Wildfire Risk to Communities:

Methods for geospatial datasets for populated areas in the United States

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INTRODUCTION

Background

The Wildfire Risk to Communities project was created in response to direction by the U.S. Congress in the 2018 Consolidated Appropriations Act (i.e., 2018 Omnibus Act, H.R. 1625, Section 210: Wildfire Hazard Severity Mapping). That legislation directed the USDA Forest Service to develop and publish, within two years, national geospatial products depicting wildfire hazard and risk for communities across the United States. The focus of the legislation was firmly on communities. The intent was to help U.S. communities understand components of their relative wildfire risk profile, the nature and effects of wildfire risk, and actions they can take to mitigate risk.

To meet the intent of the Omnibus Act, the Forest Service formed a team of experts to both develop the necessary data and build an interactive website for effective delivery of information to communities. The Forest Service's Rocky Mountain Research Station (RMRS) has invested many years developing wildfire simulation models to generate the types of geospatial data needed to map wildfire hazard and risk. Given the short timeframe of this project, the team was able to leverage modeling work already underway with the large fire simulation system, FSim, to model probabilistic components of wildfire risk for the U.S. (Short et al. 2020a). The contractor already engaged with RMRS in completing that work, Pyrologix LLC, was able to transition into being part of the Wildfire Risk to Communities team for geospatial data development. The data included in this publication were developed by Pyrologix under the direction of the Fire Modeling Institute, part of RMRS's Missoula Fire Sciences Lab. The accompanying Wildfire Risk to Communities website and community outreach material were developed by another partner in the project, Headwaters Economics, with interactive web maps and charts completed by the web development firm, Azavea.

The data published in the initial rollout of the Wildfire Risk to Communities project were built on the geospatial data from Short et al. (2020a), but they are different in some very important ways. Like the data from Short et al. (2020a), the first eight raster datasets for Wildfire Risk to Communities are comprehensive in their coverage, providing data for components of wildfire hazard and risk for all land areas in the United States (Scott et al. 2020). They were downscaled from their native 270-m pixel resolution to 30-m pixels using a process described in detail in the white paper titled "Wildfire Risk to Communities: Methods for geospatial and tabular datasets" published with Scott et al. (2020). In addition, GIS methods for spatially smoothing raster data were applied to estimate wildfire hazard and risk in developed areas adjacent to areas with wildland fuels.

With the 30-m data covering all lands complete, the next step for the Wildfire Risk to Communities project team was to produce datasets specific to populated areas. To do this well, we first needed to produce raster datasets representing the most current snapshot possible of population distribution in the United States. Only with that information in hand could we then intersect populated areas with data from Scott et al. (2020) to produce wildfire risk data specific to where people live.

The purpose of this white paper is to provide detailed descriptions of the methods used to: 1) produce spatial datasets of populated areas, and 2) create the spatial datasets included in this data publication that represent wildfire exposure and risk to populated areas in the United States.

DATA AND METHODS

Input Datasets

The input datasets used to produce the data products described here include datasets related to population, building locations, land cover, and wildfire hazard. We describe those input datasets in the following sections.

Population – U.S. Census Bureau 2018 5-year American Community Survey

The American Community Survey (ACS) is an ongoing annual survey conducted by the U.S. Census Bureau to collect updated estimates of U.S. social, economic, housing, and demographic data (U.S. Census Bureau 2017). The Census Bureau contacts over 3.5 million households every year as part of the survey. From this sample of households, the Census Bureau then produces statistical estimates of a range of population and housing characteristics at geographic subdivisions down to the Census Block Group level. Data products from the ACS include 1-year estimates from every 12 months of collected responses (limited to larger populated areas) and rolling 5-year estimates from the previous 60 months of collected responses covering all areas.

We used population and housing unit estimates for 2018 published in the 2018 5-year ACS data products (U.S. Census Bureau 2019). They are based on data collected from January 1, 2014 to December 31, 2018.

