CONTEMPORARY WILDFIRE HAZARD ACROSS NEW JERSEY

PREPARED FOR:
New Jersey Forest Fire Service

PREPARED BY:
Kevin C. Vogler, Julie W. Gilbertson-Day,
Julia H. Olszewski, Chris Moran, Joe H. Scott

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PYROLOGIX

NEW JERSEY FOREST FIRE SERVICE
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1 EXECUTIVE SUMMARY

In March 2022, Pyrologix was contracted by Timmons Group and the New Jersey Forest Fire Service to conduct a wildfire hazard assessment for the state of New Jersey. This project is part of the New Jersey Wildfire Hazard Assessment Project (NJHAZ). This effort involved three primary tasks: calibrating and updating the fuelscape, producing measures of burn probability and simulated fire perimeters, and conducting wildfire intensity modeling with measures of integrated wildfire hazard.

We leveraged an existing fuelscape, developed for the Eastern Region Wildfire Risk Assessment, as a starting point for the NJHAZ project. In that effort, feedback on fuel mapping from fuel and fire behavior specialists across the Eastern Region, including New Jersey, was implemented to calibrate the fuelscape to produce expected fire behavior results. To customize that fuelscape for the New Jersey-specific hazard assessment, we held a fuel review workshop and modified the fuelscape according to the feedback received.

Pyrologix used the updated fuelscape to simulate wildfires with the comprehensive US Forest Service fire modeling system called FSim. The product generated from this modeling is an estimate of annual burn probability across New Jersey. FSim also produced an "event set," that can be used in transmission analysis to tie wildfire risk or damage to the origin of simulated wildfires. Pyrologix also produced potential wildfire behavior characteristics using FlamMap, another US Forest Service fire modeling system.

These simulations of wildfire hazard (likelihood and intensity) were used to calculate indices of integrated hazard, including Suppression Difficulty Index, and Wildfire Hazard Potential. Pyrologix also calculated measures of wildfire risk to homes using the flame-length probabilities (i.e., Risk to Potential Structures), as well as calculations of ember exposure of homes (i.e., Structure Exposure Score, Damage Potential, and Sources of Ember Load to Buildings). These products are discussed in greater detail in the sections that follow.

1.1 PURPOSE OF HAZARD MODELING

The purpose of the New Jersey Wildfire Hazard Assessment is to provide foundational information about wildfire hazard across all land ownerships within the state of New Jersey. The foundation of any wildfire assessment is the wildfire hazard data used to characterize fire behavior on the landscape. To manage wildfire in New Jersey, it is essential that accurate and high-resolution wildfire hazard data, to the greatest degree possible, is available to drive fire management strategies. These hazard outputs can be used to inform the planning, prioritization, and implementation of prevention and mitigation activities such as prescribed fire and mechanical fuel treatments. In addition, the hazard data can be used to support fire operations and aid in decision-making for the allocation and positioning of firefighting resources.

In the quantitative framework for assessing wildfire risk to highly valued resources and assets (Scott et al. 2013) wildfire hazard is defined as a physical situation with the potential for causing damage to vulnerable resources or assets. Wildfire hazard is measured by two main factors in this risk assessment framework: 1) burn probability (or likelihood of burning), and 2) fire intensity (measured as flame length, fireline intensity, or other similar measures). Figure 1 below depicts how measurements of wildfire hazard fit into the larger quantitative wildfire risk assessment framework.

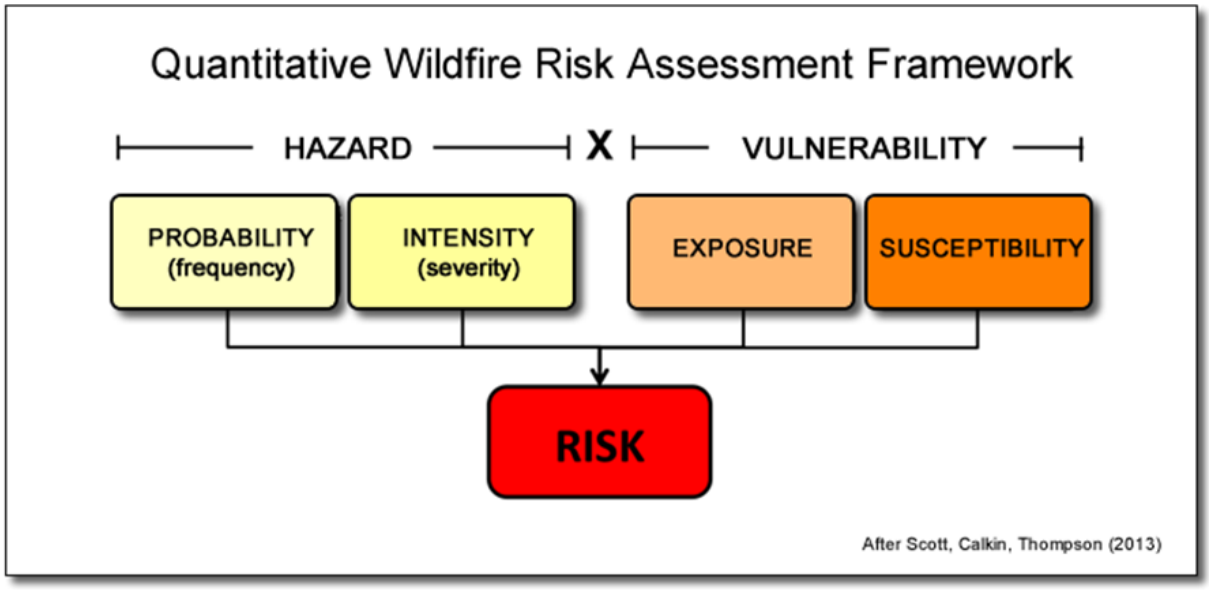

Figure 1. The components of the Quantitative Wildfire Risk Assessment Framework.

2 WILDFIRE LIKELIHOOD

2.1 OVERVIEW OF METHODS

2.1.1 FSIM

The FSim large-fire simulator was used to quantify wildfire likelihood across the assessment area at a pixel size of 90 meters. FSim is a comprehensive fire occurrence, growth, behavior, and suppression simulation system that uses locally relevant fuel, weather, topography, and historical fire occurrence information to make a spatially resolved estimate of the contemporary likelihood and intensity of wildfire across the landscape (Finney et al. 2011).

FSim focuses on the relatively small fraction of wildfires that escape initial attack and become "large" (>10 acres). Since the occurrence of large fires is relatively rare, FSim generates many thousands of years of simulations to capture a sample size large enough to generate burn probabilities for the entire landscape. An FSim iteration spans one entire year. The Fire Occurrence Areas (FOAs) in the NJHAZ project area was run with 30,000 iterations.

There is no temporal component to FSim beyond a single wildfire season consisting of up to 365 days. FSim performs independent (and varying) iterations of one year, defined by the fuel, weather, topography, and wildfire occurrence inputs provided. FSim does not account for a simulated wildfire's potential influence on the likelihood or intensity of future wildfires (even within the same simulation year). Each year represents an independent realization of how fires might burn given the current fuelscape and historical weather conditions. FSim integrates all simulated iterations into a probabilistic representation of wildfire likelihood.

In addition to estimates of wildfire likelihood, FSim produces measurements of predicted wildfire intensities. Due to the inherent challenges of estimating intensity with a stochastic simulator, estimates of fire intensity were instead developed using a custom Pyrologix utility called WildEST (Scott 2020). WildEST is a deterministic wildfire modeling tool that integrates spatially continuous weather input variables, weighted based on how they will likely be realized on the landscape. This makes the deterministic intensity values developed with WildEST more robust than the stochastic intensity values developed with FSim. This is especially true in low wildfire occurrence areas where predicted intensity values from FSim are reliant on a very small sample size of potential weather variables. The WildEST methodology is further described in section 3.

2.2 LANDSCAPE ZONES

The project boundaries used in NJHAZ are described below in sections 2.2.1 - 2.2.3 and are shown in Figure 2. Project boundaries were developed to avoid introducing artificial data artifacts (seamlines) during FSim modeling.

2.2.1 ANALYSIS AREA

The Analysis Area (AA) is the area for which valid burn probability results are produced. The Analysis Area for the project was defined as a 5-kilometer buffer on the state boundary (Figure 2) with the exception of the western edge of the state where the boundary is the Delaware river.

2.2.2 FIRE OCCURRENCE AREAS

To ensure valid Burn Probability (BP) results in the AA and prevent artificial reduction in BP near the AA boundary edge, it is necessary to allow FSim to start fires outside of the AA and burn into it. This larger area where simulated fires are started is called the Fire Occurrence Area (FOA). We established the FOA extent as a 5-km buffer on the AA. The buffer provides sufficient area to ensure all fires that could reach the AA are simulated. The Fire Occurrence Area covers roughly 5.8 million acres. For consistency with other FSim projects, we numbered the FOA boundary FOA 234.

2.2.3 FUELSCAPE EXTENT

The available fuelscape extent was delineated by adding a 5-km buffer to the FOA extent. This buffer allows fires starting within the FOA to grow unhindered by the edge of the fuelscape, which would otherwise truncate fire growth and affect the simulated fire-size distribution, potentially introducing errors in the calibration process. A map of the AA, FOA boundaries, and fuelscape extent are presented in Figure 1.

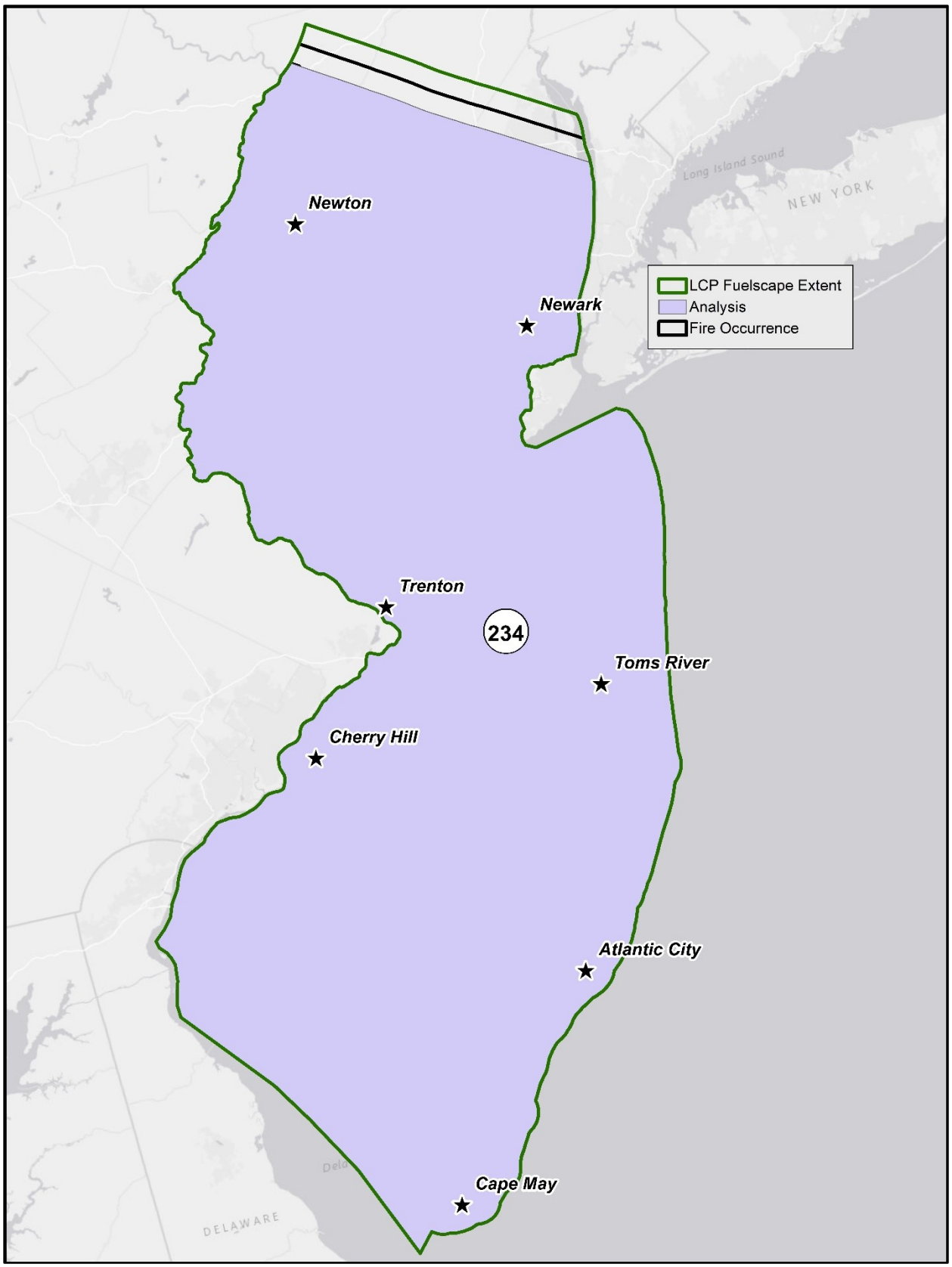

Figure 2. Overview of landscape zones for the FSim modeling.

2.3 ANALYSIS METHODS AND INPUT DATA

The FSim large-fire simulation system requires inputs characterizing the landscape, historical weather, and information about historical fires. Figure 3 below provides a graphical depiction of the various FSim inputs discussed further in sections 2.3.1 - 2.3.3

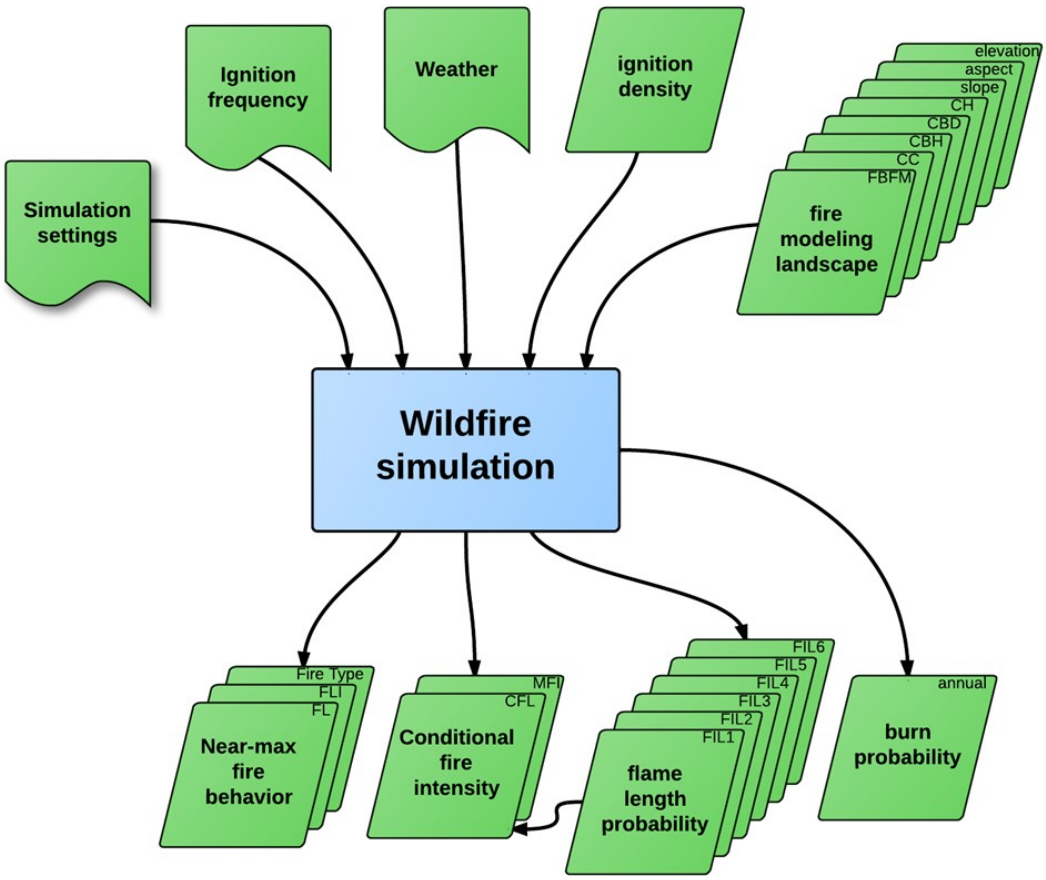

Figure 3. Diagram showing the primary elements used to derive burn probability.

