage [10]. The first of these categories is considered the Wildland-Urban Intermix, and the second is Wildland-Urban Interface [2]. However, different research questions may be interested in slightly different mapping requirements, so these standard values are not hard coded into our tool. Instead, the user inputs all the requirements for the intermix and interface including thresholds for building density, vegetation cover, buffer distance to large areas of vegetation, large vegetation area definitions, and moving window radii. The user can also request that the interface and intermix be mapped using classifications representing proximity to the most prominent vegetation types in the area.

Our tool uses vegetation data from the National Land Cover Database (NLCD) [11], and structure data from the Built-Up Property Locations (BUPL) layer from the Historical Settlement

Data Compilation for the U.S. (HISDAC-US) [1]. The tool package comes with clipped sample data for Los Angeles, CA 2020, and the user also has the option to input data for other areas of interest anywhere in the U.S. Both data sets are available back to 1985. The tool is designed so that the user can simply clip an NLCD raster to their study area of interest, and the tool will clip the BUPL layer (e.g. if using an unclipped BUPL layer (~30MB) for the entire U.S.). The NLCD raster is provided at 30-meter resolution and has many classes representing different vegetation types, as well as development data which we ignore [11]. The BUPL raster is provided at 250-meter resolution and shows the number of structures within each cell [1].

Methods:

Our tool begins with data preparation and utilizes ArcPy tools for this task. Since we are using data sources with two different resolutions, we begin by resampling the smaller resolution of the NLCD data to match the larger resolution of the BUPL data. This means that there is some loss of data resolution for vegetation, but it allows us to use the HISDAC-US data source. We also reproject the NLCD to match the BUPL projection to ensure that the rasters are comparable. Finally, we use the ExtractByMask tool to clip the BUPL data to the input NLCD extent. We found that ExtractByMask works better than ClipRaster for this purpose because the clip tool produces "NoData" values on the edges of the raster which causes problems with future steps. We also used the ArcPy SnapRaster feature to ensure that both rasters have the same size and number of rows and columns [4]. Finally, we convert both NLCD and BUPL rasters into NumPy arrays which allows us to start performing selections and map algebra operations very quickly and effectively.

After data preparation is complete, our WUI mapping method follows six general steps derived in part thanks to the method outlined by Bar-Massada, *et al* [2]. The variables used below are the accepted standard values used in WUI mapping [2, 6], and users can input different values if they want to adjust the mapping output:

1. Run a moving window on the BUPL data and select cells with at least 6.17 buildings within a 1 km radius.
2. Run a moving window on NLCD vegetation (classes 41, 42, 43, 51, 52, and 72) to select areas with greater than and less than 50% vegetation.
3. From the raw resampled/post-processed NLCD data, select vegetation groupings of 5 square kilometers in areas of at least 75% vegetation cover using Region Group tool.
4. Buffer the 5 square kilometer vegetation areas to a given radius of 2.4 km.
5. Calculate WUI intermix by adding outputs from step 1 and 2.
6. Calculate WUI interface by adding the building density output from step 1, the vegetation selection of areas less than 50% from step 2, and the large vegetation area buffer from step 4.

To run the moving window on our NumPy arrays of NLCD and BUPL data, we create a circular kernel (mask) with a user defined radius to systematically iterate over all the cells in the array. The kernel is a circular representation and is made up of square pixels. Since we are working with 250m resolution data, a radius of 1 represents one pixel of this size. Therefore, an input radius of 2 will produce approximately the recommended result of a 1 km diameter moving window mask. The kernel systematically moves across the array summing up the values in each neighborhood and outputting the average in the center cell. We run the moving window twice on the separate arrays for vegetation and development which outputs two new arrays representing the average vegetation cover, and average building density for the input radius. Next, the script will prompt the user for input values and will select the cells from these outputs which meet the user-defined criteria. We use the “numpy.where” function to perform this selection process, and most other selection processes throughout this script. The selection output raster is binary, with codes of ‘1’ representing selected cells, and ‘0’ values representing false values where the conditions are not met. This process allows the user to select areas based on threshold percentage for vegetation coverage and number of buildings within a given radius.