Population – U.S. Census Bureau 2018 Population Estimates Program

Separate from the ACS, the U.S. Census Bureau also produces estimates every year of the population for the nation, states, and counties as part of the Population Estimates Program (PEP) (https://www.census.gov/programs-surveys/popest.html). This program measures population changes through public records of births, deaths, and migration and updates population counts annually for a continuous time series between decennial census counts (U.S. Census Bureau 2020). Estimates are released every year on July 1 of the current year, referred to as the vintage year.

We used county level population estimates for the vintage year 2018 that capture changes from April 1, 2010 to July 1, 2018. (U.S. Census Bureau 2018)

Building Locations – Microsoft Building Footprints

Microsoft uses an AI assisted mapping process to identify and map building footprint polygons across the United States from Bing Imagery (https://www.microsoft.com/en-us/maps/building-footprints). We acquired version 1.1 of the Microsoft building footprint dataset, released on July 13, 2018, that includes over 125 million building footprints across all 50 states (Microsoft 2018).

Building Coverage – USGS Building Coverage Data

In early 2020, the U.S. Geological Survey (USGS) released national 30-m rasterized building data (Heris et al. 2020) developed from the initial 2018 release of Microsoft building footprint dataset (v1). One of the datasets produced by Heris et al. (2020) is a 30-m raster representing total area of building footprints (m^2) in each pixel. They used a computationally intensive process to produce precise estimates of building coverage within each pixel. In cases with duplicate or overlapping building footprints in the original Microsoft data, the USGS product could have greater than 100%. In these cases, we applied a ceiling of 100% cover.

Heris et al. (2020) noted swaths of missing building footprints in the original Microsoft dataset, which they proposed were due to a tiling error. Microsoft corrected this problem in v1.1 of their building footprints that we acquired as in input.

Population Locations – LandScan USA 2018

The LandScan USA Population Database is produced by the Oak Ridge National Laboratory at a grid size of 3 arc-seconds (approx. 90-m cell size) for the conterminous United States (CONUS), Alaska, and Hawaii (Rose et al. 2017). Population data are based on the 2010 Census and updated to 2017 population from estimates provided by the American Community Survey (ACS). LandScan attempts to spatially resolve population information reported at the Census block level (Bhaduri et. al 2007) by distributing population to raster cells using dasymetric modeling and numerous spatial data sources including daytime and nighttime imagery, administrative boundaries, topography, land cover, and coastlines (Rose et al. 2017).

We used centroids of populated LandScan pixels in Alaska to represent building locations because Microsoft building footprints were not available across the whole state.

Land Cover – LANDFIRE

We used LANDFIRE raster data to identify burnable vs non-burnable and habitable vs uninhabitable land covers. We used the most recent version of LANDFIRE data available at the time of processing[1]. The data cover three different extents; each extent used a different spatial reference (projection) (see table below).

Non-burnable land cover was defined as areas mapped by LANDFIRE as any of the non-burnable fuel models in the Scott and Burgan Fire Behavior Fuel Models (FBFM40) raster: urban (91), permanent snow/ice (92), non-burnable agriculture (93), open water (98) and bare ground (99) (LANDFIRE 2017, LANDFIRE 2019, Scott and Burgan 2005). We considered everything else burnable land cover. We used both 30-m and 270-m resolution versions of the burnable land cover raster at different stages of data processing for Wildfire Risk to Communities.

Habitable land cover was defined as all land cover types except open water and permanent snow/ice.