2.3.1 FUELSCAPE

The foundation of any wildfire hazard assessment is a current condition fuelscape, calibrated to reflect the fire behavior potential realized in recent historical wildfire events. The Eastern Region Wildfire Risk Assessment (ERRA) fuelscape, based on LANDFIRE Remap (LF 2.0.0) data, was leveraged to generate the fuel inputs of this calibrated fuelscape. LANDFIRE 2.2.0 topography layers (slope, aspect, and elevation) were used in place of LF Remap topographic data to take advantage of recent corrections in the aspect calculation from true north. A report describing the methods used to produce the ERRA fuelscape is available online for further information[1].

[1] ERRA Fuelscape report: http://pyrologix.com/reports/ERRA_FuelscapeReport.pdf

The fuelscape consists of geospatial datasets representing surface fuel models (FM40), canopy cover (CC), canopy height (CH), canopy bulk density (CBD), canopy base height (CBH), and topography characteristics (slope, aspect, elevation). The fuelscape datasets were combined into a single landscape (LCP) file that was used as an input to fire modeling programs.

We held a fuelscape review workshop with New Jersey Forest Fire Service staff on May 26, 2022, to discuss the fuel adjustments needed. In general, the ERRA fuelscape provided a solid starting point, with only a few areas highlighted for further refinement. These topics are highlighted in the following sections.

2.3.1.1 PHRAGMITES

We received feedback from workshop participants that areas containing the grass Phragmites spp., mapped as fuel model GR8, required further refinement to produce the expected fire behavior results. The overall comment echoed by fuelscape reviewers was to shift burn probability (BP) and flame lengths away from coastal phragmites and toward the Pine Barrens region. After exploring fuel mapping options, we ultimately converted all GR8 fuel models (used to represent phragmites grasses) to GR6 and verified the fire behavior would produce desirable results. Additionally, the rate of spread in FSim was reduced by 1/3 to mimic the impacts of limited fuel availability in phragmites.

2.3.1.2 PINE BARRENS

The fuelscape reviewers noted a mismapping of an Existing Vegetation Type (EVT) in the Pine Barrens area. The ERRA fuel mapping rule for EVT 2456 (representing the Northern Atlantic Coastal Plain Pitch Pine Lowland vegetation) used a grass fuel model (GR5) with no canopy and TL2/TL6 with canopy characteristics to represent areas that reviewers claimed should exhibit the same fire behavior as the adjacent, pine barrens EVT (EVT 2355 - Northern Atlantic Coastal Plain Pitch Pine Barrens). We explored fire behavior modeling results and ultimately implement SH9 in place of the GR5 and changed fuel models TL2 and TL6 to SH8 with a canopy overstory to produce more active fire behavior and generate the potential for crown fire.

2.3.1.3 FUEL REGENERATION IN FIRE SCARS

Fuelscape reviewers observed that select past fire scars were incorrectly mapped with grass or grass-shrub fuel models when the fuel on the ground had substantial pitch-pine regeneration – nearly to the point of fully recovered. To address these issues, we converted pixels [incorrectly] mapped as EVT 2319 (Atlantic Coastal Plain Northern Bog) and within a historical fire perimeter (MTBS year before 2015) to fuel model SH8. We also used BpS code 1848 (Northern Atlantic Coastal Plain Pitch Pine Barrens) to change 'Recently burned' EVTs from a grass to a shrub fuel model (SH8 or SH9).

Further detail on the NJHAZ-specific fuelscape edits was provided as part of the fuelscape data deliverables. A map of the final fuel model groups across the fuelscape is shown in Figure 4.

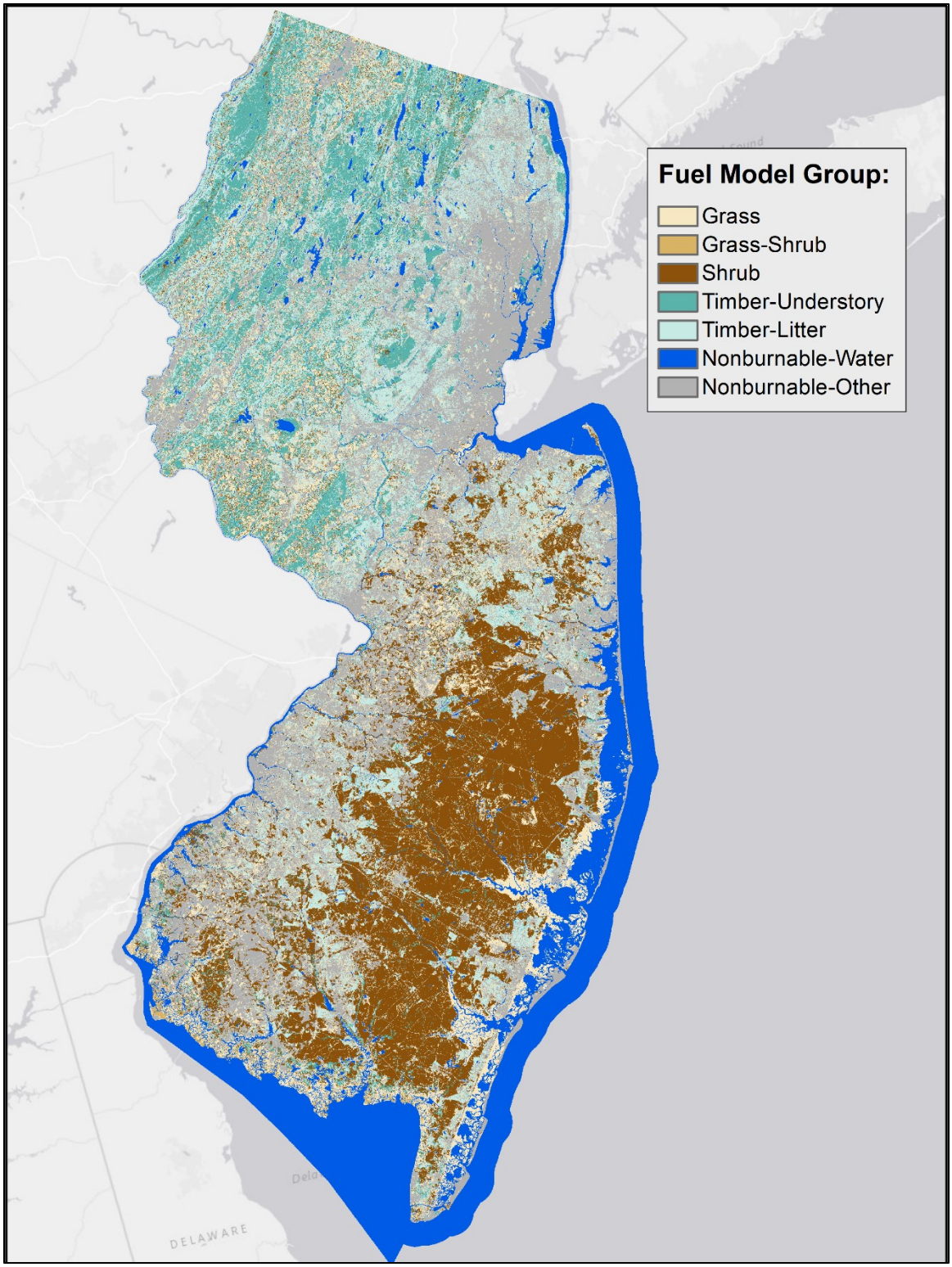

Figure 4. Map of fuel model groups across the New Jersey fuelscape extent.

2.3.2 HISTORICAL WILDFIRE OCCURRENCE

The Fire Occurrence Database (FOD), which spans 29 years from 1992-2020, was used to quantify historical large-fire occurrence (Short 2021). A pre-release version of the FOD data (Short, personal communication) was used to develop model inputs (the fire-day distribution file [FDist] and ignition density grid [IDG]) as well as model calibration targets. Table 1 provides a summary of the annual number of large fires per million acres, mean large-fire size, and annual area burned by large fires per million acres for the NJ Fire Occurrence Area (Figure 1). To calculate historical calibration targets in FSim, we defined a large fire as greater than 10 acres.

Table 1. Historical large-fire occurrence, 1992-2020, in the NJHAZ FOAs.

FOA	Mean annual number of large fires	FOA area (M ac)	Mean annual number of large fires per M ac	Mean large-fire size (ac)	Mean annual large-fire area burned (ac)
234	18.6	5.75	3.23	300	5,580

2.3.2.1 IGNITION DENSITY GRID

FSim uses a geospatial layer called the Ignition Density Grid (IDG) to represent the relative large-fire ignition density. FSim stochastically places wildfires according to the IDG, thereby accounting for the spatial variability in historical wildfire occurrence. The entire landscape is saturated with wildfire over 30,000 simulated iterations, but more ignitions are simulated in areas that have previously experienced large-fire development.

The Ignition Density Grid (IDG) was generated using the ArcGIS Kernel Density tool with a 25-km search radius and a 90-m cell size. Kernel density output from the FOD point layer was divided by kernel density output from a point layer representing burnable fuels. All fires equal to or larger than 10 acres reported in the FOD were used as inputs. A map of the IDG can be seen in Figure 5. The IDG enables FSim to produce a spatial pattern of large-fire occurrence consistent with what was observed historically.

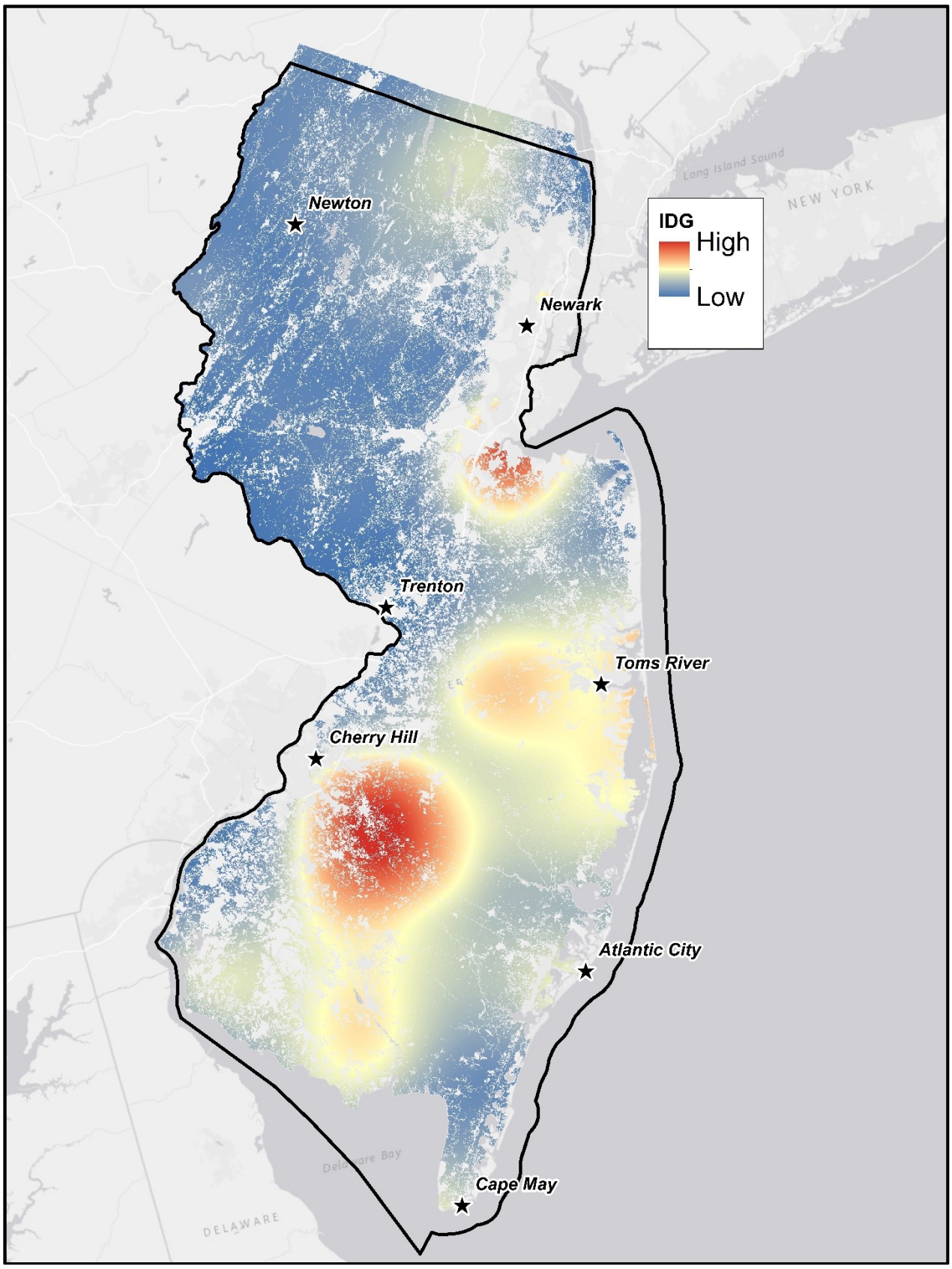

Figure 5. Ignition Density Grid for the NJHAZ Fire Occurrence Area.

2.3.3 HISTORICAL WEATHER

FSim requires two weather-related inputs: monthly distribution of wind speed and direction and seasonal trend (daily) in the mean and standard deviation of ERC-G. We used two data sources for these weather inputs. For the wind speed and direction distributions, we used the hourly (1200 to 2000 hours), 10-minute average values (2 mi/h calm wind), recorded at the selected Remote Automatic Weather Station (RAWS). A station with a relatively long and consistent record and moderate wind activity was selected to produce the most stable FSim results.

Energy Release Component (ERC) values were extracted from gridMET 4-km weather grids. This nationally available dataset provides values that are not influenced by periods of RAWS inactivity outside of the fire season. The RAWS station selected for winds and the ERC sample site are shown in Figure 6 and Table 2 and discussed further in the following sections.

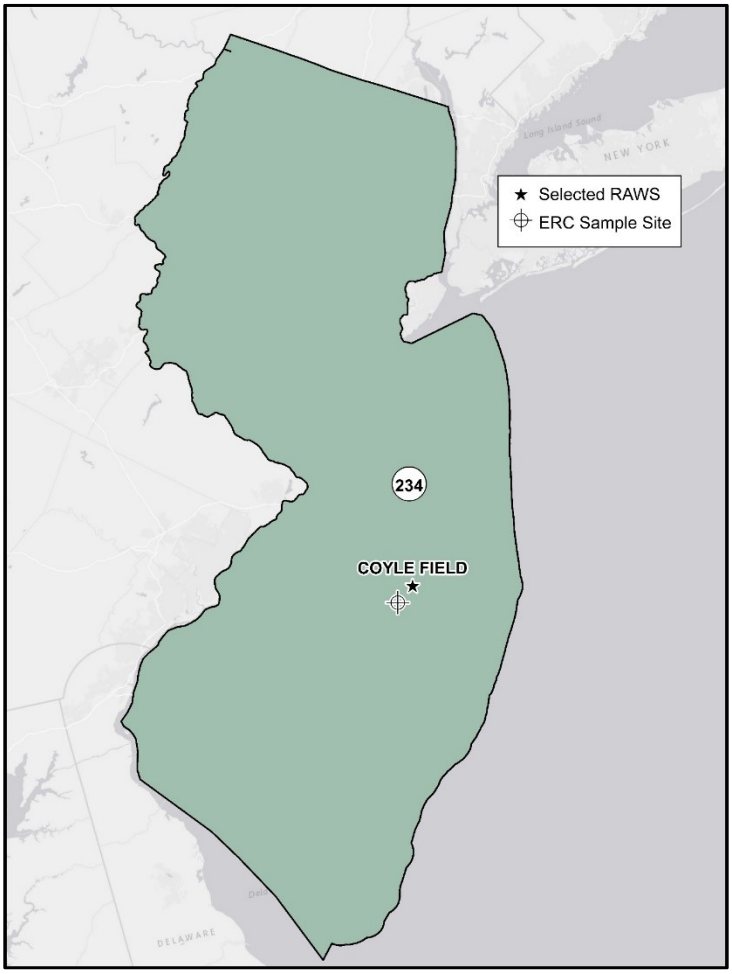

Figure 6. Map of the RAWS and ERC sample points that were used for the New Jersey FSim project. Selected RAWS data were used to generate hourly sustained wind speed and direction distributions.

