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| |  |  | | --- | --- | | |  | | --- | | **Supplementary File 1 - Climate Change Atlas Description** | | |
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The Tree Atlas incorporates a diverse set of information about potential changes in the distribution of tree species’ habitat in the eastern United States over this century. DISTRIB-II uses measures of relative abundance, referred to as importance values (IV), for 125 eastern tree species. Inputs include tree species distribution data from the U.S. Forest Service Forest Inventory and Analysis (FIA) program and environmental variables (pertaining to climate, soil properties, elevation, and daylength), which are used to model current species abundance with respect to current habitat distributions by using statistical techniques. DISTRIB then projects future importance values and suitable habitat for individual tree species by using downscaled GCM data. It is not designed to produce precise results for a particular community, site, or year in the future, but rather provide the general trend of habitat suitability under modelled conditions.  **Multistage modelling approach**  Our modelling approach is designed to help determine (Figure 1):   * How habitat suitability for tree species may change under future climates * The likelihood that modelled future habitats are colonized by the species * How much can unmodelled factors like disturbances and biological characteristics change future outcomes   **Figure 1**. Primary components of the multi-stage modelling scheme.  Our multi-stage approach uses two models, [DISTRIB](#DISTRIB_Model)-II and [SHIFT](#SHIFT_Model), and one decision support system, [MODFACs](#MODFACs) (Figure 2). DISTRIB predicts potential suitable species habitats for 125 tree species under current and future climates.  SHIFT is used to determine the likelihood of the tree species colonizing these new suitable habitats. [DISTRIB-II+SHIFT](#DISTRIBSHIFT) gives the potential colonization by 2100. MODFACs (Modification factors) which uses a scoring system based on literature survey can be used to look at how outside disturbances and biological factors might influence the future distributions of these species. The results of each of these components can be explored via the [tree atlas](https://www.fs.fed.us/nrs/atlas/). This multi-stage approach can be used to explore and evaluate the impact of climate change on species habitat distributions better than a single-model approach. See [(Iverson 2011)](https://treesearch.fs.fed.us/pubs/38757) for details of our strategy.  Our approach has been used as a decision support system to plan for better management under current and future disturbances via [regional assessments](https://www.fs.fed.us/nrs/atlas/products/#ra) and assessments of other spatial units within the eastern US.    **Figure 2.** Flowchart depicting workflow to produce the DISTRIB-II and SHIFT outputs. DISTRIB-II predicts current and future habitat suitability/quality (HQ) and SHIFT calculates colonization likelihoods (CL) and ModFacs estimates Adaptability (Adap).  We briefly discuss each component of the schematic diagram below. Please refer to [citations](#Citations:) for more detail.  **Data**  **FIA data**. For trees, response variables are the importance values (IV) of 125 tree species. IVs is a relative measure of abundance which is calculated from US Forest Service's Forest Inventory and Analysis (FIA) data for 37 states east of the 100th meridian. It consisted of 84,204 plots and over 4 million tree records. The importance values were calculated as  Importance Value Formula where x is the species, BA is the basal area and NS is the number of stems. AllSpp indicates all species present in the plot. Therefore, IV is a measure of relative abundance. Its value ranges from 0 to 100; the latter indicating monotypic stands of the species. As the relative number of stems and relative basal area for each species were weighted equally to calculate IV for each plot, some species with large numbers of smaller stems (e.g., *Ulmus, Acer, Fraxinus* spp.) may be calculated as more important than species with fewer, but larger stems (e.g., some *Quercus*). To minimize species that have too few samples to build a respectable model, species were only included if they had at least 60 grid cells with at least two FIA plots per cell. This filter resulted in a total of 125 species in the analysis.  