Wildfire Hazard – Nationwide FSim Outputs

The input datasets related to wildfire hazard were developed by the Forest Service at RMRS's Missoula Fire Sciences Lab. Short et al. (2020a) used the large fire simulation system (FSim) to simulate at least 10,000 fire season iterations in each of 136 distinct regions of relatively uniform

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[1] During our analysis, LANDFIRE released new data for their west and central GeoAreas (version 2.0.0, i.e., LANDFIRE Remap 2016). We updated our habitable land cover data to include this release for those GeoAreas. We continued to use LANDFIRE 2014 (version 1.4.0) for the eastern GeoAreas, Alaska, and Hawaii.

contemporary wildfire activity (pyromes) across the United States (Short et al. 2020b). In each pyrome, modeling outputs were calibrated to fire occurrence records from recent decades (Short 2017). The resulting national datasets of annual burn probability and conditional flame-length probability (the likelihood of different fire intensities) have a spatial resolution of 270-m and were used as primary inputs to the landscape-wide Wildfire Risk to Communities data products in Scott et al. (2020) that were subsequently used as inputs to the data products described here.

Methods for Specific Raster Datasets

For this release of the Wildfire Risk to Communities data, we produced a series of seven nationwide raster datasets covering CONUS, Alaska, and Hawaii. All rasters have 30-m spatial resolution. Specifics for each dataset are described in the sections that follow.

Population Density (PopDen)

Population Density is a 30-m raster of residential population density (people/km^2) as of 2018. We generated the PopDen raster using both the PEP and ACS population estimates for 2018 from the U.S. Census Bureau, Microsoft building footprint data, LandScan USA data for Alaska, and land cover data from LANDFIRE.

Our approach to generating the population density raster generally follows the methods used by the Westwide Wildfire Risk Assessment (Sanborn Map Company 2016) to produce the Where People Live raster, which represents housing-unit density rather than population density. The primary steps are described below.

1. *Estimate 2018 census block population count*

   We estimated 2018 population count for a census block using two approaches—one based on 2018 5-year ACS data and another based on 2018 PEP data. The final estimated population count for a given block was taken to be the larger of the two estimates. PEP and ACS estimate population at different times of the year and with different definitions of residency—using the larger of ACS and PEP avoids the potential for undercounting population due to these differences.

   2018 5-year ACS

   The 2018 5-year ACS population data are estimates resolved only to the block-group, not to the block. With initial testing, we found this was inadequate to allocate residential population spatially across the landscape because blocks within a block group can have buildings but not residential population (for example, census blocks that consist entirely of industrial and commercial). We downscaled the block-group population to the block level by allocating the block-group population to its blocks in proportion to the decennial census proportions.

   In other words, if a particular block accounted for 10% of the decennial census population of the block group to which it belongs, then we allocated 10% of the ACS block-group population to that block. This approach maintains the ACS population within a block group but also allocates that population to individual blocks. This approach prevents allocating population to commercial or industrial blocks with little or no residential population.

2018 PEP

In a second approach, we leveraged 2010 and 2018 PEP data (by county) to increase (or decrease) the decennial census block population by the fractional population change for the county containing the block.

Final 2018 census block population

We estimated the final 2018 population for a census block as the larger of the 2018 5-year ACS and 2018 PEP-adjusted decennial census population estimates. This approach was used to capture seasonal residences, which are captured in the ACS data, and group quarters (prisons, dormitories, etc.), which are captured in the decennial census.

2. *Allocate population to building points*

We calculated building footprint area (m^2) from the Microsoft building footprint polygons (v1.1) and converted the data to point features (footprint centroids). We removed buildings with a footprint smaller than 40 m^2 (430 ft^2) on the assumption that such structures are more likely to be false-positives or outbuildings than primary residential structures. We also removed building points located on water, as determined by the LANDFIRE fuel model raster. These footprints appeared to be non-residential buildings such as docks and boat houses. Removing these points from the building dataset was necessary to maintain fidelity to the input census data.

For each census block nationwide, we divided the 2018 census block population count obtained in the first step by the count of remaining building points in the block. This ratio is the effective population count per building point—the population represented by each building point. This became a block-level population-per-building-centroid attribute in the building points dataset.

The Microsoft building footprints were not available across all of Alaska, so we substituted the centroids of populated LandScan pixels for qualifying building points, but otherwise used the same method as described above.