Table 2. Selected RAWS for the NJ Fire Occurrence Area.

FOA	Station ID	Station Name
234	280051	Coyle Field

2.3.3.1 FIRE-DAY DISTRIBUTION FILE (FDIST)

Fire-day Distribution files are used by FSim to generate stochastic fire ignitions based on the historical relationship between large fires and ERC. The FDist files were generated using a custom FSim auxiliary software utility that summarizes historical ERC and wildfire occurrence data, performs logistic regression, and then outputs the results in the required FDist format.

The FDist file provides FSim with logistic regression coefficients that predict the likelihood of a large fire occurrence as a function of ERC and tabulates the distribution of large fires by large-fire day. A large-fire day is a day when at least one large fire occurred historically. The logistic regression coefficients together describe large-fire day likelihood *P(LFD)* at a given ERC(G) as follows:

$$P(LFD) = \frac{1}{1 + e^{-B_a * - B_b * ERC(G)}}$$

Coefficient *a* describes the likelihood of a large fire at the lowest ERCs, and coefficient *b* determines the relative difference in the likelihood of a large fire at lower versus higher ERC values.

2.3.3.2 FIRE RISK FILE (FRISK)

Fire risk files were generated using a custom FSim auxiliary software utility and updated to incorporate simulated ERC percentiles and the grid convergence angle. These files summarize the historical ERC stream for the FOA, along with wind speed and direction data for the selected RAWS.

2.3.3.3 FUEL MOISTURE FILE (FMS)

Modeled fire behavior is robust to minor changes in dead fuel moisture, so a standardized set of stylized FMS input files (representing the 80th, 90th, and 97th percentile conditions) for 1-,10-, 100-hour, live herbaceous, and live woody fuels was developed (Table 3).

Table 3. Fuel Moisture values used in wildfire simulation for the 80th/90th/97th percentile ERCs.

Fuel Model Group	1-hr	10-hr	100-hr	Live-Herb	Live-Woody
Grass / Shrub	8 / 7 / 6	9 / 8 /78	10 / 9 /8	90 / 65 / 45	110 / 100 / 90
Timber / Slash	10/ 9 /8	11 / 10 / 9	12 / 11 / 10	90 / 65 / 45	110 / 100 / 90

2.3.3.4 ENERGY RELEASE COMPONENT FILE (ERC)

We sampled a time series of historical ERC-G values in the FOA from the 4-km resolution, gridMET historical dataset (Abatzoglou 2013). Historical ERC-G grid values were extracted for the years 1979-2020 and historical fire occurrence data were available from 1992-2020. We used the overlapping years of 1992-2020 to develop a logistic regression of the probability of a large-fire day (>10 acres) as a function of ERC.

Historical ERCs were sampled at an advantageous location within the FOA based on the highest density of historical large fires. These historical ERC values were used in conjunction with the FOD to generate FSim's FDist input file, but not to generate the FRisk file. ERC percentile information in

the FRisk file was generated from the simulated ERC stream, described below. This approach ensures consistency between the simulated and historical ERCs. For the simulated ERCs in FSim, we implemented the feature of FSim that allows the user to supply a stream of ERC values for the FOA. We generated 1,000 years of daily ERC values sampled from the gridMET ERC dataset.

2.4 WILDFIRE SIMULATION

The FSim large-fire simulator was used to quantify wildfire hazard across the landscape at a pixel size of 90 m (2 acres per pixel). For the FOA, we parameterized and calibrated FSim based on the mean large-fire size and number of fires from the last 15 years of the FOD period (2006 – 2020). We then used FSim to start fires only within the FOA but allowed those fires to spread outside of the FOA. This is consistent with how the historical record is compiled.

2.4.1 MODEL CALIBRATION

FSim simulations for the FOA were calibrated to the FOD mean from the last 15 years of the FOD period (2006 – 2020). FSim was calibrated such that the simulated annual number of large fires was within 10% of mean annual number of large fires, and the mean annual large-fire area burned. Additionally, care was taken to verify that simulated wildfire size distributions matched the historical record and allow for the occurrence of simulated fires larger than any observed historically. While only large-fire sizes (>10 acres) were considered in calibration, numerous small fires were also simulated. However, the impact of small fires on landscape-level burn probability is typically negligible.

To calibrate the FOA, we started with baseline inputs and a starting rate-of-spread adjustment (ADJ) factor file informed by experience on previous projects. The final simulation was completed at 90-m resolution with 30,000 iterations. The final model input files and settings can be seen in Table 4.

Table 4. Summary of final-run inputs for the FOA.

Final run	Iterations	ADJ file	Trimming factor	FRisk	FDist file	LCP file
234r7	30,000	Foa234r7	3.0	foa_234_Weibull_PMF	FOA_234_v3	FOA_234_90v1_lcp

2.5 WILDFIRE MODELING RESULTS

The FSim model produces estimates of burn probability as well as measures of fire intensity including flame length probabilities and mean fireline intensity. While FSim does generate measures of wildfire intensity, the WildEST-derived intensity estimates (described below in section 2.5.1) are more reliable than those generated stochastically within FSim. The WildEST intensity values were used in all calculated effects analyses. The FSim model generated 90-m resolution estimates of burn probability. These results were further downscaled to 30-m resolution to match the WildEST intensity resolution using a methodology described in section 2.5.1. Burn probability results are presented in Figure 7.

2.5.1 UPSAMPLING FSIM RESULTS

FSim's stochastic simulation approach can be computationally intensive and therefore time-constraining on large landscapes. A challenge is to determine a resolution sufficiently fine to retain detail in fuel and terrain features yet produce calibrated results in a reasonable timeframe. Additionally, Highly Valued Resources and Assets (HVRA) are often mapped at the same resolution as the final burn probability (BP) produced by FSim. To enable greater resolution on HVRA mapping and match the native resolution of WildEST results, we chose to upsample the FSim BP rasters to 30 m.

We upsampled the FSim BP raster using a multi-step process. First, we used the ESRI ArcGIS Focal Statistics tool to perform two rectangular, low-pass filters at the 90-m resolution, calculating the mean value of burnable pixels only, within a 3-pixel by 3-pixel moving window. These steps allowed us to "backfill" burnable pixels at 30 m that were coincident with nonburnable fuel at 90 m. We subsequently resampled the resulting BP raster to 30 m using bilinear resampling. If burnable pixels had BP values of zero after running two low-pass filters, we set a threshold value of 1-in-10,000 (0.001) to avoid assigning zero probability values to burnable pixels that had some burning potential.

The intent of smoothing burn probability values from nearby burnable fuel onto adjacent nonburnable pixels is to capture the low likelihood, but high consequence event of an urban conflagration or wildfire that results in significant home loss in developed, urban areas. Without accounting for any potential burnability in developed areas, simulated wildfires would stop at the edge of burnable fuel. To address this issue, we smooth probabilities from adjacent wildlands within a specified distance as described below.

Before running the smoothing steps, we masked the 30 m resampled raster to burnable pixels only. Additionally, we removed BP values from small, burnable islands less than 500 ha. The purpose of removing nonburnable fuel and small burnable islands is to prevent smoothing from these pixels and, to prevent golf courses and urban parks from spreading wildfires to nearby homes.

The resulting resampled raster was then smoothed again using the ESRI ArcGIS Focal Statistics tool to perform three low-pass filters at a 30-m resolution, allowing for spread from burnable pixels to nearby nonburnable pixels. Each focal smoothing operation incrementally reduces burn probability by including zero values from nonburnable pixels (other than water and ice) in the focal mean calculation. This reduces burn probability on nonburnable fuel relative to the burnable fuel nearby. The 900-m smoothing distance is consistent with work by Caggiano et al. (2020) showing that all home losses to wildfire from 2000 to 2018 were within 850 m of wildland vegetation.

One additional step was applied in the upsampling process to address a smoothing artifact in areas with fragmented, burnable fuel. We stamped the 30-m bilinearly resampled raster (produced in the first step) back on top of the raster resulting from the three smoothing steps; retaining the smoothed values only where no BP value was present in the original 30-m raster. The final burn probability raster resulting from the upsampling process is presented in Figure 7.

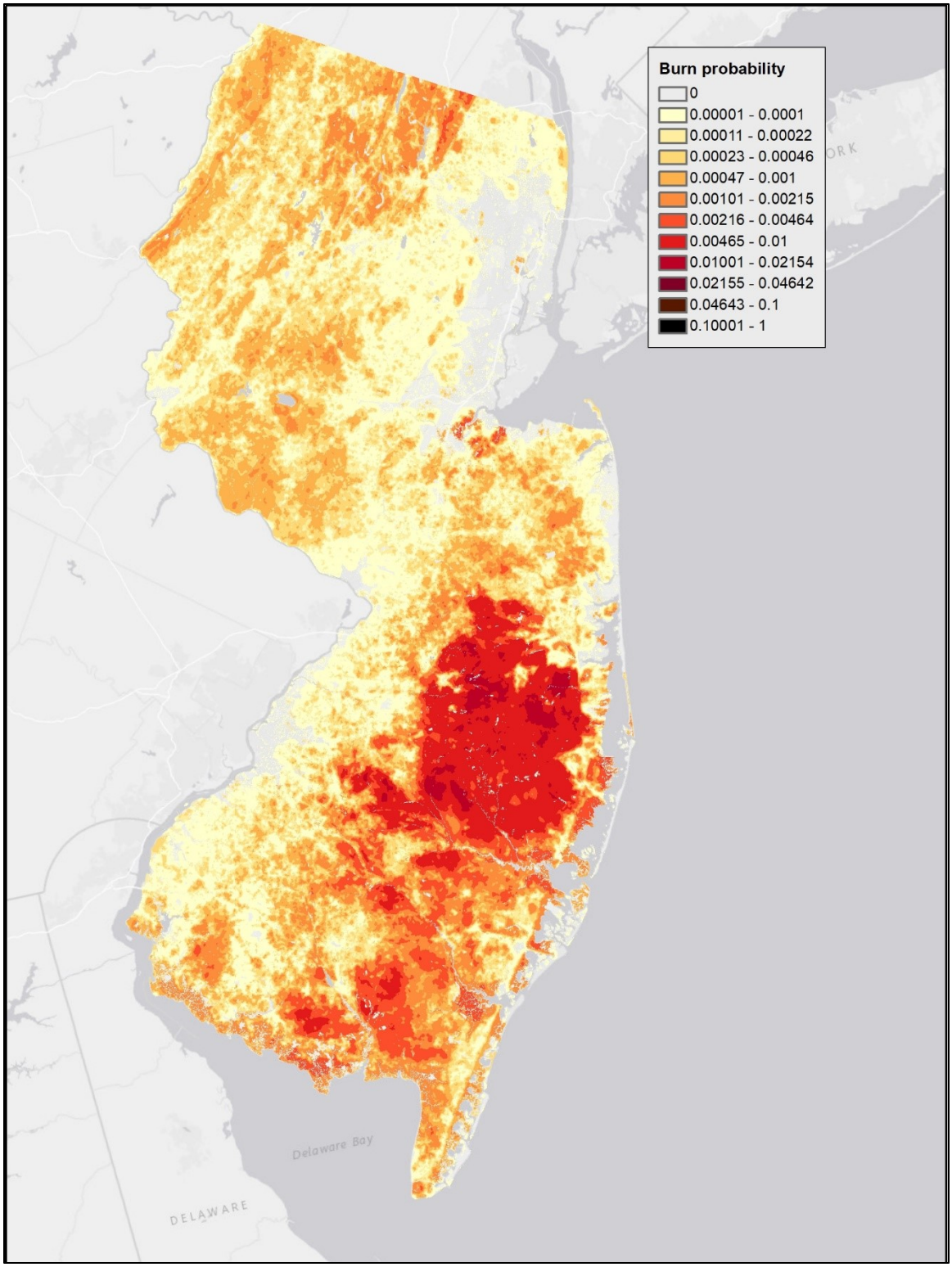

Figure 7. Map of integrated FSim burn probability results for the NJHAZ analysis area at 30-m resolution.

3 WILDFIRE BEHAVIOR CHARACTERISTICS

3.1 OVERVIEW OF METHODS

To estimate wildfire characteristics in NJHAZ, we used a scripted geospatial modeling process called WildEST. WildEST uses the command-line version of FlamMap to perform 216 basic deterministic simulations of fire behavior characteristics for a range of weather types (combinations of wind speed and fuel moisture content). Additionally, we integrate the dead fuel moisture conditioning feature of FlamMap, so dead fuel moisture content is sensitive to canopy cover and topography (slope, aspect, and elevation). We also use pre-calculated Wind Ninja grids representing terrain-adapted wind speed and direction. These grids were generated at 120-m resolution and then upsampled to 30-m resolution before use in FlamMap.

Rather than weighting the 216 results solely according to the temporal relative frequencies (TRFs) of the weather types, the WildEST process integrates results by weighting them according to their weather type probabilities (WTP), which gives higher weight to high-spread conditions in the calculations. The process of developing the WTP rasters is described in section 3.1.2 below.

The majority of WildEST results apply to the head of the fire. However, for use in fire-effects calculations, WildEST also generates Flame-Length Probability rasters (FLPs) that incorporate non-heading spread directions (Scott 2020a), which have considerably lower fire intensity than the head fire. These "fire-effects FLPs" or “Net Value Change (NVC) FLPs" are analogous to FLP rasters produced by FSim.

We use the weather type probability (WTP) weighting process in WildEST to produce head-fire characteristics rasters (e.g., mean flame length), fire-type probability rasters, ember characteristics rasters, and non-heading characteristics rasters (for use in an effects analysis). Together, these rasters are useful for mapping the fire behavior that characterizes each pixel on the landscape. Each output is described in the following sections 3.2.1 - 3.2.5.

3.1.1 FSIM VERSUS WILDEST

Our use of command-line FlamMap in WildEST for this landscape-scale wildfire hazard assessment is a departure from what has been standard practice for USFS wildfire risk assessments that use FSim. Typically, such wildfire hazard assessments have used FSim for both the wildfire likelihood (burn probability) and wildfire intensity (flame-length probability) components of the assessment. Pyrologix developed the WildEST process to address a few shortcomings present when using FSim for fire intensity results.

3.1.1.1 SPATIAL RESOLUTION

The spatial resolution (grid cell size) is limited to the resolution used for the main FSim fire occurrence modeling. For national-scale projects the resolution is 270-m; landscape-scale projects are at 120-m or 90-m. FSim cannot use 30-m resolution due to excessive run time. In contrast,

WildEST does not contain this limitation and can produce results at a 30-m resolution on large landscapes.

3.1.1.2 MODEL TYPE

FSim is a Monte Carlo simulator, so the fire intensity results it produces are limited to 1) the mean fireline intensity of simulated fires that burned each grid cell, and 2) the conditional probability that flame length will be in each of six flame-length classes, called Fire Intensity Levels (FILs). In FSim, flame length always accounts for the effect of relative spread direction (heading, flanking, backing). Because the flame-length probabilities (FLPs) are determined by tallying the relative fraction of times a grid cell burned in each FIL[2], they suffer from a problem of low sample size, especially in places where BP is low. For example, where BP is 1-in-500 (0.002), a pixel would burn 20 times over 10,000 iterations. The flame length of those 20 fires is tallied into six flame-length bins. That is a small sample size to provide a stable estimate of the true flame-length probabilities. Running FSim a second time could generate vastly different FLPs for the same pixel.

WildEST is deterministic, so it does not suffer from a Monte Carlo simulator's sample-size problem. Additionally, WildEST can be used to generate both head-fire and non-heading fire intensity results.

3.1.1.3 FIRE CHARACTERISTICS PRODUCED

FSim produces only two measures of fire intensity for each simulation: conditional flame length (CFL) and flame-length probability (FLP) for six Fire Intensity Levels.

In contrast, we use WildEST to generate a wide array of fire characteristics, including the rate of spread, heat per unit area, type of fire, crown fraction burned, and maximum ember travel distance. These additional fire characteristics allow the calculation of additional measures of wildfire hazard, including ember production and ember load, and Suppression Difficulty Index.