Step 3 involves selecting large vegetation areas and is important because proximity to these areas is correlated to fire risk [3]. We use the ArcPy RegionGroup tool which groups continuous/connecting blocks of cells together. We not only need to consider which groups of vegetation are large enough, but also consider the percent vegetation cover of the area, with a commonly used value of 75% [2]. Therefore, we first select areas meeting the vegetation cover percentage (75%) using the vegetation percent coverage map generated from the moving window earlier. Then, we use the RegionGroup tool to select vegetation areas larger than a threshold of 5 square km. We use the ArcPy SearchCursor to get a count of the number of cells per group. Our script then calculates the number of cells needed for the size input by the user (in square km), and applies this value to select the correct areas from the RegionGroup output. This allows the user to select larger or smaller vegetation areas if needed.

Step 4 involves making a buffer around the large vegetation areas because proximity to these areas is an important consideration of the WUI. The recommended buffer distance is 2.4km [2]. In order to perform a buffer on a raster, we have followed the method of Bar-Massada, *et al* [2]. Using ArcPy tools, this involves converting the large vegetation area raster into a polygon, buffering the polygon, and then converting the buffer back to a raster.

Once these operations are complete, we simply ensure that all the required rasters are available in NumPy array format, and then add the appropriate arrays together as outlined in steps 5 and 6 above to calculate WUI intermix and interface separately. Finally, we combine these classes into a final raster which differentiates between intermix and interface.

Mapping WUI with Vegetation - Methods:

Our tool also incorporates the option to map the WUI with vegetation classes. This is useful for quickly observing what types of fuels are near certain WUI areas which can help assess fire risk [12]. The tool maps vegetation into two classes of 'forest' (NLCD classes 41, 42, 43) or 'shrubland' (NLCD classes 52, 71) or both. If the user answers 'yes' to vegetation mapping, the script will run an additional two arrays through the moving window for the forest and shrubland selections. In this case, the kernel radius of the moving window applied to these arrays is a fixed value of 1 because this will prevent larger user input radii from unnecessarily expanding vegetation class selections (e.g. if a user wants to map general WUI with a larger radius). From the output arrays, we select forest and shrubland areas with coverage greater than 20%. Next, we buffer these areas to 2.4 km using the same polygon buffering method outlined earlier. The goal of using a moving window and buffering the vegetation classes is to produce a vegetation map that overlaps with the final WUI map we create. Generally, the WUI map will not overlap completely with vegetation because many areas of the WUI are developed and are classified as developed in the NLCD raster. Applying a moving window ensures that we are selecting vegetation areas with a meaningful amount of each specific vegetation type. Buffering ensures that no WUI areas are left blank without a vegetation class. This vegetation mapping process is applied after the normal WUI map has been created. This allows us to simply apply our buffered vegetation map to the WUI map by adding the NumPy arrays. The result retains the normal WUI map footprint and intermix vs. interface classes, but now includes extra classes to identify the most prominent types of vegetation in proximity to the WUI.