Blocks with buildings but no population

The Microsoft building footprint dataset includes buildings within census blocks with a population count of zero. These footprints usually represent commercial or industrial buildings, but they can also represent false positives in the building footprint dataset. Because there is no population in these blocks, their population-per-building values are all zero and they do not contribute to the final PopDen raster.

Blocks with population but no buildings

There are cases where a census block has a population count but no buildings. We refer to these as “missing blocks” because we are missing buildings to allocate the population to. This can occur for several reasons. In the decennial census, people experiencing homelessness are counted in the census block where they reside at the time of the census, even if that is not within a building. Sometimes that occurs in census block with no buildings. In other cases, the geography of a census block does not contain any buildings, but it may yet be assigned the population of a nearby building.

To distribute population within a missing block, we first estimated the mean population density across the block as the census block population count divided by the habitable land cover within the block (all but water and permanent snow/ice). If the mean population density was greater than 1 person per 100 acres, we allocated the population count uniformly across the habitable land cover in the block before generating the final PopDen raster. If the mean population density was less than or equal to 1 person per 100 acres, we reset the population count to zero. Setting this minimum mean density was necessary to avoid including large areas of very low population density in the final raster.

3. *Generate the PopDen raster from the building points*

To produce the PopDen raster, we first converted the building points to a 30-m raster where the raster value is the sum of the population-per-centroid attribute of all building centroids within each raster grid cell. We combined this with the estimated population count raster for missing blocks to produce a complete population count raster. We then generated a smoothed density raster using a three-step process:

1. Calculate a 200-m radius moving-window sum of the 30-m population count raster;
2. Calculate a 200-m radius moving-window sum of habitable land cover (in km^2);
3. Divide the smoothed population count raster produced in step 1 by the smoothed habitable land cover raster produced in step 2 to generate population density in people/km^2.

Finally, we converted the PopDen raster values to integers. Values less than 0.25 people/km^2 were set to zero. Values between 0.25 and 1 were given a value of 1 person/km^2. All other values were rounded to the nearest integer.

Housing Unit Density (HUDen)

HUDen is a 30-m raster of housing-unit density (housing units/km^2) as of 2018. We generated the HUDen raster using both the PEP and ACS population estimates for 2018 from the U.S. Census Bureau, Microsoft building footprint data, LandScan USA data for Alaska, and land cover data from LANDFIRE.

Our approach to generating the housing unit raster generally follows the methods used by the Westwide Wildfire Risk Assessment (Sanborn Map Company 2016) to produce the Where People Live raster, which also represents housing-unit density. The primary steps are described below.

1. *Estimate 2018 census block population count*

We estimated 2018 population count for a census block as described for the PopDen raster above. This involved creating two population estimates for each census block—one based on 2018 5-year ACS data and another based on 2018 PEP data. The final estimated population count for a given block was taken to be the larger of the two estimates.

2. *Allocate population to building points*

As described for the PopDen raster, we acquired and processed the Microsoft building footprint polygons (v1.1) and converted them to point features (footprint centroids). For each census block nationwide, we divided the 2018 census block population count obtained in the first step by the count of building points in the block. This created a block-level population-per-building-centroid attribute in the building points dataset. As with PopDen, we used centroids of populated LandScan pixels for qualifying building points in Alaska because the Microsoft building footprints were not available across the whole state.

Blocks with buildings but no population

The Microsoft building footprint dataset includes buildings within census blocks with a population count of zero. These footprints usually represent commercial or industrial buildings, but they can also represent false positives in the building footprint dataset. Because there is no population in these blocks, the buildings are not considered to be housing units and they do not contribute to the final HUDen raster.

Blocks with population but no buildings

As described for the PopDen raster, there are cases where a census block has a positive population count but no buildings. We refer to these cases as "missing blocks" because we are missing buildings to allocate the population to. Although these census blocks were included in the PopDen raster, they are not included in the HUDen raster because no housing units are present.