3.1.1.4 SPATIAL PRECISION OF WEATHER DATA

FSim is limited to using just one stream of weather for a large area (millions of acres). FSim does not support dead fuel moisture conditioning, which accounts for the effects of elevation, canopy cover, slope steepness, and of aspect on dead fuel moisture content. Additionally, FSim has limited support for applying terrain-adapted winds using WindNinja.

WildEST uses gridded historical weather data at a spatial resolution of 4 km for NJHAZ. We use both fuel moisture conditioning and WindNinja at 30-m resolution to produce continuously variable fire characteristics results, free of seamlines due to weather inputs.

3.1.1.5 TOPOLOGY EFFECTS

One advantage of FSim is that it inherently accounts for any effects of fire spread topology[3] on fire intensity. For example, the land on the lee side of a large nonburnable feature (such as a lake) is less

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[2] The Fire Intensity Levels (FILs) reported by FSim are: 0-2 ft, 2-4 ft, 4-6 ft, 6-8 ft, 8-12 ft, and >12 ft for FILs 1-6, respectively.

[3] Fire spread topology is the network of possible fire spread pathways given the fire environment.

likely than other parts of the landscape to experience a head-fire, because a heading fire cannot spread across the lake. Instead, a fire must flank past or around this location, resulting in lower fire intensity. This topology effect is pronounced for short-duration fires or when there is a single fire-carrying wind direction. If fire can be carried across the landscape in multiple directions, the topology effect is smaller.

WildEST cannot address such topological effects. Each location is evaluated using only the fuel, weather, and topography at the location, with no consideration for adjacent nonburnable features that could potentially reduce intensity by reducing the potential for heading spread.

3.1.2 WEATHER-TYPE PROBABILITY RASTERS

Weather type probabilities (WTPs) are a set of weighting factors derived from the integration of the frequency weather types and the observed spread potential within each of these types. Each day in the 2000-2021 gridMet dataset is classified to one of 216 weather types created from the unique combination of eight wind directions, nine wind speeds, and three fuel moisture classes. A spread potential index for each day is also estimated through a combination of temperature, humidity, wind speed, large-fire probability, and energy release component (ERC). Each raster in the delivered set of 216 rasters represents the fraction of the total spread potential within each weather type for a given 4-km pixel. WTPs are primarily used in the WildEST process for weighting fire behavior characteristics.

We used a bias-corrected, 4-km gridded daily weather dataset derived from gridMET historical weather (Abatzoglou 2013) for the 22-year period 2000-2021 to derive weather type probabilities used to weight the fire characteristics in the WildEST process. The gridMET dataset provides daily wind speed grids but contains bias on annual timescales relative to other national products with finer spatial resolutions. We corrected this bias using the National Renewable Energy Laboratory (NREL) annual average wind speed dataset (Draxl et al. 2015) by deriving a daily correction factor from the overlapping time periods of the two datasets (2007-2013).

The area burned index (ABI), calculated for each day in the 2000-2021 timeframe as follows:

$$ABI = SPI * WS^2 * BurnMinutes * LFP$$

where SPI is the Schroeder Probability of Ignition (Schroeder 1969), a function of temperature and fine fuel moisture content, WS is the open wind speed in mi/h, burn minutes is defined from a lookup table (Table 5) as a function of wind speed and daily energy release component (ERC) percentiles, and LFP is the large fire probability as a function of daily ERC.

Table 5. Burn minutes table for calculating area burned index (ABI).

Wind Speed Bin (mi/h)	ERC < 80th percentile	ERC 80-90th percentile	ERC 90-97th percentile	ERC >= 97th percentile
0-3	30	30	30	30
3-8	30	30	60	120
8-13	30	60	120	180
13-18	60	120	180	240
18-23	120	180	240	300
23-28	180	240	300	450
28-33	240	300	450	600
33-38	300	450	600	600
>= 38	450	600	600	600

The large fire probability (LFP) is determined by logistic regressions derived from observed large fires within a pre-release version (Short, personal communication) of the USFS fire occurrence database (FOD; Short 2021) and the corresponding gridMET ERCs. A 150-km moving window was used to select nearby large fire observations and separate logistic regressions were developed for each 4-km pixel. We also normalized for the burnable area in the 150-km window by dividing the large-fire probability by the fraction of burnable area to prevent bias due to coastlines and other areas with less burnable land. We defined 216 unique weather scenarios based on wind speed, wind direction, and moisture content. The weather parameters associated with each ABI value were binned according to the reported weather conditions for a given day, which define the 216 weather types.

There are nine wind speed bins:

0-3, 3-8, 8-13, 13-18, 18-23, 23-28, 28-33, 33-38, and >= 38 mi/h

There are eight wind direction bins:

337.5-22.5, 22.5-67.5, 67.5-112.5, 112.5-157.5, 157.5-202.5, 202.5-247.5, 247.5-292.5, 292.5-337.5^0

And three equilibrium moisture content bins:

<4, 4-6, and 6-12%

The ABI values were then summed within a weather-scenario bin and divided by the total ABI for all weather scenarios for a given 4-km pixel – thereby collapsing the daily ABI values across 20 years into 216 weather-type probability (WTP) rasters as fractions of the total ABI. These fractions were smoothed and upsampled to 30-m resolution using a 3x3 weighted sum at 4-km, with bilinear resampling to snap to the 30-m fuel model raster. The percentage rasters were renormalized once more after upsampling to 30-m to ensure the WTPs summed to one across all weather types in each 30-m pixel. Note that if the equilibrium fuel moisture content was above 12 percent, then the ABI values for those conditions were not included in the sums.

3.2 FLAME FRONT CHARACTERISTICS

The WildEST flame front characteristics include head-fire rate of spread and head-fire flame length, as well as conditional probabilities for fire type and operational control exceedance probabilities. These characteristics are described below in sections 3.2.1 - 3.2.5. WildEST also produces "fire-effects" flame-length probabilities, which are calculated in a way that incorporates non-heading spread directions (section 3.2.5). Great care was taken to eliminate artificial data artifacts (seamlines) in the fuelscape and the WTPs. As a result, the head-fire characteristics rasters are also free of such artifacts.

3.2.1 RATE OF SPREAD (ROS)

Rate of spread (ROS) is the weighted-average rate of spread in meters per minute for a given pixel in the fuelscape, including any contribution of crown fire spread rate under a given weather type (Figure 9). Weighted ROS is calculated as the sum-product of 216 ROS rasters and their corresponding WTPs.

3.2.2 FLAME LENGTH (FL)

Flame length is the weighted-average flame length in feet for a given pixel in the fuelscape, including any contribution of crown fire under a given weather type (Figure 10). Weighted FL is calculated as the sum-product of 216 FL rasters and their corresponding WTPs.

3.2.3 FIRE-TYPE PROBABILITY (FTP)

Fire-type probability rasters indicate the conditional probability that a given pixel will experience a certain type of fire. At a given pixel, the sum of fire-type probabilities equals 1 (100 percent). The FTPs indicate the range of fire types that can be produced by the fire environment and their relative prevalence.

We define seven fire types (Table 6). The non-fuel "fire type" is assigned to pixels that do not have burnable fuel in the fuelscape and therefore do not experience any type of fire. The possible raster values for non-fuel probability are either 0 (burnable fuel is present) or 1 (the pixel is nonburnable). Similarly, the surface fire type is assigned to pixels with burnable fuel but without forest canopy present. In these cases, surface fire is the only possibility. We distinguish this type from an underburn because the latter indicates that crowning was possible, but not achieved. The raster value for this fire-type probability is 1 if the pixel is burnable but does not have a canopy or 0 for all other cases.

The remaining five fire types require a pixel to have 1) a burnable surface fuel model and 2) a tree canopy present, representing the possibility of a crown fire under some conditions. Raster probability values range from 0 to 1. Crown fire types are commonly classified as either passive or active. But passive crown fire represents a large range of crowning behavior from a single tree torching up to nearly continuous large-group torching. We, therefore, divided passive crown fire into three sub-classes based on the crown fraction burned (CFB) estimated for the fire environment. Crown fraction burned represents the fraction of the canopy fuel contributing to the overall rate of spread and intensity.

Table 6. The WildEST Type of Fire classification.

Type of fire	Burnable land cover?	Forest canopy present?	Crown Fraction Burned (%)
Non-fuel	No		-
Surface	Yes	No	-
Underburn	Yes	Yes	0
Low-grade passive	Yes	Yes	0<CFB<25
Mid-grade passive	Yes	Yes	25<CFB<60
High-grade passive	Yes	Yes	60<CFB<90
Active	Yes	Yes	90<CFB

The fire-type rasters are additive for a given pixel, with the sum of all seven fire-type rasters for a given pixel equaling one. The seven fire-type probabilities are shown in Figure 11.

3.2.4 PROBABILITY OF OPERATIONAL CONTROL

Operational-control probability rasters indicate the probability that the head-fire flame length in each pixel will exceed a defined threshold for a certain type of operational control. The three levels of control are manual control, mechanical control, and extreme fire behavior. We estimate these probabilities by summing the WTP values for all weather types for which head-fire FL exceeds the threshold value.

Manual control is generally considered to have a threshold of 4 feet during wildfire operations. Therefore, the probability of exceeding manual control raster displays the likelihood of exceeding 4-foot heading flame lengths.

Similarly, mechanical control is generally considered to have a threshold of 8 feet, and the probability raster displays the likelihood of exceeding 8-foot heading flame lengths. Extreme fire behavior utilizes the general threshold of exceeding 11-foot flame lengths.

This information could be used as a supplement to the Suppression Difficulty Index when planning wildfire suppression operations for a given area of the landscape. The operational control probabilities are shown in Figure 12.

3.2.5 "FIRE-EFFECTS" FLAME-LENGTH PROBABILITIES

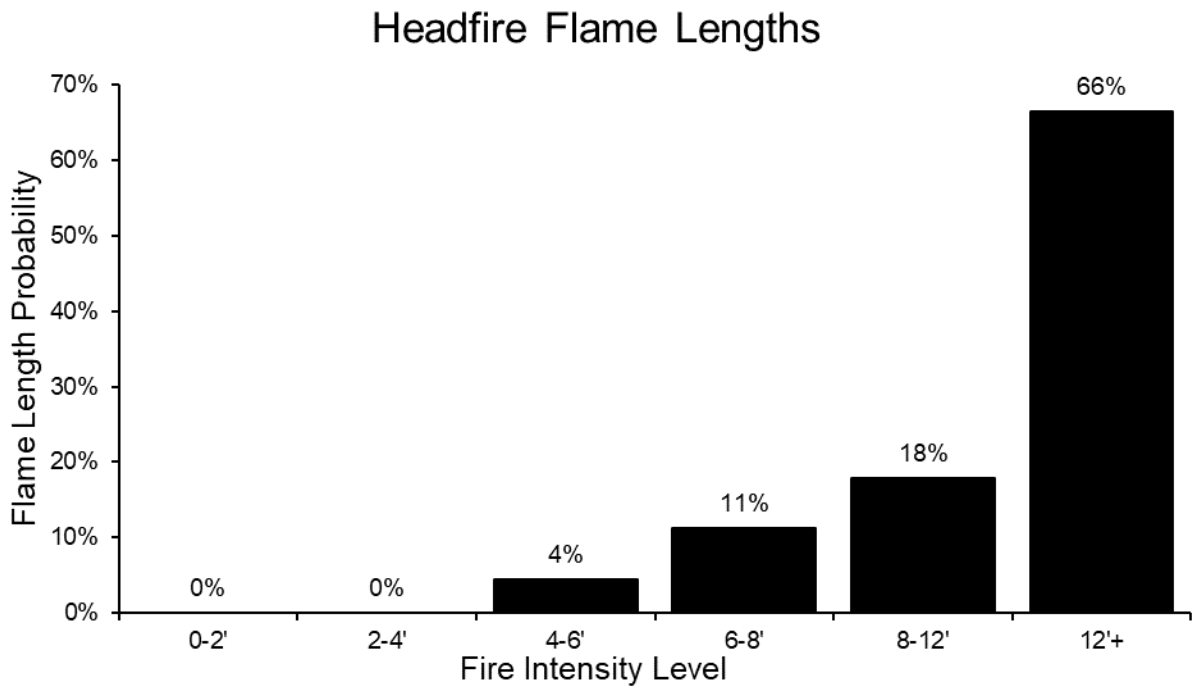
All the WildEST results described thus far apply to the head of a fire, but a free-burning wildfire spreads in all directions and therefore exhibits a range of flanking and backing behavior in addition to heading behavior. Flanking and backing fires exhibit a lower spread rate and intensity than at the head of a fire (Catchpole et al. 1982; Catchpole et al. 1992) FSim and other stochastic wildfire simulators inherently capture non-heading fire spread and intensity. The deterministic approach we use in WildEST inherently captures only head-fire spread and intensity, so we apply adjustments to head-fire intensity based on the geometry of an assumed fire spread ellipse (Scott 2020).

The FLP differences between heading and non-heading FLPs are illustrated in Figure 8, which is an example fuel complex at a single pixel consisting of surface fire behavior fuel model TU5, with a

canopy base height of 0.3 m and a canopy bulk density of 0.11 kg/m^3. For that fuel complex (and for the climatology of that location), we estimate that head-fire flame length will exceed 12 feet 66 percent of the time the pixel burns, and never produce flame lengths less than 4 feet. After accounting for flanking and backing behavior, we estimate flame length will exceed 12 feet only 42 percent of the time and will be lower than 4 feet 5 percent of the time.

The WildEST non-heading characteristics include non-heading FLPs, which we call "fire-effects" FLPs because they are designed for use in an Effects Analysis in a landscape wildfire risk assessment as described in USFS GTR-315 (Scott et al. 2013). These fire-effects FLPs are a close analog to FSim's FLPs and are used for the same purpose.

We compare head-fire flame length probabilities with non-head-fire flame length probabilities for a single pixel. Fire-effects flame-length probabilities are shown in Figure 13.



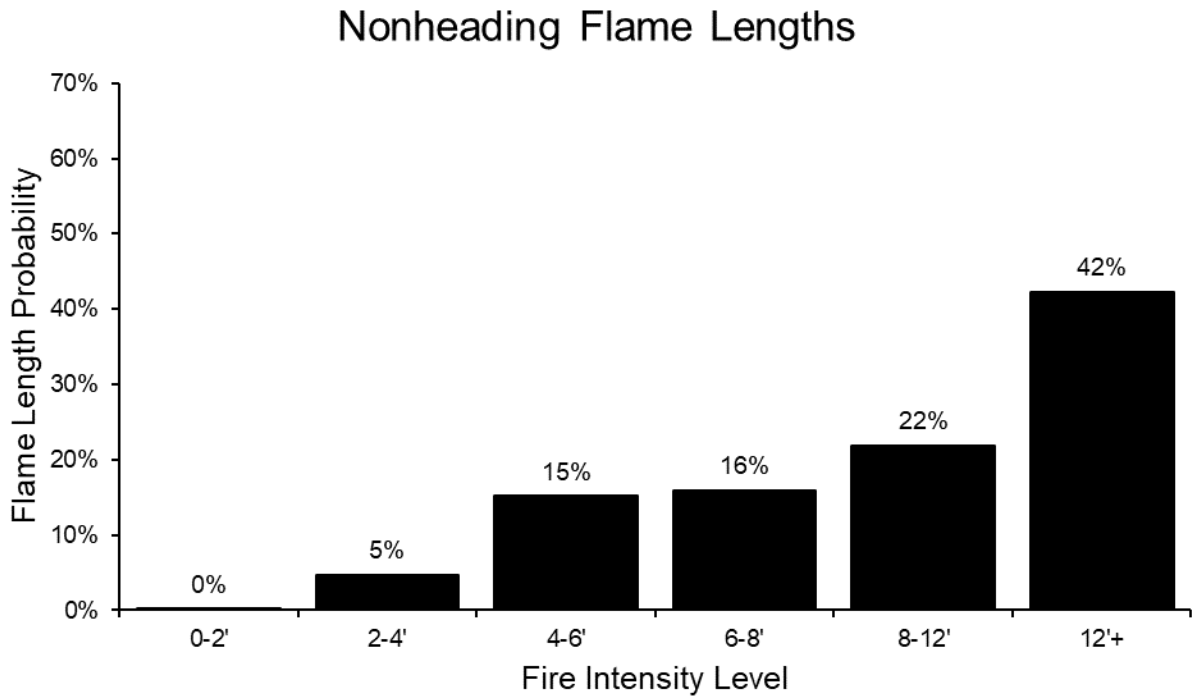


Figure 8. Head-fire flame-length probabilities (top) and non-heading (or "fire effects") flame-length probabilities (bottom) for a single pixel.