To incorporate both the area and the relative abundance of each species, we calculated area-weighted importance values. These were surrogates for the strength of suitable habitat across a species’ distribution (not a probability of occurrence, though likely similar for many species), or an indication of the potential of the cell to host the species. The area-weighted, or summed IV values, is calculated as the average IV for a cell multiplied by the area of the cell.  **Environmental data.** For the tree DISTRIB-II model we used 45 predictors which consist of 7 climate variables, 7 elevation classes, 30 soil properties and 1 physiographic variables (Table 1).  **Table 1.** Environmental data used to predict habitat suitability of eastern U.S. tree species. Data was either aggregated to 10 and 20 km grids or derived from aggregated data.   |  |  |  |  | | --- | --- | --- | --- | | **Category** | **Variable** | **Description** | **Native Resolution** | | Climate1 | [PANN] Annual precipitation | Mean 30-year (1981–2010) monthly precipitation (mm). | 800 m | | [PGrow] May-Sept. precipitation | Mean 30-year (1981–2010) monthly precipitation for May – September (mm). | | [TANN] Annual mean temperature | Mean 30-year (1981–2010) monthly temperature (°C). | | [TGrow] May-Sept. mean temperature | Mean 30-year (1981–2010) monthly temperature for May – September (°C). | | [TWINavg] Mean temperature of coldest month | Mean 30-year (1981–2010) monthly temperature of coldest month (°C). | | [TSUMavg] Mean temperature of warmest month | Mean 30-year (1981–2010) monthly temperature of warmest month (°C). | | [Aridity] Aridity Index | A conditional ratio of precipitation and Thornthwaite potential evapotranspiration (see (Koch, Smith & Coulston 2013)) | 10 and 20 km | | Elevation2 | [ElvMIN] Minimum | Minimum value | 90 m | | [ElvMEAN] Mean | Mean value | | [ElvMAX] Maximum | Maximum value | | [ElvMEDIAN] Median | Median value | | [ElvMIN] Range | Range between minimum and maximum values | | [ElvStdDev] Standard deviation | Amount of deviance among elevation | | [ElvCV] Coefficient of variation | The CV of elevation | | Solar3 | [DayLenCV] Day length coefficient of variation | The CV of 12 monthly day lengths derived from the latitude of grid cells. | 10 and 20 km | | Soil4 | [AWC] Available water capacity (cm) | The quantity of water that the soil is capable of storing for use by plants | 30 m | | [AWS] Available water supply (cm) | The total volume of water that should be available to plants when the soil, inclusive of rock fragments, is at field capacity | | [BD3RDBAR] Bulk density (g/cm3) | The ovendry weight of the soil material < 2 mm in size per unit volume of soil at water tension of 1/3 bar | | [CACO3] Calcium carbonate | The percent of carbonates, by weight, in the fraction of the soil < 2 mm in size | | [CEC7] Cation-exchange capacity | The total amount of extractable cations that can be held by the soil, expressed in terms of milliequivalents per 100 grams of soil at neutrality (pH 7.0) or at some other stated pH | | [DEP2WATTBL] Depth to water table (cm) | Depth to a saturated zone in the soil | | [KSAT] Permeability (cm/hr) | Saturated hydraulic conductivity or the ease with which pores in a saturated soil transmit water | | [KFACTRF] Erosion K factor | The susceptibility of a soil to sheet and rill erosion by water estimated by percentage of silt, sand, and organic matter and on soil structure and saturated hydraulic conductivity | | [TFACTOR] Erosion T factor (tons/acre/year) | An estimate of the maximum average annual rate of soil erosion by wind and/or water that can occur without affecting crop productivity over a sustained period | | [CLAY] Percent clay | Mineral soil particles that are < 0.002 mm in diameter | | [SAND] Percent sand | Mineral soil particles that are 0.05 mm to 2 mm in diameter | | [SILT] Percent silt | Mineral soil particles that are 0.002 to 0.05 mm in diameter | | [OM] Organic matter content (% by weight) | Plant and animal residue in soil