3. *Calculate the number of housing units per building point*

The number of people per housing unit varies. Similarly, the number of housing units represented by a single building point varies. In the case of group quarters (dormitories, nursing care facilities, prisons, etc.) and multi-family residential buildings, there are many housing units per building point. In the case of resort communities, there can be many residential building points (e.g., rental condominiums) relative to the population count. Therefore, our process of converting population counts to housing unit counts consisted of two steps.

First, we calculated the ratio of people per household for each U.S. county ("county ratio") using data published in the 2018 5-year ACS. We divided the 2018 ACS population estimate for a county by the 2018 ACS number of housing units for that county. This ratio represents the number of people per housing unit in each county.

Second, we divided the population-per-building-centroid attribute in the building points dataset (consistent across a census block) by the appropriate county ratio to produce a new housing-units-per-building-centroid attribute.

4. *Generate the HUDen raster from the building points*

To generate a HUden raster, we first converted building centroids (points) to a 30-m raster where the raster value is the sum of the housing-units-per-centroid attribute of all building centroids within each raster grid cell. We then generated a smoothed density raster using a three-step process:

1. Calculate a 200-m radius moving-window sum of the 30-m housing-unit count raster;
2. Calculate a 200-m radius moving-window sum of habitable land cover (in km^2);
3. Divide the smoothed housing-unit count raster produced in step 1 by the smoothed habitable land cover raster produced in step 2 to generate housing-unit density in housing units/km^2.

Finally, we converted the HUDen raster values to integers. Values less than or equal to 0.1 HU/km^2 were set to zero. Values between 0.1 and 1 were given a value of 1 HU/km^2. All other values were rounded to the nearest integer.

Building Coverage (BuildingCover)

BuildingCover is a 30-m raster depicting the percent of land area covered by buildings as of 2018. It includes all buildings and can be used to complement the HUDen raster, which just reflects residential buildings. We generated the BuildingCover raster using the latest Microsoft building footprint data (v1.1), a USGS dataset of building coverage developed from older Microsoft building footprint data (Heris et al. 2020), and land cover data from LANDFIRE. BuildingCover is not available in Alaska because source data were not available across the whole state.

We estimated building coverage by augmenting the published USGS data with updated Microsoft footprint data. We did not replicate the detailed modeling methods used by USGS. Instead, we used a much simpler approach that meets the needs for a building coverage raster and fills in gaps where Heris et al. (2020) acknowledge the earlier Microsoft data were missing buildings. The primary steps in developing our BuildingCover raster are described below.

1. *Estimate building footprint area*

   In areas where building coverage information was missing from the USGS dataset, we produced our own simplified total footprint coverage raster. We first divided Microsoft building footprints into two categories: small and large. The intention behind this was to reduce computational demands stemming from the sheer number of buildings while not losing spatial distribution of larger building footprints, which occurs when substituting building centroids for larger footprint polygons.

   Small buildings

   With our raster resolution of 30-m, a single pixel has an area of 900 m^2. Therefore, we identified building footprints with an area equal to or less than 900 m^2 as small buildings and mapped them with a single centroid point. We removed any points located on water or ice, as determined by the LANDFIRE FBFM40 dataset. We then summed footprint area for all remaining small building centroids within a pixel to obtain the footprint contribution from small buildings.

   Large buildings

   We defined large buildings as covering more than a single 30-m pixel, with an area greater than 900 m^2. We wanted to allocate building footprints appropriately for any given building footprint shape, but without committing to the high computational effort used to create the USGS building coverage data. To do so, we first converted the footprint polygon to a finer resolution raster of 10-m (100 m^2). If the centroid of any 10-m pixel intersected with a large building footprint, the pixel was assigned a value of 100 m^2. This 10-m raster was then aggregated to the desired 30-m resolution, summing the 10-m pixels to determine the footprint contribution from large buildings. Note that our water and ice raster (LANDFIRE FBFM40) had a 30-m resolution so rather than remove pixels for large buildings at the 10-m resolution we applied a mask during our moving window steps below to prevent placement of large buildings on water or ice.