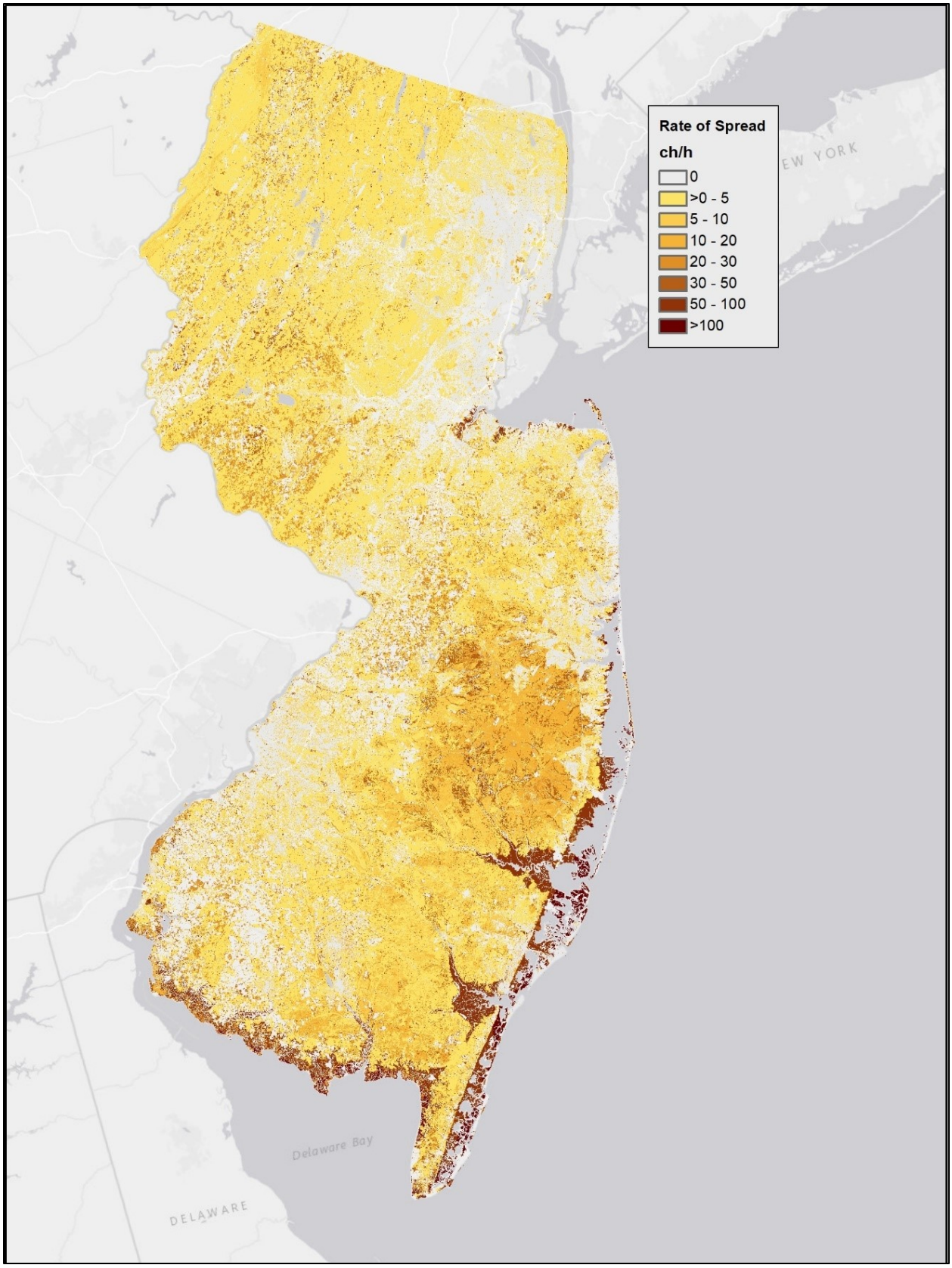


Figure 9. Map of WildEST 30-m Rate of Spread (m/min) for the NJHAZ analysis area.

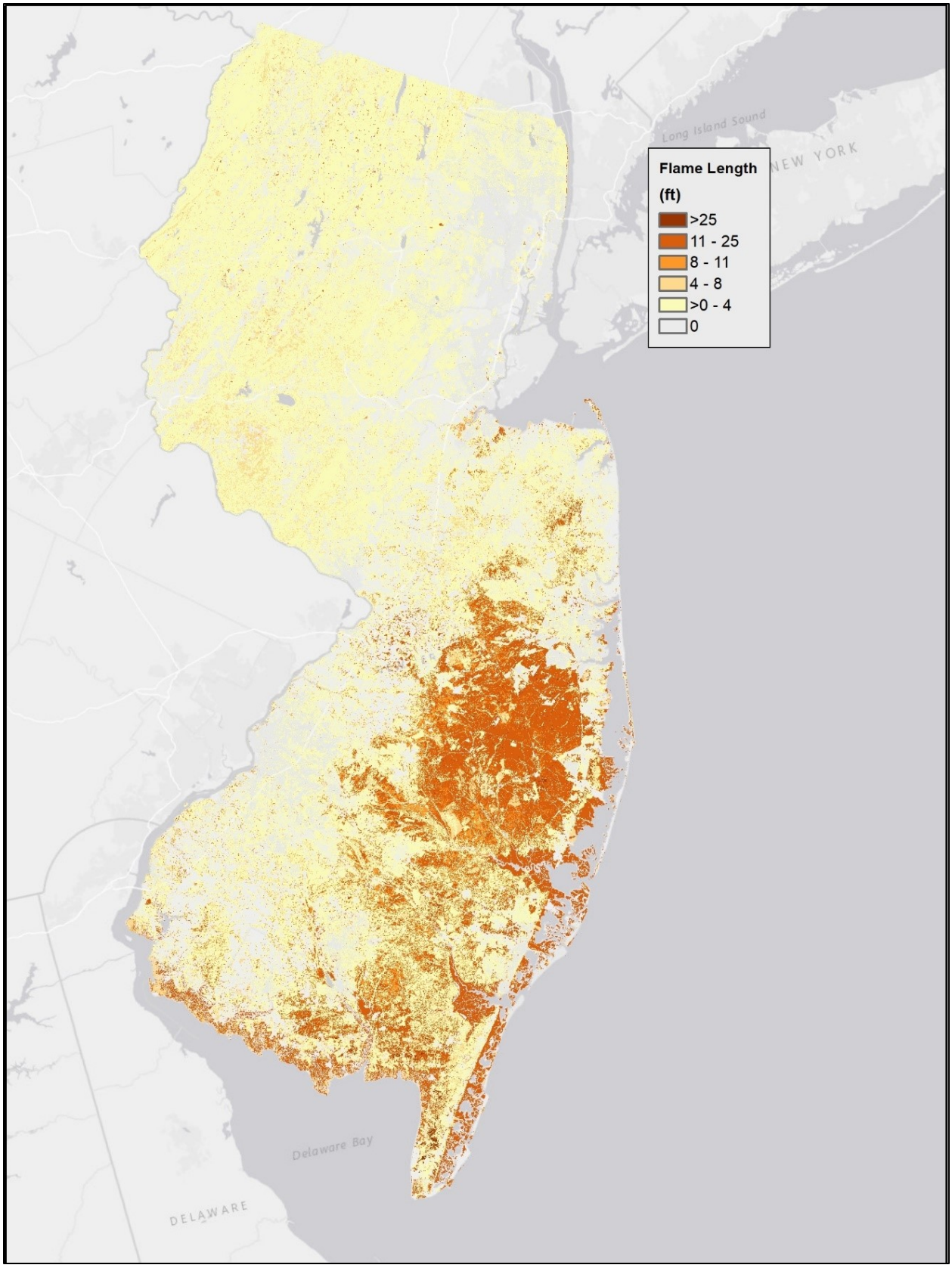


Figure 10. Map of WildEST 30-m Mean Flame Length (ft) for the NJHAZ analysis area.

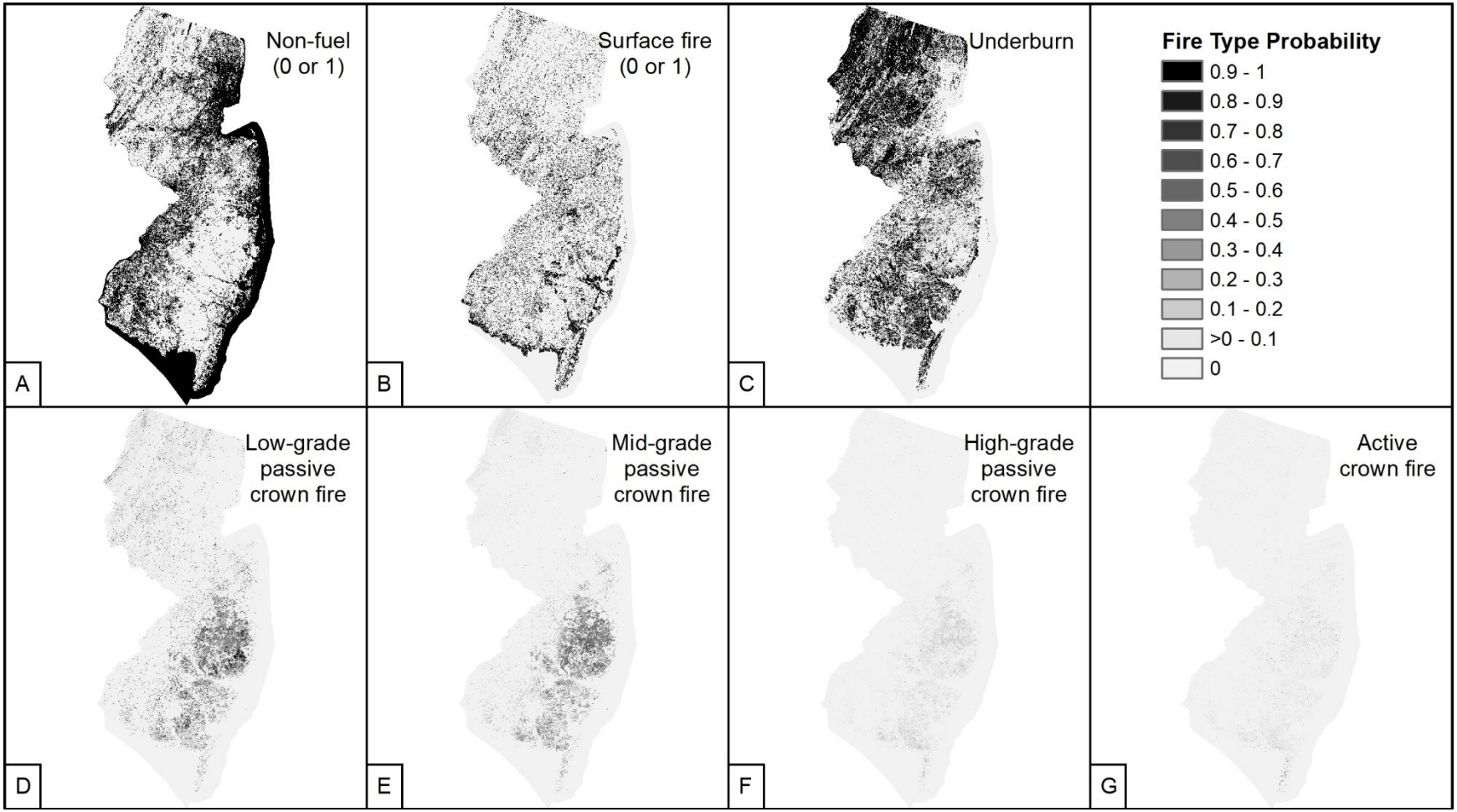


Figure 11. Map of WildEST 30-m Fire Type Probabilities for the NJHAZ analysis area. These include (A) non-fuel, (B) surface, (C) underburn, (D) low-grade passive crown fire, (E) mid-grade passive crown fire, (F) high-grade passive crown fire, and (G) active crown fire. Probabilities range in value from 0 to 1, with (A) and (B) being binary rasters of only values 0 and 1.

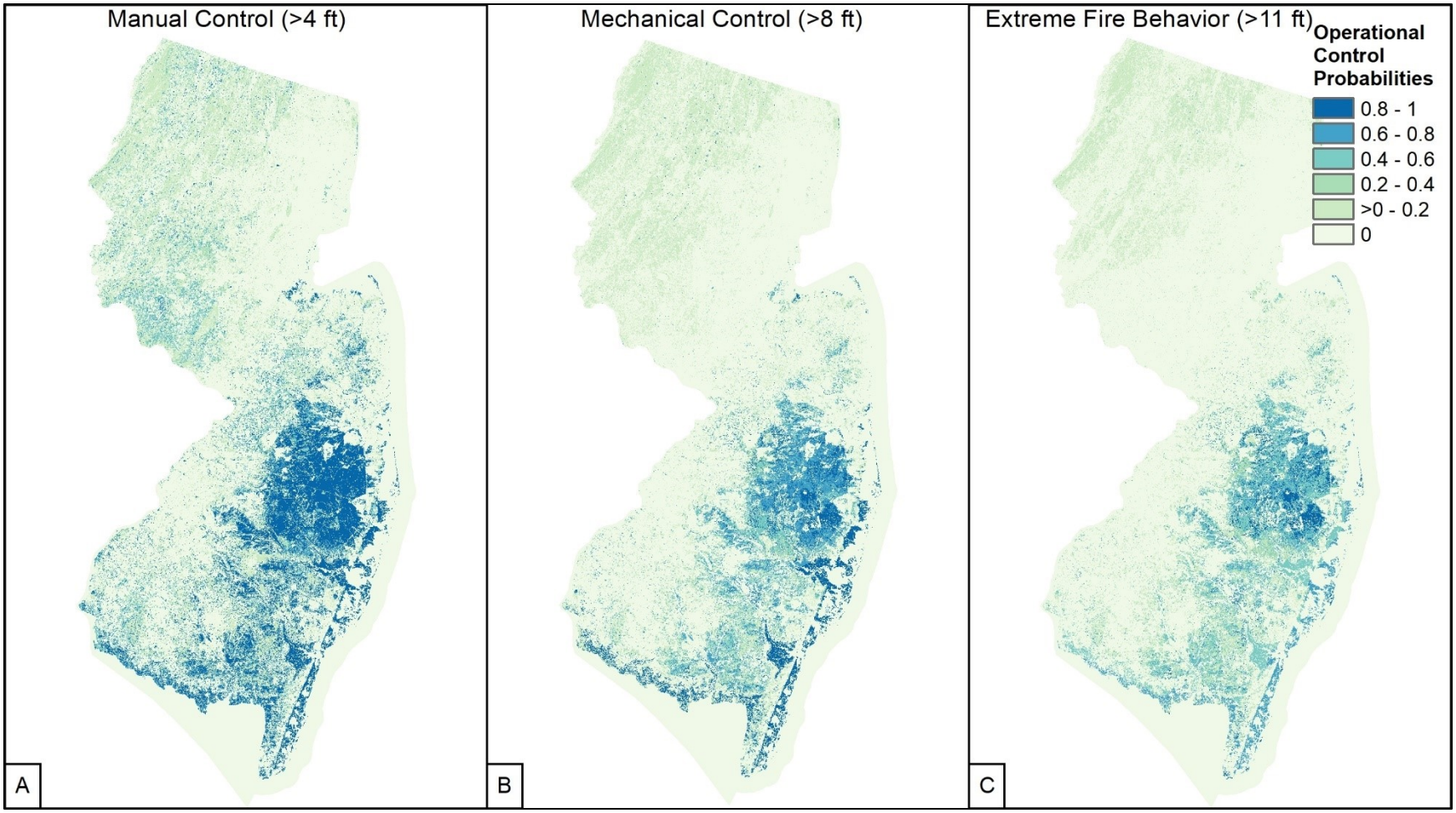


Figure 12. Map of WildEST 30-m Operation Control Probabilities for the NJHAZ analysis area.