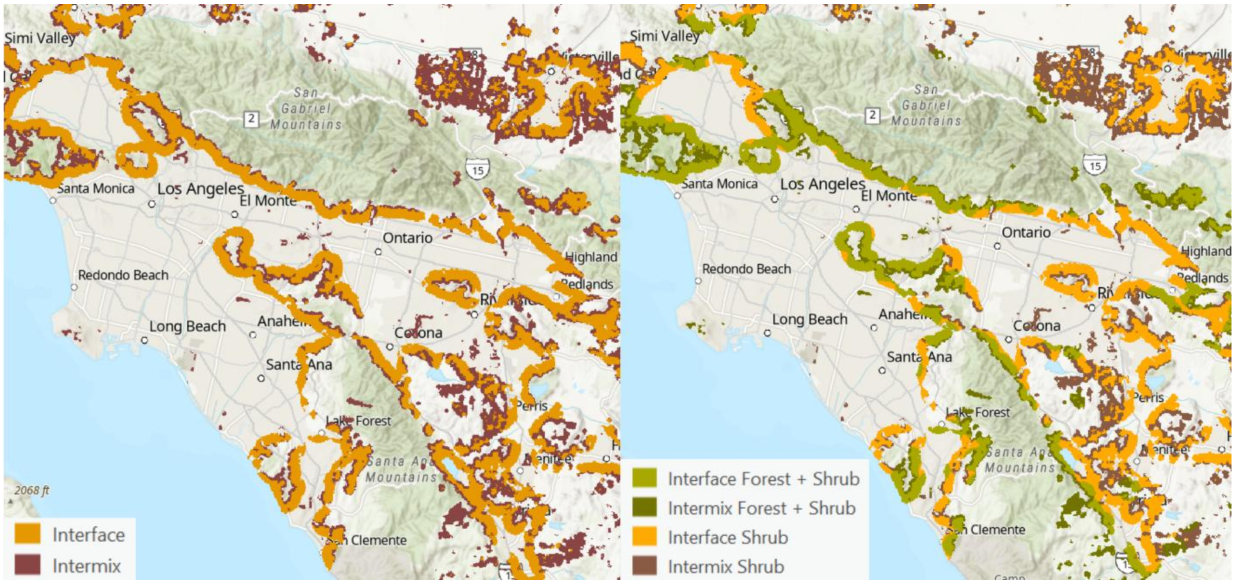

Figure 1. Left: a basic WUI map generated for Los Angeles, 2020. Right: WUI map with added classes differentiating vegetation types in proximity to the WUI. In this case, there are only 4 classes, but other locations could have up to 6 classes which would include areas of primarily forest classes.

Assessing WUI Mapping - Methods:

To assess the quality and accuracy of WUI maps generated by our tool, we have integrated a way for the user to compare a generated output WUI map to a WUI map created by the SILVIS Lab at the University of Wisconsin-Madison [6]. For this tool to work accurately, WUI maps must be generated/downloaded for years as close together as possible. WUI maps from the SILVIS Lab can be downloaded in large shapefiles, and our script incorporates data preprocessing steps to make this data comparable. This means that the user can simply download raw SILVIS data for their area of interest and feed it into the script for comparison. Our tool selects WUI areas from the SILVIS data, converts to raster format, reprojects, and clips (ExtractByMask) the SILVIS WUI map to the area of interest. Once this is completed, we combine intermix and interface classes for both our generated WUI map, and the WUI map from SILVIS. The goal of this is to compare the agreement/overlap of the two maps. Using NumPy arrays, our script adds these two maps together and calculates the four values making up a confusion matrix [5], where the SILVIS map is defined as the so-called “true” map. From the confusion matrix values, statistics of accuracy, precision, recall, and an F1 score are calculated. These values are an indication of the amount of agreement/overlap between the two maps, with low values near “0” representing low agreement, and high values near “1” representing high agreement between the maps. Our script also incorporates the “SKLearn” library to verify our results. At this time, we find that the statistics calculated by “SKLearn” are higher than the same statistics calculated by our own method for currently unknown reasons. Therefore, further discussion of these statistics will refer to those calculated by the “SKLearn” module because we believe they are currently more reliable.

Assessing WUI Mapping – Results:

While running the tool, we found that changing certain inputs can lead to more agreement between the SILVIS map and our generated map. For example, Question 3 of our script asks the user to input a building density threshold, with the standard value being 6.17 buildings per cell [2]. However, we suggest an alternative threshold of 1. This is because upon examination of the BUPL data, we found many examples of locations where the number of buildings per cell is less than 6.17, and these areas are commonly mapped as ‘intermix’ by the SILVIS map [6]. However, if we apply the threshold of 6.17 in our model, we exclude these areas, and there is less agreement between the maps.