2. *Generate the BuildingCover raster*

   To generate the BuildingCover raster, we first calculated the total building footprint for a given 30-m pixel by using the USGS total area where available (cover > 0), and otherwise using the sum of the small building footprint contribution and the large building footprint contribution. We then generated the smoothed BuildingCover raster using a three-step process:

   1. Calculate a 75-m radius moving-window sum of the combined 30-m building footprint area raster on habitable land cover (m^2);
   2. Calculate a 75-m radius moving-window sum of habitable land area (m^2);
   3. Divide the smoothed building-area raster produced in step 1 by the smoothed habitable land cover raster produced in step 2 to generate proportion of building coverage.

The moving window consists of 21 30-m pixels (a 5x5 matrix with the four corner cells omitted), which covers approximately 4.7 acres (1.9 ha). The final raster produced in step 3 represents the proportion of the habitable portion of that 4.7-acre moving window covered by building footprints.

Finally, we created the BuildingCover raster by multiplying the building cover proportion raster values by 100 to convert to percentages and rounding to the nearest integer (values less than or equal to 1 percent were set to zero).

Building Exposure Type (BuildingExposure)

BuildingExposure is a 30-m raster that characterizes the spatial coincidence of wildfire hazard with where housing units and buildings are located. The BuildingExposure raster delineates whether buildings at each pixel would be directly exposed to wildfire from adjacent wildland vegetation, indirectly exposed to wildfire from indirect sources such as embers and home-to-home ignition, or unlikely to be exposed to wildfire due to distance from direct and indirect ignition sources (> 1 mile). It is a companion to the Exposure Type raster included in Scott et al. (2020).

We created BuildingExposure from the Exposure Type raster in Scott et al. (2020). The methods used to create that Exposure Type raster across all lands included these general steps:

1. Set all pixels with burnable land cover in the LANDFIRE FBFM40 dataset to a value of 1;
2. Apply three iterative 510-m focal means to spread values into areas mapped with non-burnable fuels (i.e., communities);
3. Make adjustments for small patches of burnable vegetation within non-burnable areas (e.g., urban and suburban parks).

These methods are described in greater detail in the methods white paper included in supplemental files with Scott et al. (2020). To create the BuildingExposure raster, we assigned values from the Exposure Type raster only to pixels where either HUDen > 0 or BuildingCover > 0.

The values in the BuildingExposure raster range from 0 to 1. Where the underlying land cover is considered burnable, the value of the BuildingExposure is 1 indicating pixels where buildings would be directly exposed to wildfire. Where land cover is non-burnable urban, agricultural, or bare ground and the burn probability from Scott et al. (2020) is non-zero (i.e., within approximately 1 mile of a 500-ha contiguous area of burnable vegetation), buildings would be indirectly exposed to wildfire. The BuildingExposure value in these areas is between 0 and 1. Finally, where the land cover is non-burnable and the burn probability is zero, the value of the BuildingExposure is 0 indicating buildings with very little to no exposure. Pixels where both HUDen and BuildingCover are zero were set to NoData.

Housing Unit Exposure (HUExposure)

HUExposure is a 30-m raster that depicts the expected number of housing units within a pixel potentially exposed to wildfire in a year. This is a long-term annual average and not intended to represent the actual number of housing units exposed in any specific year. It is calculated as the product of wildfire likelihood and housing unit count. Pixels where the housing unit density raster is zero are NoData in the HUExposure raster.