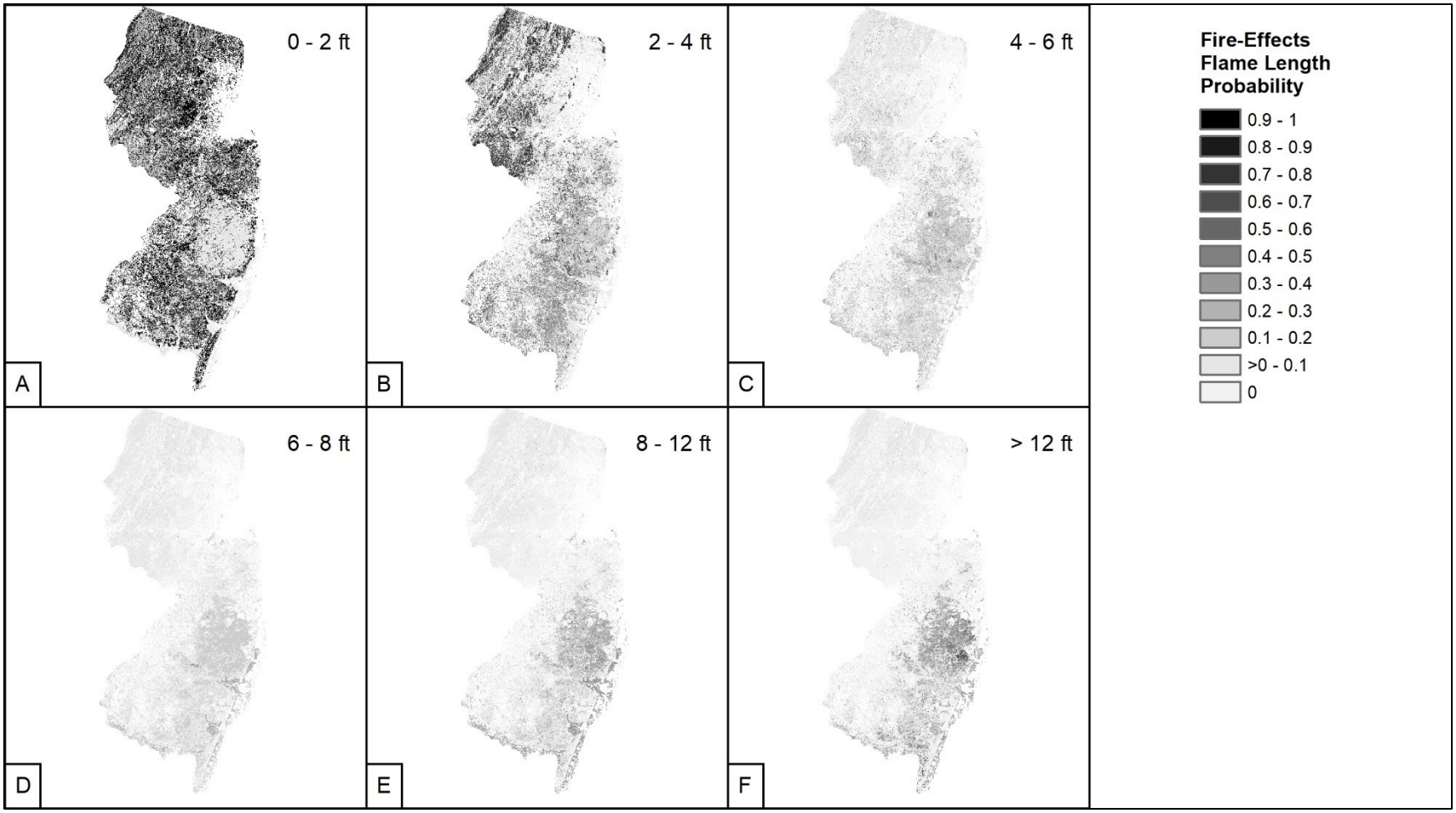


Figure 13. Map of WildEST 30-m fire-effects FLPs for the NJHAZ wildfire hazard analysis area. Panels A-F shows the FLP for the fire-effects flame-length bin specified. The sum of panels A-F for any given pixel equals one.

3.3 EMBER CHARACTERISTICS

The WildEST modeling contains a module for producing indices of conditional and expected ember production and load. The Conditional Ember Production Index (cEPI) is an index of the relative number of embers lofted at a given landscape pixel if a fire were to occur. Ember Production Index (EPI) is the expected value of cEPI; it is the expected annual relative number of embers lofted from a given landscape pixel. The Conditional Ember Load Index (cELI) is a relative index of the relative number of embers that land at a given landscape location, including nonburnable pixels. Finally, Ember Load Index combines the conditional ELI and the likelihood of that ember load occurring. All ember characteristics are based on head-fire behavior.

The Conditional Sources of Ember Load to Buildings (cSELB) is a relative index of the number of embers lofted that eventually land on a pixel with building cover (if a fire were to occur). Sources of Ember Load to Buildings (SELB) is the expected value of cSELB; it is an index of the expected annual number of embers that land on pixels with building cover. We used the nationally available BuildingCover (Scott et al. 2020) dataset produced by the Wildfire Risk to Communities project to identify pixels with building cover. The BuildingCover dataset was built from Microsoft building footprints. These are described below in sections 3.3.1 - 3.4.5.

3.3.1 EMBER PRODUCTION INDEX

The Conditional Ember Production Index (cEPI) represents the relative number of embers produced at a pixel as a function of the fire environment. Being "conditional", cEPI does not account for variation in burn probability across the landscape (Figure 14, A). The expected ember production index (EPI) is calculated by multiplying cEPI and burn probability (BP):

$$EPI = cEPI * BP$$

Given that EPI does incorporate burn probability, this index can help identify both the likelihood of areas being visited by fire and their potential for producing embers—information that is useful for fuel treatment prioritization to reduce ember production (Figure 14, B).

3.3.2 EMBER LOAD INDEX

The ember load indices represent the relative ember load at a pixel. Similar to ember production, ember load is also based on surface and canopy fuel characteristics, climate, and topography at the pixel. Ember load incorporates downwind ember travel. The conditional Ember Load Index (cELI) does not account for burn probability and can be used to identify where on the landscape hardening buildings to resist ember ignition may be needed (Figure 14, C).

The Ember Load Index (ELI) incorporates burn probability; however, ELI is not simply the multiplication of condition ember load (cELI) and burn probability (BP). Rather, BP is incorporated into calculations of the ember production before the distribution of embers across the landscape to determine ember load. Given that ELI incorporates burn probability, this index can be used to identify where on the landscape hardening buildings may be needed to resist ignition and the priority for doing so according to the likelihood of the area being visited by fire (Figure 14, D).

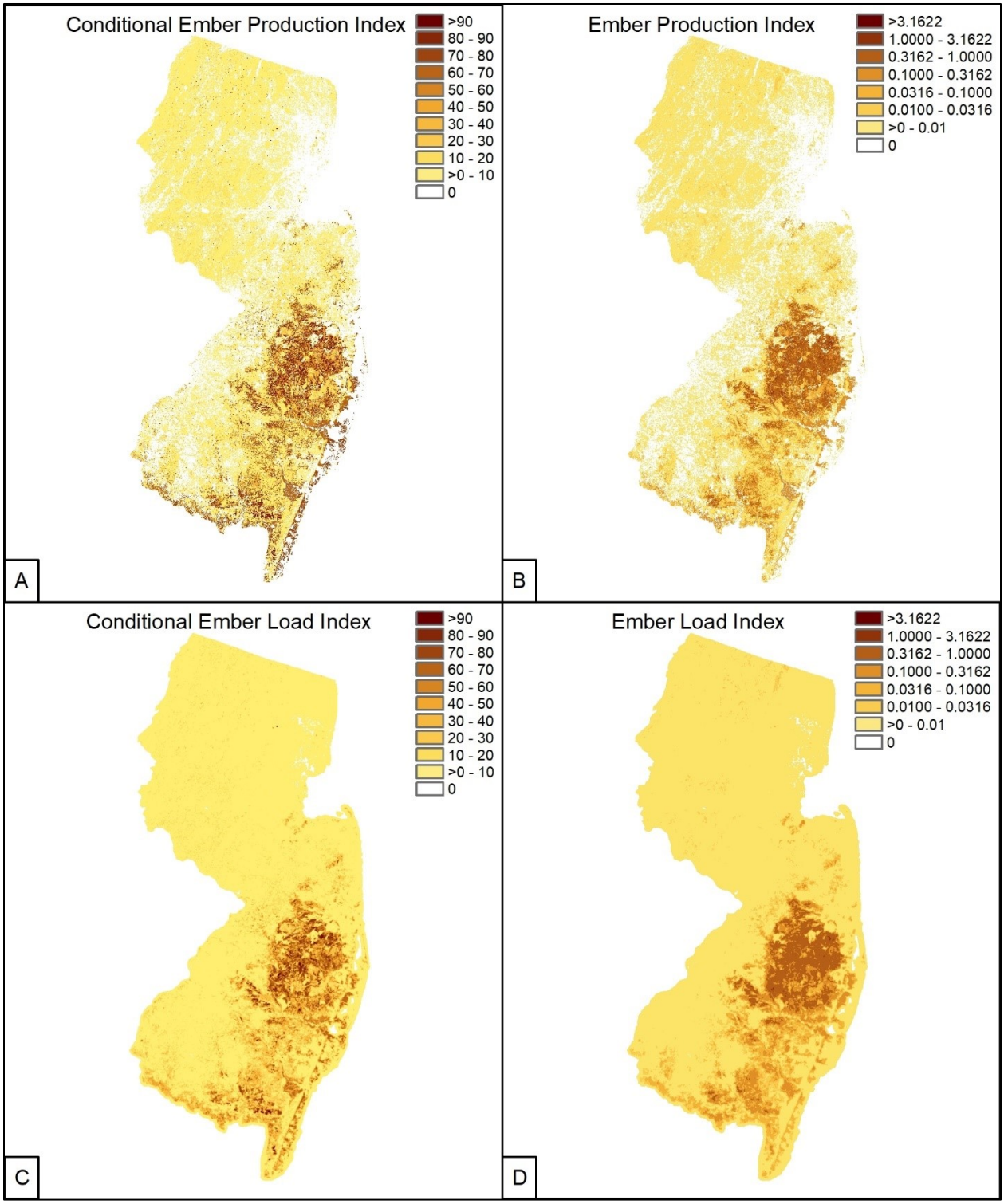


Figure 14. Map of WildEST 30-m ember indices for the NJHAZ analysis area. These include (A) conditional Ember Production Index, (B) Ember Production Index, (C) conditional Ember Load Index, and (D) Ember Load Index.

3.4 RISK TO HOMES

3.4.1 CONDITIONAL RISK TO POTENTIAL STRUCTURES

Conditional risk to potential structures (cRPS) dataset represents the potential consequences of fire to a home at a given location if a fire were to occur and if a home were located there. It is a measure that integrates wildfire intensity with generalized consequences to a home on every pixel but does not account for the actual probability of fire occurrence.

The response function characterizing potential consequences to an exposed structure was applied to all burnable fuel types on the landscape regardless of whether an actual structure is present or not. The response function does not consider building materials of structures and is meant as a measure of the relative effect of fire intensity on structure exposure. The RPS response function is provided below:

Table 7. Risk to Potential Structures response function by flame length class.

Fire Intensity Level	Response Function value
0<FL<2	25
2<FL<4	40
4<FL<6	55
6<FL<8	70
8<FL<12	85
12<FL	100

These results were calculated using 30-m “fire-effects” flame-length probabilities from the WildEST wildfire behavior results and then smoothed into nonburnable areas to match the extent of the burn probability raster. A cRPS value of 0 means no damage to a structure, and a value of 100 represents a complete loss.

3.4.2 RISK TO POTENTIAL STRUCTURES (RPS)

The expected risk to potential structures (RPS) dataset represents a measure that integrates wildfire likelihood and intensity with generalized consequences to a home on every pixel. For every place on the landscape, it poses the hypothetical question, "What would be the relative risk to a house or other structure if one existed here?" This allows comparison of wildfire risk in places where homes already exist to places where new construction may be proposed. RPS is calculated by multiplying conditional risk to potential structures (cRPS) and burn probability (BP):

$$RPS = cRPS * BP$$

Figure 15 and Figure 16 show cRPS and RPS, respectively.

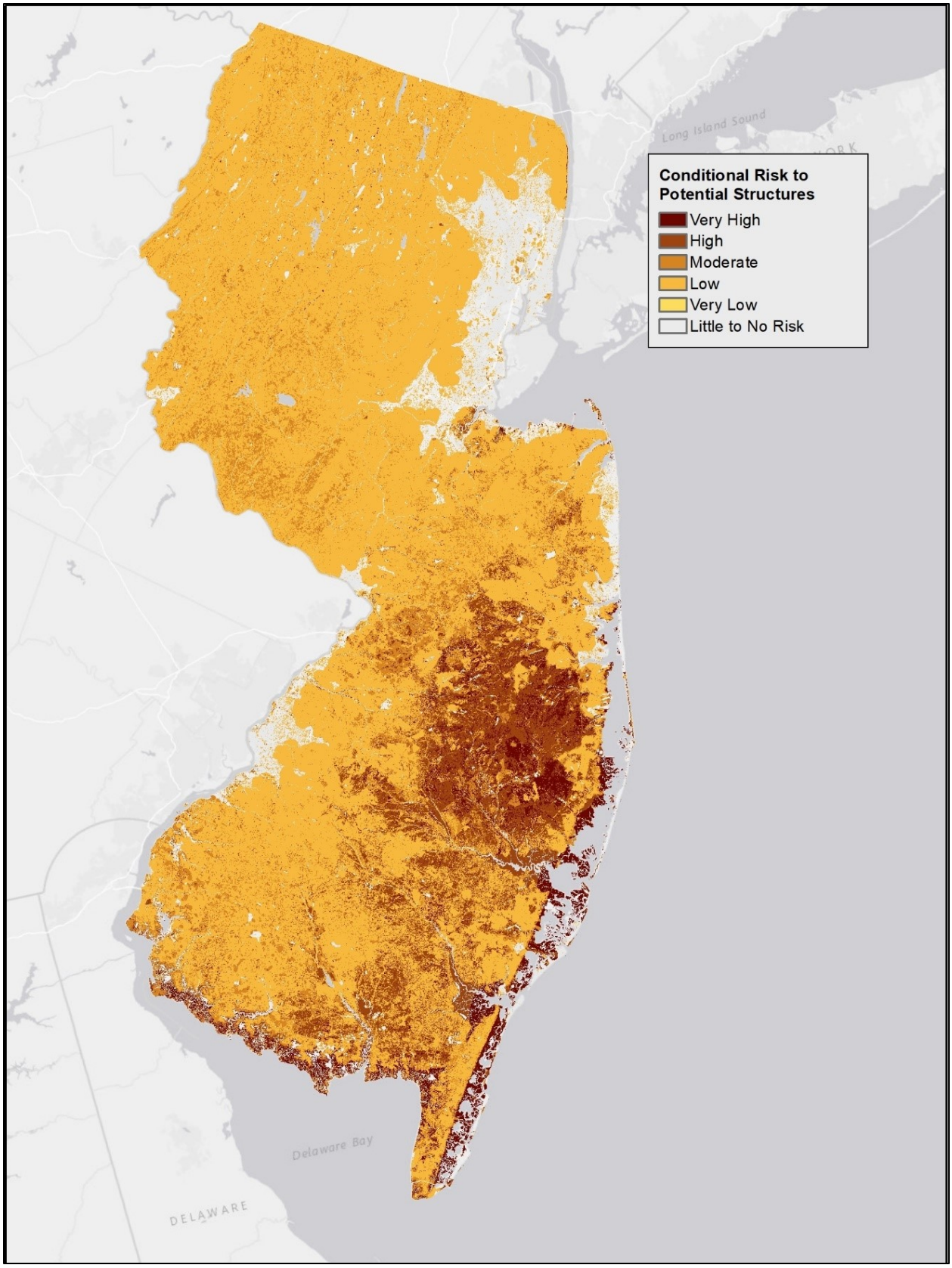


Figure 15. Map of 30-m resolution Conditional Risk to Potential Structures for the NJHAZ analysis area.