Figure 3 (Appendix p. 12) shows the difference between the selected WUI areas when using different building density thresholds and shows the underlying BUPL data that represents low-density developed areas below the threshold of 6.17. A larger example of this can be found in Figure 4 (Appendix p. 12). Figure 5 (Appendix p. 13) shows a side-by-side comparison of our generated WUI map (using building threshold 1) and the SILVIS WUI map. Visually, the two maps in Figure 5 share very similar WUI selections. To better understand the differences in agreement between these maps, and using different thresholds, we have used the “SKLearn” library incorporated within our tool to compare the results. The figure below explores these statistics.

Figure 2. This figure compares the generated WUI map when using a building threshold of 1 (left) vs. 6.17 (right) to a SILVIS map. Both maps are using data from 2020.

In the figure above, notice that in both matrices, the highest values are in the “Negative-Negative” category. This is because in both maps, WUI selections do not cover the majority of the mapping area, and therefore negative selections get the highest count. Also, notice the matrix using the threshold of 1 has a higher value in the “True-True” category when compared to the matrix using the threshold of 6.17. This is one indication of higher agreement with the threshold of 1. Finally, we compare the statistics from the SKLearn report. The values are in general higher for the threshold of 1, when compared to the threshold of 6.17. This is especially apparent for the “True values” which represent the statistics applied to the overlap, as opposed to the “False values” which are statistics that apply to the negative values (non-WUI areas). These results lead us to recommend using the lower building threshold of 1 to achieve higher agreement with SILVIS maps when mapping WUI using our tool, because the method may ‘under-select’ WUI if this threshold is set to the value of 6.17.

Assessing WUI Mapping – Discussion:

Considerations need to be made when comparing WUI maps. For example, the SILVIS Lab WUI maps use NLCD data and U.S. Census data for buildings/developments [6]. This building data source is different than the HISDAC-US data source we use, meaning this difference in data is an area where inconsistencies between the maps can arise. This may be a reason why we found that a lower building threshold produces more agreement between our maps. The U.S. census data appears to be classifying these low-density areas differently than the HISDAC-US data, which is likely why we had to reduce the threshold to increase agreement.

Another consideration when making these comparisons is that WUI maps from the SILVIS Lab are only available once a decade due to the low temporal resolution of the U.S. census data [6]. This means it’s important to compare generated maps and SILVIS maps for years as close to each other as possible. While our method allows users to generate WUI maps every 5 years (HISDAC-US temporal resolution) [1], this could lead to inaccurate comparison results if a mid-decade WUI map was compared to a SILVIS map.

Future Work:

Future work for this project could include generating historical WUI maps for comparison with maps of suburban/urban burn areas to analyze the accuracy of the model at predicting which areas are at risk. The tool could also be run on data for all available years, and for the entire U.S. to produce a database similar to the SILVIS Lab WUI map database. The

SILVIS Lab has also used their WUI maps to produce WUI change maps which represent how much the WUI has increased over time [6]. Our method opens the possibility for creating WUI change maps as well, and on a finer temporal scale. Another area of future work could involve WUI mapping with building density classes [6]. Our method for mapping WUI with vegetation classes could easily be applied to building density as well, and this type of map may be useful for understand how populations are affected by the WUI [6].

Conclusion:

The Wildland-Urban Interface is an important and ever-changing consideration for an expanding society. It presents unique risks and challenges that are best prepared for if city planners have an accurate map of the WUI. The goal of our tool is to understand where the WUI is, what vegetation fuels are nearby, and provide a method to determine how it has changed over time. The tool also aims to give the user an idea of how well the mapping process works by running agreement statistics with another trusted WUI map. The tool also gives the user the freedom to quickly test different variables within the WUI mapping process to be more specific for different criteria. This tool, and others like it, can be used to help manage our society's suburban sprawl more safely.