We calculated HUExposure using the 30-m burn probability (BP) raster from Scott et al. (2020) and the HUDen raster. We first converted HUDen to a 30-m raster of housing unit count by multiplying density (HU/km^2) by 0.0009 (km^2/pixel) to get housing units per pixel. The equation for housing unit exposure, then, is simply:

$$HUExposure = HUCount * BP$$

Values of HUExposure are floating point decimal numbers that represent the annual average housing units exposed per pixel, over the 10,000+ annual simulation iterations (Short et al. 2020a). They provide a relative measure of the number of homes that could be exposed to wildfire.

Housing Unit Impact (HUImpact)

HUImpact is a 30-m raster that represents the relative potential impact of fire to housing units at any pixel, if a fire occurs there. It is an index that incorporates the general consequences of fire on a home as a function of fire intensity and uses flame length probabilities from wildfire modeling to capture likely intensity of fire. HUImpact does not include the likelihood of fire occurring, and it does not reflect mitigations done to individual structures that would influence susceptibility. It is conceptually similar to Conditional Risk to Potential Structures (cRPS) in Scott et al. (2020), but also incorporates housing unit count and exposure type. Specific steps in calculating HUImpact are described below.

1. *Create a conditional housing unit risk (cHURisk) raster*

   To create cHURisk, we took the cRPS raster from Scott et al. (2020) and multiplied it by the housing unit count raster created in the process of calculating HUExposure (see description above). The cHURisk raster represents the potential consequences of fire to housing units at a given location, if a fire occurs there. A central component of cRPS, and subsequently cHURisk, is a response function that represents the generalized susceptibility of structures to being damaged by wildfire of different intensities. For the six fire intensity levels (FILs) from Short et al. (2020a), these response function values were: 25, 40, 55, 70, 85, and 100 for FIL1 through FIL6 respectively. A value of 0 means no damage to a structure, and a value of 100 means complete loss.

2. *Generate the HUImpact raster*

   We calculate HUImpact with the following equation:

   $$HUImpact = cHURisk * BuildingExposure$$

   Where buildings are directly exposed to wildfire, the value of BuildingExposure is 1 and cHURisk values are unchanged. Where buildings are indirectly exposed to wildfire, the value of BuildingExposure is between 0 and 1, so HUImpact is reduced with increasing distance from areas of direct exposure.

   To produce the final integer version of the HUImpact raster, we multiplied by 1,000,000 and rounded to the nearest integer. Pixels where the housing unit density raster is zero are NoData in the HUImpact raster.

It is important to note that by using a consistent response function for all homes, we assume that all homes are equally susceptible to wildfire. In reality, an individual home's ability to survive wildfire is driven largely by local conditions that can be highly affected by a homeowner's or community's efforts toward mitigating wildfire susceptibility. The condition of vegetation in the immediate area around a home (known as the "Home Ignition Zone") and the construction materials used in building a home (Quarles et al. 2010) could result in very different response function values for individual homes (Cohen 2019). Consideration of this local variation in susceptibility is well beyond the scope of the Wildfire Risk to Communities project, and HUImpact should be considered a landscape metric rather than specific to any one home.

Housing Unit Risk (HURisk)

HURisk is a 30-m raster that integrates all four primary elements of wildfire risk - likelihood, intensity, susceptibility, and exposure - on pixels where housing unit density is greater than zero. It is an index with similarities to Risk to Potential Structures (RPS) in Scott et al. (2020), but it also incorporates housing unit count.

We calculated the HURisk raster at 30-m resolution by multiplying the 30-m cHURisk raster (representing the intensity, susceptibility, and exposure components of risk) by the 30-m BP raster from Scott et al. (2020)(representing wildfire likelihood). HURisk is analogous to the expected Net Value Change (eNVC) metric presented by Scott et al. (2013), if the only highly-valued resource or asset is housing units. The equation for HURisk is simply:

$$HURisk = cHURisk * BP$$

To produce the final integer version of the HURisk raster, we multiplied by 1,000,000 and rounded to the nearest integer. Pixels where the housing unit density raster is zero are NoData in the HURisk raster.

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