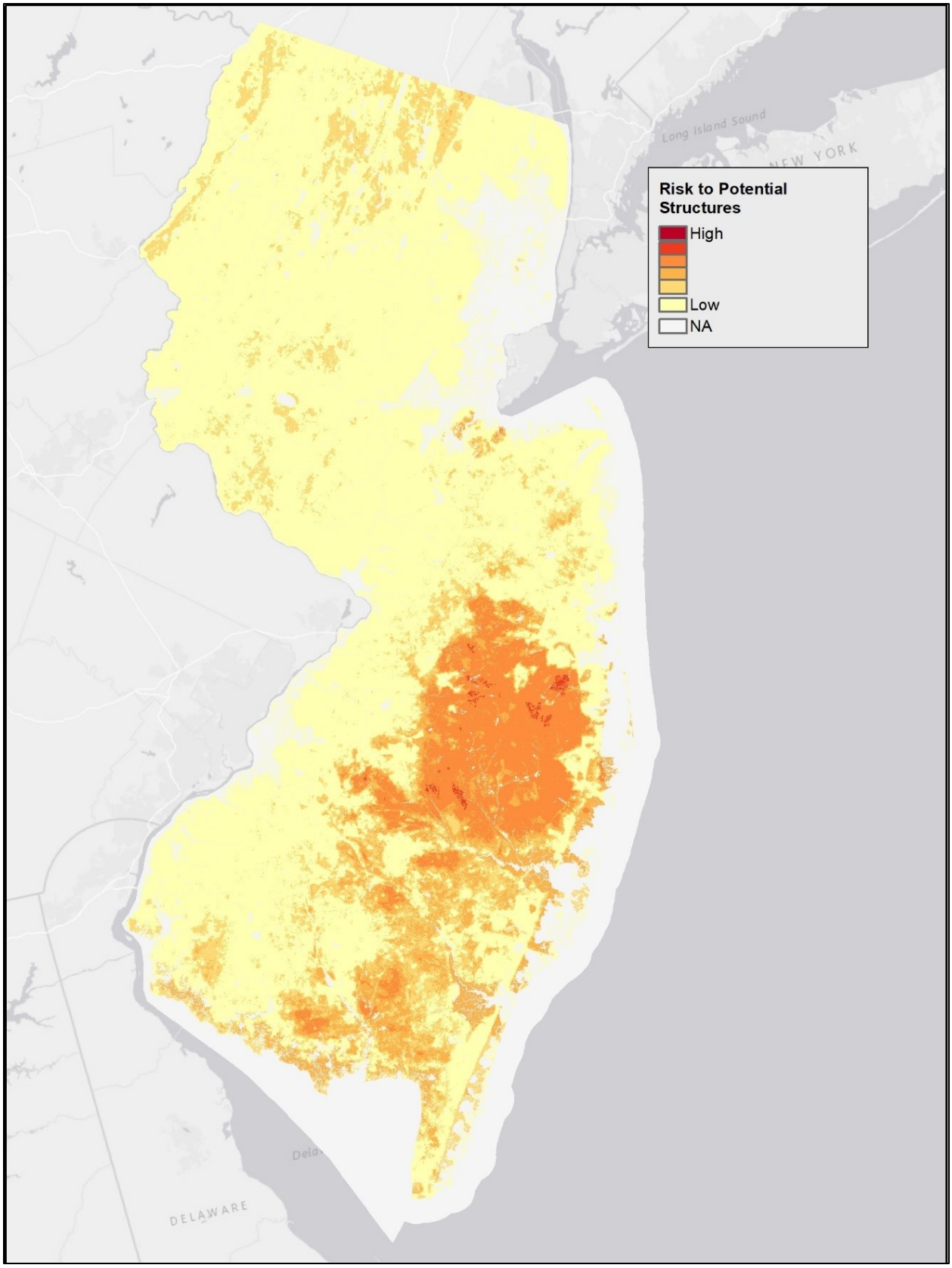


Figure 16. Map of 30-m resolution Risk to Potential Structures for the NJHAZ analysis area.

3.4.3 DAMAGE POTENTIAL

Like cRPS, Damage Potential (DP) is a relative measure representing the potential consequences of fire to a home at a given location if a fire were to occur and if a home were located there. Whereas cRPS uses only flame length as an input variable, DP incorporates cELI with cRPS. The range of values for cELI is roughly equal to the range for cRPS, so DP is calculated as the arithmetic mean of cRPS and cELI for each pixel across the landscape.

$$DP = \frac{cRPS + cELI}{2}$$

Figure 17 shows the map of Damage Potential for the New Jersey area.

3.4.4 STRUCTURE EXPOSURE SCORE

Like RPS, Structure Exposure Score (SES) is a relative measure that integrates wildfire likelihood with generalized consequences to a home on every pixel (assuming a home is present). Whereas RPS uses only flame length as an input variable for consequence, SES incorporates ember load in addition to flame length. SES is calculated by combining annual burn probability (natural log-transformed) and Damage Potential. The transformation on burn probability used in SES transfers more of the weight to the intensity values than is represented by RPS.

Like RPS, SES varies considerably across the landscape. We used a standard geometric-interval classification to define the ten classes of SES, where each class break is 1.5 times larger than the previous break. So, homes located within Class X are 1.5 times more exposed than those in Class IX, and so on. The map of SES for the New Jersey area is shown in Figure 18.

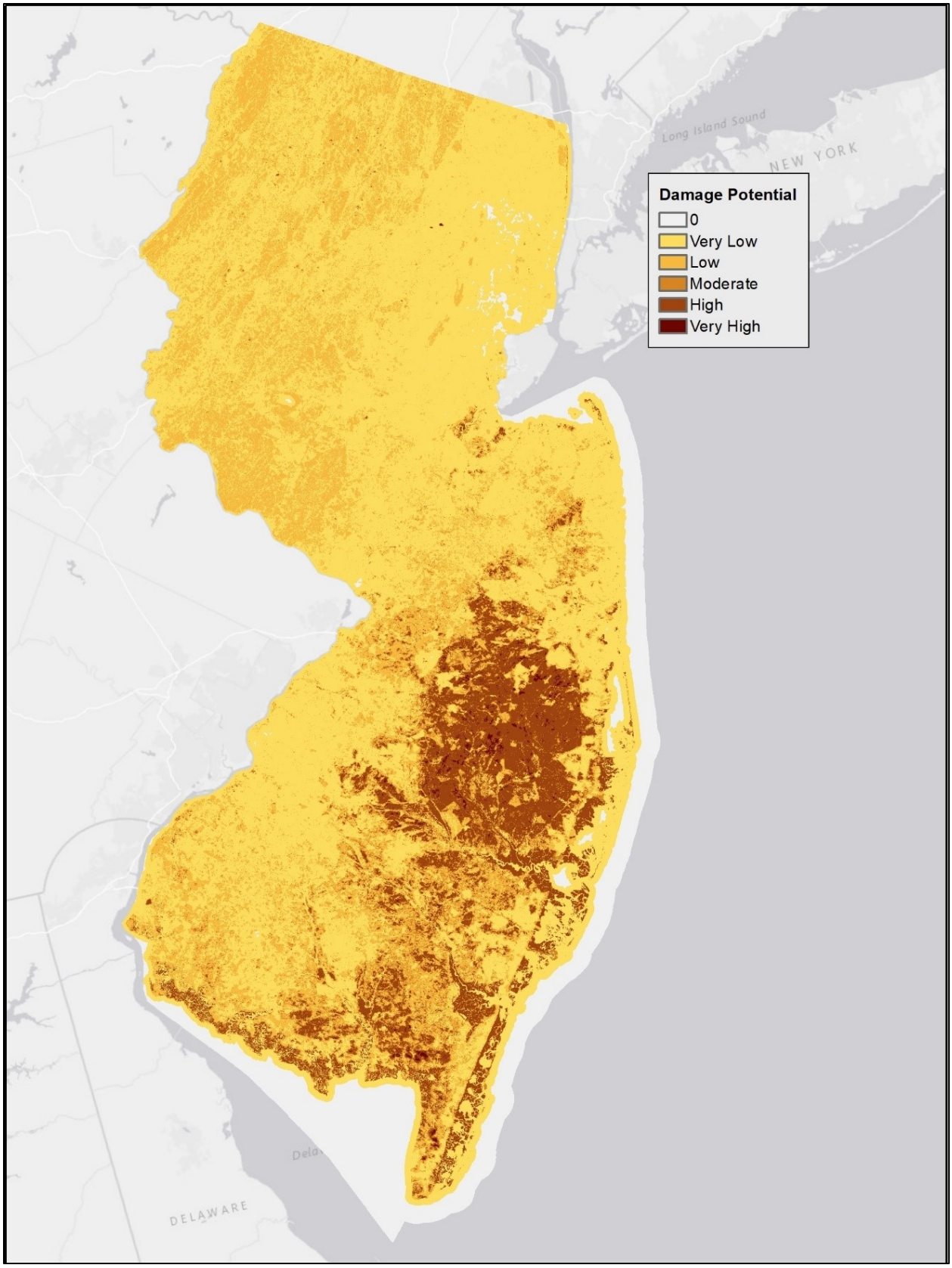


Figure 17. Map of 30-m resolution Damage Potential for the NJHAZ analysis area.

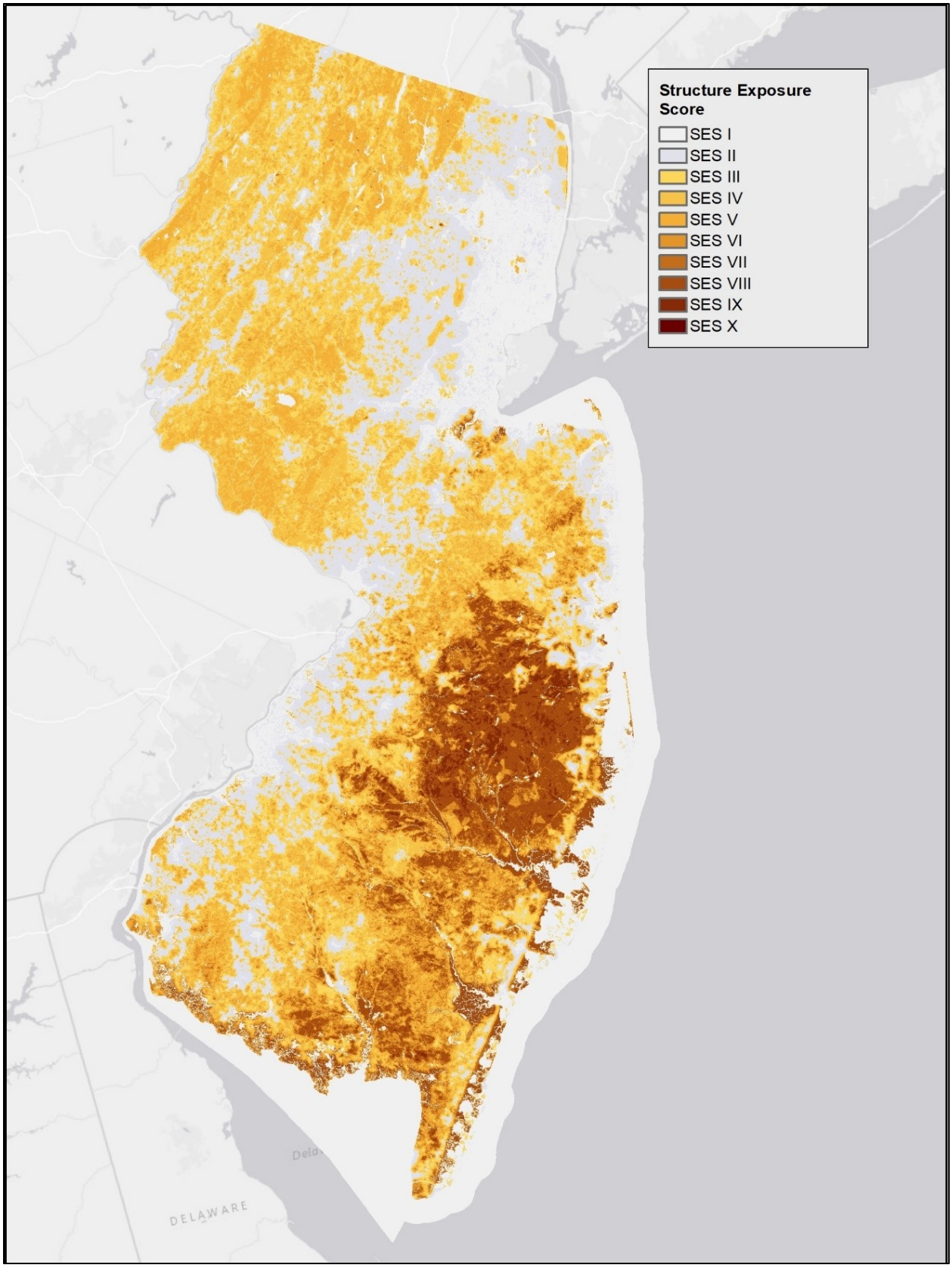


Figure 18. Map of 30-m resolution Structure Exposure Score for the NJHAZ analysis area.

3.4.5 SOURCES OF EMBER LOAD TO BUILDINGS

The ember transport model used in WildEST tracks the travel of embers from each source pixel to downwind receiving pixels. The relative number of embers landing on a given receiving pixel is summed across all potential source pixels. If the receiving pixel has a nonzero WRC Building Cover value (meaning the pixel is within 75 m of a qualifying building), then we separately sum the relative number of embers from the source pixel. The final SELB raster represents the expected annual relative ember production that lands on building cover across all weather types.

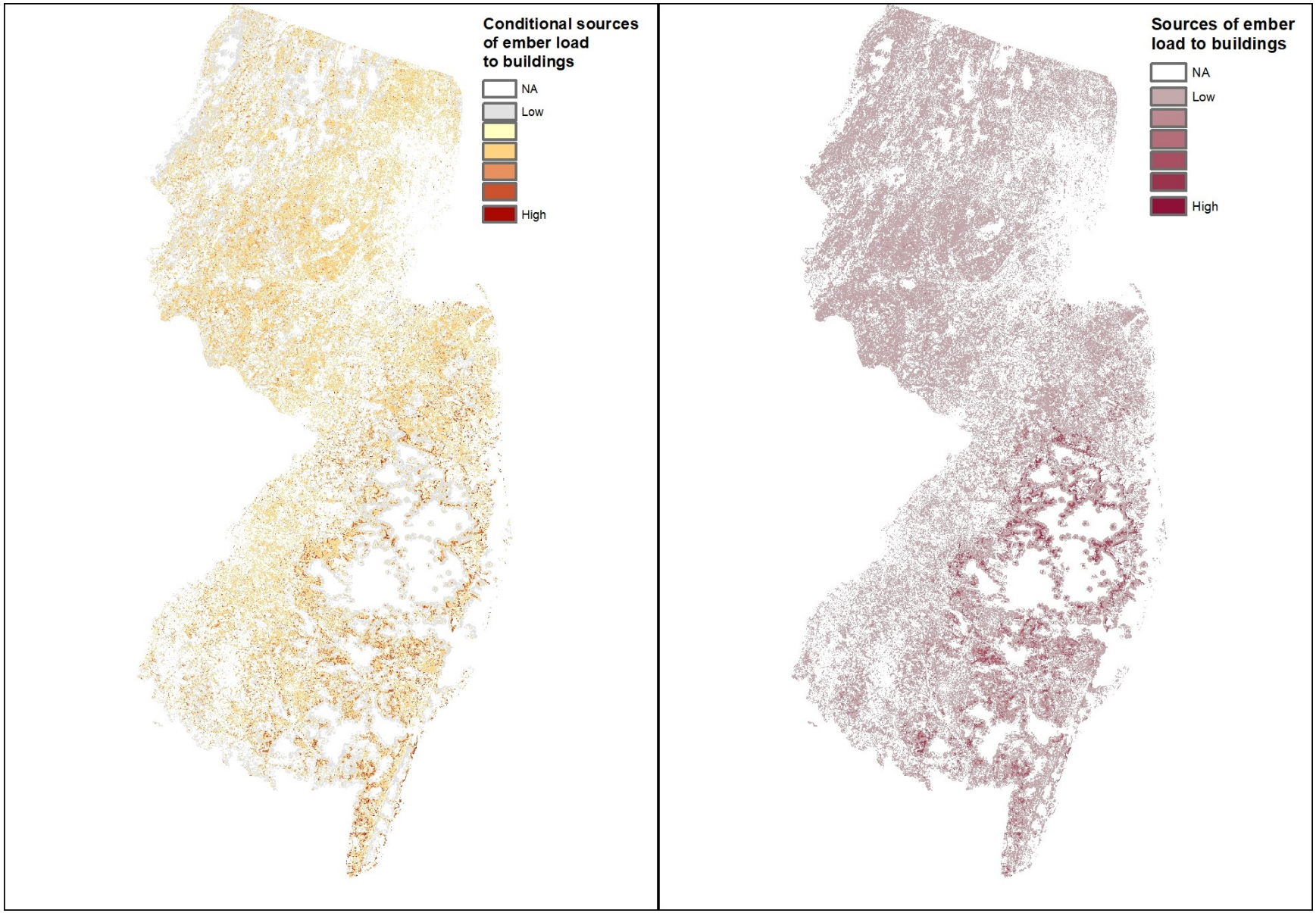


Figure 19. Conditional sources of ember load to buildings (left) and Sources of ember load to buildings (right) for the NJHAZ analysis area.