References

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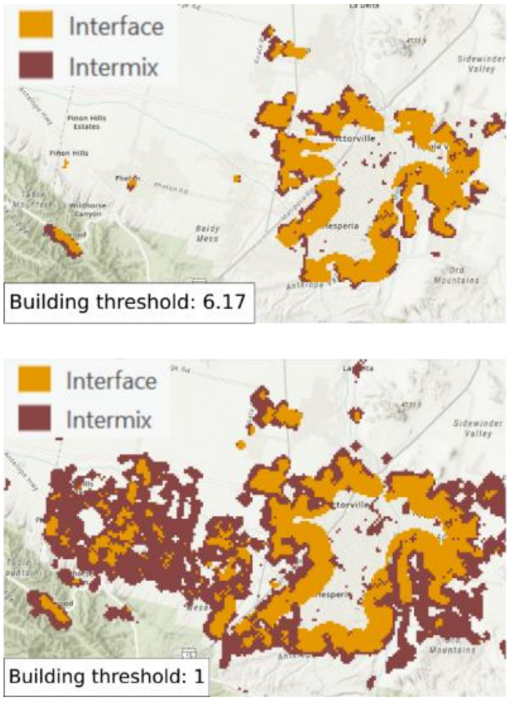
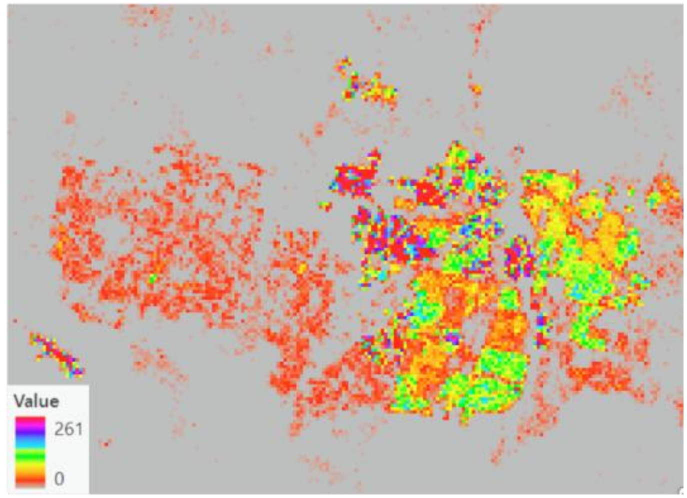
Appendix:





Above: Notice the red area on the left. These pixels have values mostly ranging 0 to 5. This means they are not selected by a 6.17 building threshold, but will be selected with a threshold of 1. Figures to the left represent this difference.

Figure 3. Left: Mapping differences between different building thresholds, as well as the underlying data that is causing this. The top left shows that the threshold of 6.17 is excluding a lot of area when compared to the bottom left.