3.5 INTEGRATED MEASURES

3.5.1 WILDFIRE HAZARD POTENTIAL (WHP)

Wildfire Hazard Potential (WHP) is an index that quantifies the relative potential for wildfire that may be difficult to control. WHP can be used as a measure to help prioritize where fuel treatments may be needed to reduce the intensity of future wildfires.

We calculated WHP following the methods established by Dillon et al. (2015) and Dillon (2018). The original methods utilize lower-resolution FSim inputs, while our approach uses higher-resolution inputs including 30-m vegetation inputs (derived from LANDFIRE 2016), 30-m calibrated fuel model outputs, 30-m New Jersey burn probability results, and 30-m fire-effects flame-length probabilities from the WildEST wildfire behavior results. WHP is shown in Figure 20.

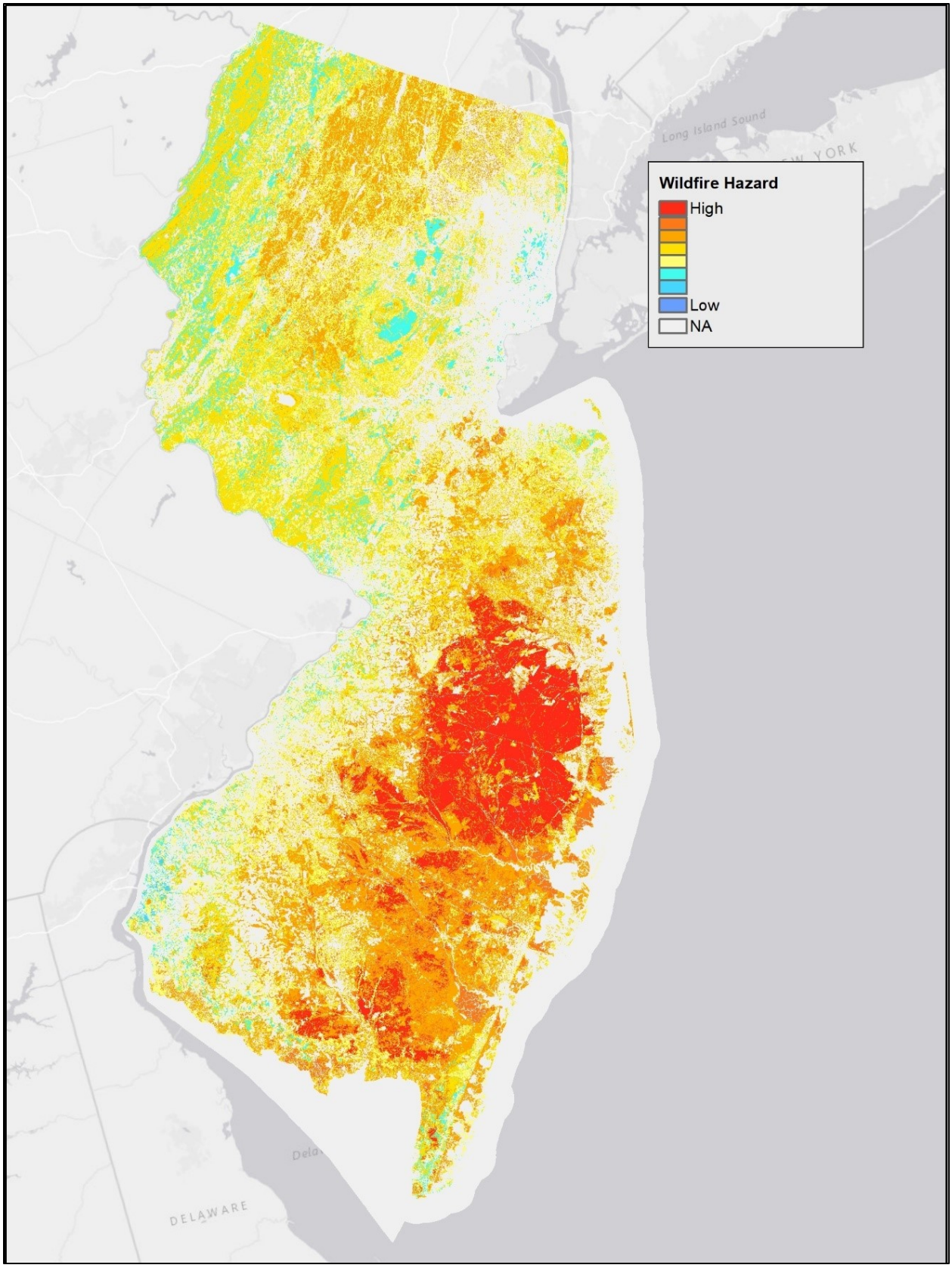


Figure 20. Map of 30-m resolution Wildfire Hazard Potential for the NJHAZ analysis area.

3.5.2 SUPPRESSION DIFFICULTY INDEX (SDI)

This dataset is a raster representing the Suppression Difficulty Index (SDI) across the project area. Wildfire Suppression Difficulty Index is a quantitative rating of the relative difficulty in performing fire control work. SDI factors in topography, fuels, expected fire behavior under severe fire weather conditions, firefighter line production rates in various fuel types, and accessibility (distance from roads/trails) to assess relative suppression difficulty.

We utilized the version of the SDI methods that was adopted for general use in the 2020 fire season. The SDI can be used to help inform strategic and tactical fire management decisions. Fire behavior inputs were modeled in WildEST at 30-m resolution, incorporating both temporal frequencies of weather types and the influence of high-spread conditions as well. Additional information on the SDI is available in O'Connor et al. (2016), Rodriguez y Silva et al. (2014), and Rodriguez y Silva et al. (2020). SDI is shown in Figure 21.

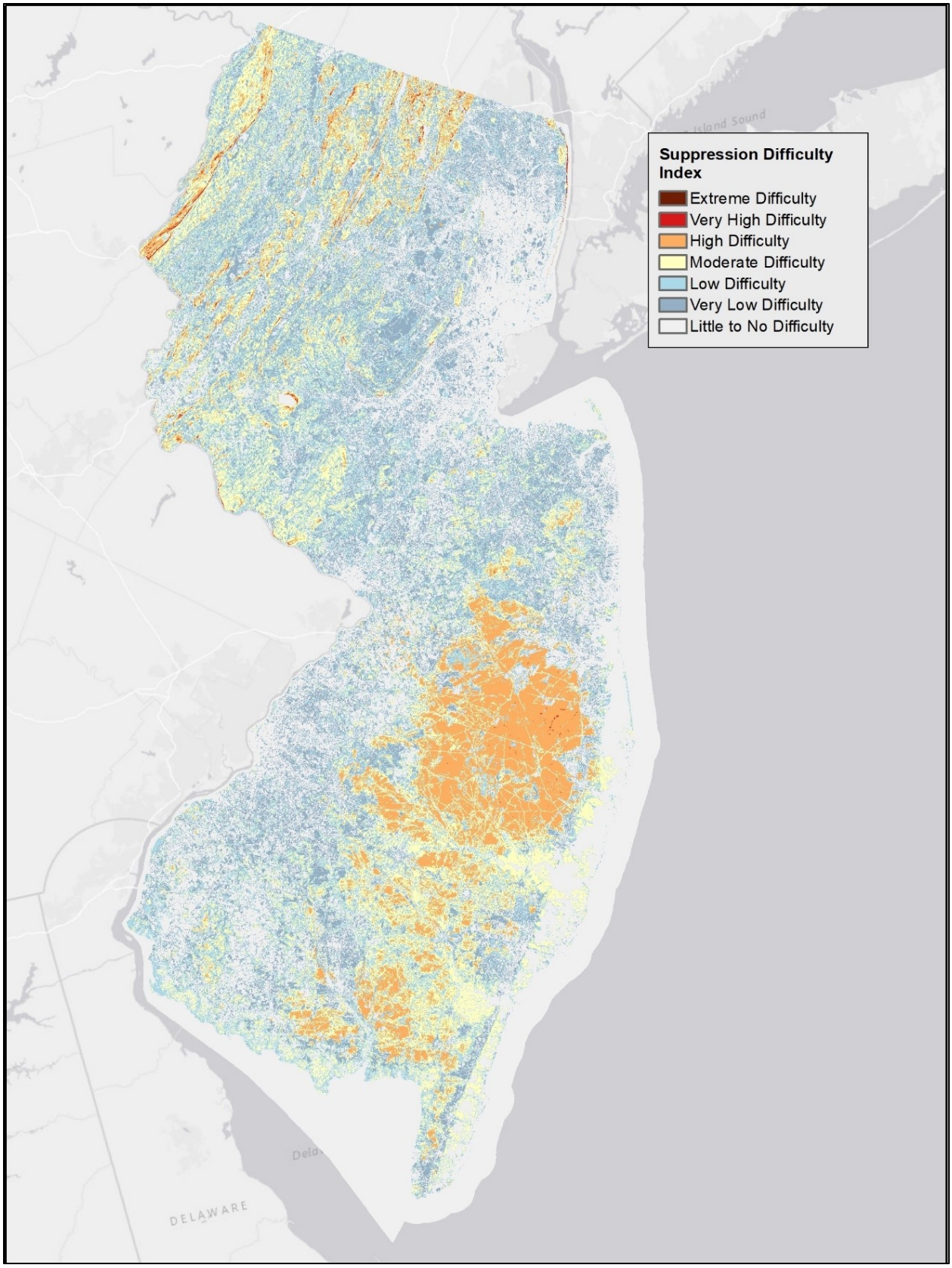


Figure 21. Map of 30-m resolution Suppression Difficulty Index for the NJHAZ analysis area.

4 DISCUSSION

The New Jersey Wildfire Hazard Assessment Project, whose methods and results are described in this report, provides foundational information about wildfire hazard for the state of New Jersey and adjacent land ownerships. This analysis can provide great utility in a range of applications including resource planning, prioritization and implementation of prevention and mitigation activities, and wildfire incident response planning.

The results represent some of the finest scale wildfire hazard data produced to date. The assessment utilized gridded 4-km historical, weather data produced by gridMET (Abatzoglou 2013) in the WildEST fire behavior calculations. This dataset, when processed to produce downscaled 30-m Weather-Type Probability rasters, generated seamlessly variable weather across the New Jersey analysis extent. We applied WildEST, a spatial wildfire characteristics simulation process based on FlamMap, at the native 30-m fuelscape resolution to provide fine-scale fire behavior results across the analysis area. Additionally, the calibrated wildfire likelihood analysis produced for this assessment was completed at 90-m resolution and built upon lessons learned from the Eastern Region Risk assessment (ERRA).

This report documents the wildfire hazard analysis completed for this project and represents the best available science across a range of disciplines. While this report was generated by Pyrologix LLC, the overall analysis was developed as a collaborative effort with local and state partners in New Jersey providing input and feedback.

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6 DATA PRODUCTS

The New Jersey Wildfire Risk Assessment Project required the development of a wide range of data products. The section below outlines those datasets, with a brief description, based on provided data deliverables. More detailed descriptions of data product background and development procedures can be found in the metadata of each data product.

Data Product	Description
Annual burn probability raster (30m)	Folder 2_1 contains the original 90-m BP and an upsampled, 30-m BP raster in standalone TIFF format. The 30-m raster should be used in standard applications. The folder also contains an ESRI ArcMap 10.3 layer file for recommended BP symbology.
Event set (minimum 30,000 years)	Folder 2_2 contains FSim ignition and perimeter feature classes for the FOA in the New Jersey assessment.

Data Product	Description
Fire Behavior Modeling and Integrated Hazard	
Flame Front Characteristics	Folder 1 contains the 30-m rasters for: • Weighted rate of spread (wROS) • Weighted flame length (wFL) • Weighted fireline intensity (wFLI) • Weighted heat per unit area (wHPA) • Characteristic 1-hr fuel moisture content • Characteristic wind speed Each raster is in TIFF format. This folder also contains the corresponding ESRI ArcMap 10.3 layer file for each raster with recommended symbology.
Fire-type probability (FTP)	Folder 2 contains seven 30-m fire-type probability rasters in TIFF format. The subfolder also contains the corresponding ESRI ArcMap 10.3 layer files for recommended symbology.
Operational Control Probabilities	Folder 3 contains the 30-m rasters for: • Probability of manual control • Probability of mechanical control • Probability of extreme fire behavior Each raster is in TIFF format. The folder also contains the corresponding ESRI ArcMap 10.3 layer file for each raster with recommended symbology.
Fire-effects flame-length probabilities (FLPs)	Folder 4 contains six 30-m fire-effects flame-length probability rasters in TIFF format. The subfolder also contains the corresponding ESRI ArcMap 10.3 layer files for recommended symbology.
Ember Production and Load Indices	Folder 5 contains the 30-m rasters for: • Conditional Ember Production Index (cEPI) • Ember Production Index (EPI) • Conditional Ember Load Index (cELI) • Ember load Index (ELI) Each raster is in TIFF format. The folder also contains the corresponding ESRI ArcMap 10.3 layer file for each raster with recommended symbology.
Wildfire Risk to Homes	Folder 6 contains four 30-m rasters in TIFF format: • Conditional Risk to Potential Structures (cRPS). • Expected Risk to Potential Structures (RPS). • Damage Potential (DP) • Structure Exposure Score (SES) • Sources of Ember Load to Buildings (SELB) • Conditional Sources of Ember Load to Buildings (cSELB) The folder also contains the corresponding ESRI ArcMap 10.3 layer files for each raster with recommended symbology.
Integrated Measures	Folder 7 contains four 30-m rasters in TIFF format: • Suppression Difficulty Index (SDI). • Wildfire Hazard Potential (WHP). Each raster is in TIFF format. The folder also contains the corresponding ESRI ArcMap 10.3 layer file for each raster with recommended symbology.

7 CHANGE LOG

The change log documents changes made to this document after the initial submission.

Date	Location of Change	Author	Description of Change
10/31/2022	-	-	Initial submission

THANK YOU

Assessment and Report Contributors:

Joe H. Scott
Principal Wildfire Analyst

Julie Gilbertson-Day
Program Manager

Kevin Vogler
Fire Modeling Lead

Jim Napoli
Spatial Wildfire Analyst

Chris Moran, PhD
Chief Fire Scientist

Michael Callahan
Software Engineer

Julia Olszewski
Spatial Wildfire Analyst

Jack Campanella
Software Engineer

Melissa Jaffe
Spatial Wildfire Analyst

The New Jersey Wildland Fire Risk Assessment was conducted by Pyrologix, a wildfire hazard and risk assessment research firm based in Missoula, Montana.

For More Information Please Visit:

www.pyrologix.com

www.wildfirehazard.com