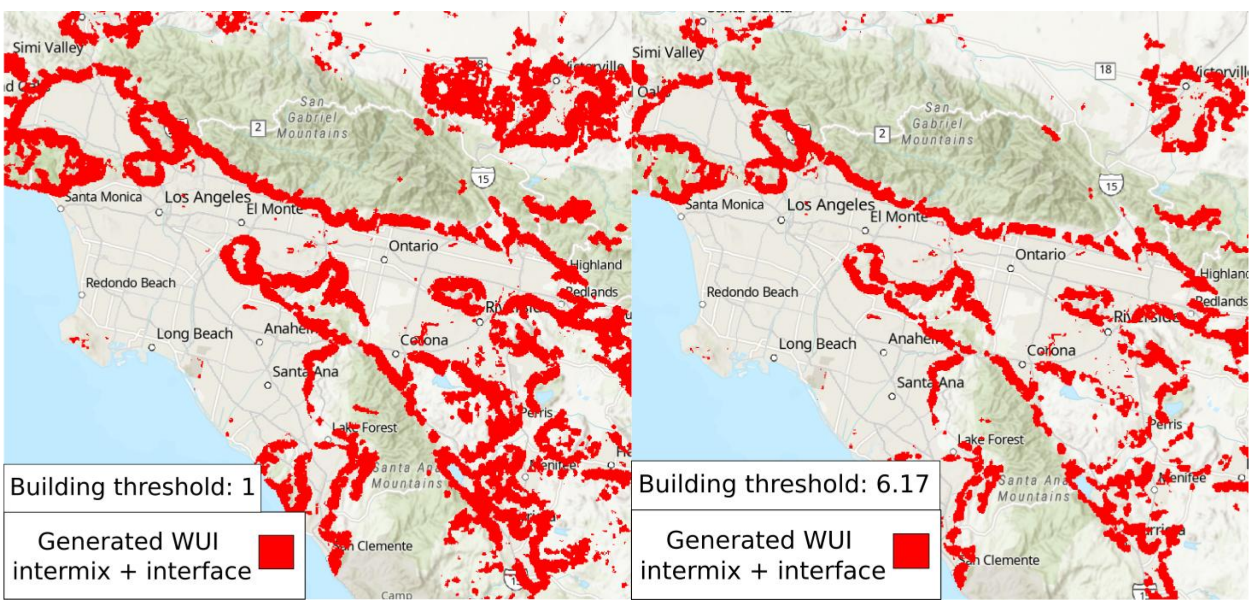


Figure 4: Visual comparison of different building thresholds.

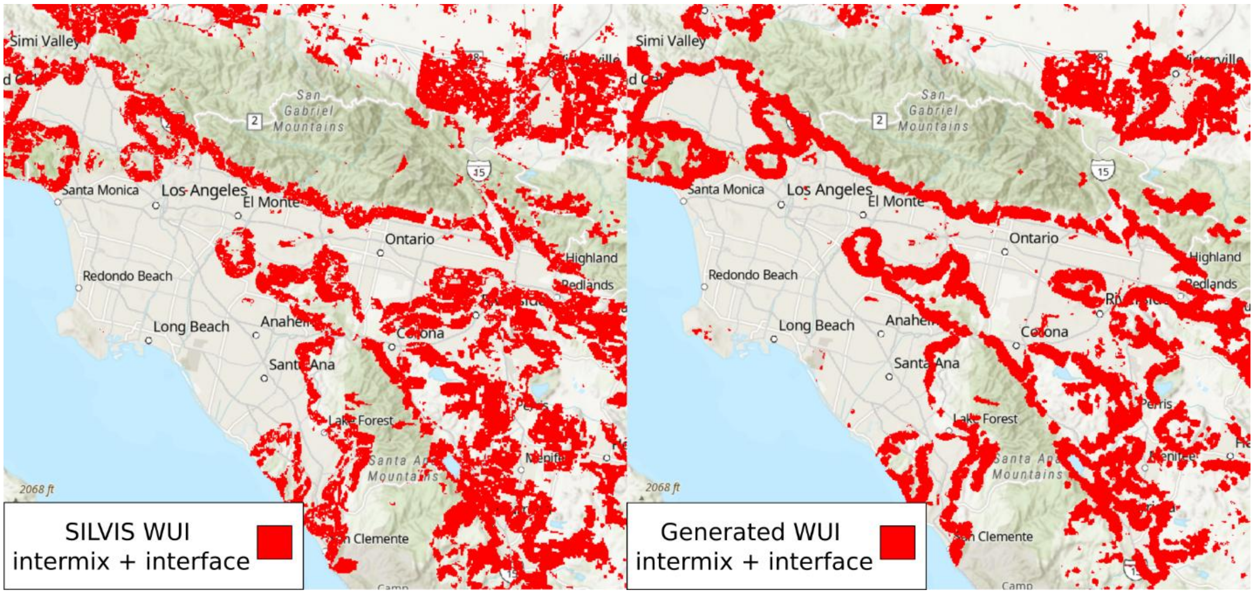


Figure 5. Left: SILVIS Lab WUI map for 2020. Right: WUI map for 2020 generated with our tool using a building density threshold of 1. This threshold was also applied to Figure 1 maps.