material < 2 mm in diameter at various stages of decomposition | | [PH] pH | A measure of acidity or alkalinity | | [SIEVE10] Percent passing sieve No. 10 | Soil fraction passing a number 10 sieve (2.00 mm square opening) | | [SIEVE200] Percent passing sieve No. 200 | Soil fraction passing a number 200 sieve (0.074 mm square opening) | | [SProd] Soil productivity5 | Productivity Index derived from family-level Soil Taxonomy information | | Soil taxonomic order | The percentage of each of nine taxonomic orders: Alfisols, Aridisols, Entisols, Histosols, Inceptisols, Mollisols, Spodosols, Ultisols, and Vertisols | | Soil texture | The percentage of texture class as defined by USDA standard terms: clayey, loamy, sandy, or other |   1 PRISM Climate Group. 2014. Oregon State University, <http://prism.oregonstate.edu>.  2 Farr, T. G., P. A. Rosen, E. Caro, R. Crippen, R. Duren, *et al.* (2007). The Shuttle Radar Topography Mission. Reviews of Geophysics **45**(2) DOI: 10.1029/2005rg000183  3 Forsythe, W. C., E. J. Rykiel, R. S. Stahl, H.-i. Wu and R. M. Schoolfield (1995). A model comparison for daylength as a function of latitude and day of year. Ecological Modelling **80**(1): 87-95.  4 Soil Survey Staff. Gridded Soil Survey Geographic (gSSURGO) Database for the Conterminous United States. United States Department of Agriculture, Natural Resources Conservation Service. Available online at https://gdg.sc.egov.usda.gov/. May, 24, 2016 (FY2016 official release).  5Schaetzl, R. J., F. J. Krist Jr and B. A. Miller (2012). A taxonomically based ordinal estimate of soil productivity for landscape-scale analyses. Soil Science **177**(4): 288-299.  **Climate data.** We used a range of models and scenarios to capture projections of future temperature and precipitation. Data included current (1981-2010) annual and seasonal mean temperature (°C) and annual and seasonal precipitation totals (mm) based on Parameter-elevation Regressions on Independent Slopes Model, (PRISM), and end of century (2070-2099) values from three General Circulation Models (GCM) under the 4.5 and 8.5 Representative Concentration Pathways (RCP).  To model habitat suitability under future climates, we swapped the current climate with future values predicted by 3 GCM models (CCSM4, GFDL CM3, and HadGEM2-ES) under two Representative Concentration Pathways (RCPs: RCP4.5-low emissions and RCP8.5-high emissions).This resulted in the following scenarios for current climate and out to 2100 (see also [Iverson et al. 2019](https://www.nrs.fs.fed.us/pubs/57857)):   * Current climate (1980-2010) * CCSM4 – RCP4.5 (2070-2099) * CCSM4 – RCP8.5 (2070-2099) * GFDL CM3 – RCP4.5 (2070-2099) * GFDL CM3 – RCP8.5 (2070-2099) * HadGEM2-ES – RCP4.5 (2070-2099) * HadGEM2-ES – RCP8.5 (2070-2099) * Avg. of 3 GCMs – RCP4.5 (2070-2099) * Avg. of 3 GCMs – RCP8.5 (2070-2099)   These climate models and RCPs capture, for the entire eastern U.S. study area, a wide distribution space in projected change (see Figure 3 and Table 2). Further, the mean change across these combinations fall along a strong temperature gradient, from an estimated annual temperature increase of 2.5 °C (4.5 °F) with CCSM45 to 6.5 °C (11.7 °F) with Had85, and with an overall mean increase of 4.5 °C (8.1 °F). The potential change in precipitation was higher for all scenarios by end of century, but for many locations, a reduction in future precipitation is forecast (i.e., points below the horizontal 0 change line), especially for Had85 and GFDL85 (see figure). Coupled with higher temperatures, especially these scenarios will likely inflict additional physiological stress on organisms for some future periods. This trend is especially true when examining growing season temperatures, which reach 28.4 °C (83.1 °F), an increase of 6.8 °C (12.2 °F), for both GFDL85 and Had85. To make matters worse for plant growth, both Had45 and Had85 showed growing season precipitation decreases by end of century, even though annual precipitation was slightly higher (Table 2).  **Figure 3**. Distribution of annual temperature and precipitation changes from a baseline period (1981–2010) as modeled for 2070-2099, for 41,683 10-km cells across the eastern US.    **Table 2**. Average climate conditions in the eastern US currently and for three models (CCSM4, GFDL CM3, and HadGEM2-ES) for the 4.5 and 8.5 RCPs.   |  |  |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | --- | --- | | Variable |  | CCSM4 |  | GFDL CM3 |  | HadGEM2-ES |  | |  | Current | RCP 4.5 | RCP 8.5 | RCP 4.5 | RCP 8.5 | RCP 4.5 | RCP 8.5 | | Precip\_annual (mm) | 1048 | 1113 | 1162 | 1203 | 1233 | 1121 | 1110 | | Precip, May-Sept (mm) | 509 | 527 | 519 | 573 | 585 | 504 | 457 | | Temp\_annual (°C) | 12.7 | 15.2 | 17.1 | 16.3 | 18.6 | 16.8 | 19.2 | | Temp, May-Sept (°C) | 21.6 | 24.0 | 26.3 | 26.0 | 28.4 | 25.7 | 28.4 | | Temp, warmest month (°C) | 24.8 | 26.6 | 28.1 | 28.1 | 29.7 | 28.0 | 29.9 | | Temp, coldest month (°C) | -0.9 | 1.2 | 2.1 | 1.6 | 2.0 | 1.3 | 3.3 | | Temp, absolute minimum (°C) | -11.3 | -8.6 | -6.5 | -7.2 | -5.7 | -7.4 | -4.0 | | Temp, absolute maximum (°C) | 33.8 | 35.9 | 39.3 | 39.1 | 42.5 | 38.5 | 41.9 |   **The Hybrid Grid**  A hybrid lattice, composed of 10 and 20 km grids established by FIA plot density, was used to represent landscape conditions. An iterative algorithm determined whether sufficient FIA plots existed within each 20-km grid to warrant increasing the resolution to 10 km. The 10-km grids were accepted if ≥ 50% of the four 10-km cells within a 20-km cell contained two or more FIA plots, otherwise the focal 20-km cell was retained. Figure 4 presents the area of the eastern US that has 20 vs 10 km grid cells, while Figure 4 presents the number of FIA plots represented per cell of the 20 km grid, the 10 km grid, and the hybrid grid used in DISTRIB-II. All 84,204 annualized FIA records sampled during the period 2000 – 2016 were processed, and aggregated to cells with native resolutions of either 10 × 10 km or 20 × 20 km to represent the mean IV within the grid cell. We strove to increase spatial resolution, over that of our previous effort, where the FIA data would support it; to that end, a hybrid lattice was generated through an iterative algorithm to determine whether resolution could be increased to 10 × 10 km, or maintained at 20 × 20 km (see [Peters et al. 2019](https://www.nrs.fs.fed.us/pubs/58353)). The resulting hybrid lattice for the eastern U.S. had 29,357 cells, 84.7% of which were comprised of 10 × 10 km cells (Figure 4). The 20 × 20 km cells were largely confined to highly agricultural areas, mostly in the western portion of the eastern U.S. This process enabled a more equitable distribution of FIA plots among cells (Figure 5).    **Figure 4.** Extent of DISTRIB-II models and distribution of 10-km and 20-km grid cells within the hybrid lattice.    **Figure 5.** Count of Forest Inventory and Analysis (FIA) plots within A) 10-km grids, B) 20-km grids, and C) hybrid lattice of 10- and 20-km grids. The accompanying table includes the total cell count and mean (range) of FIA plots among cells.  **DISTRIB-II Model**  The DISTRIB model predicts suitable habitat as depicted by IVs for tree species under current (~2000) and future (~2100) climates. The DISTRIB-II species model has served as the core of the multi-stage approach. The FIA data and the DISTRIB-II model provides a basis for depicting the species current distribution as well as how the habitat for these species might change with changing climatic conditions.  The DISTRIB-II model is based on a robust approach that uses an ensemble of decision-trees, a technique called RandomForest for prediction. See [Prasad et al. (2006)](https://www.nrs.fs.fed.us/pubs/8071) for details of the ensemble modelling technique. Using 45 predictors that includes climate, soil, elevation, and daylength variables as discussed in the [Data section](#Data), tree DISTRIB-II models the IVs of 125 tree species that are mapped as suitable habitats of the species.  Future distributions are modelled by swapping the current climate with GCM predicted future climates as discussed in the Data section. Future:Actual ratios of IV determine the change classes as follows: 0.9 to 1.1 (no change), 0.5-0.9 (small decreaser), <0.5 (large decreaser), 1.1-2.0 (small increaser), and >2.0 (large increaser). For species occupying <10% of the area of interest, they are deemed rare and have a different set of thresholds for change classes: large decrease (<0.2), small decrease (0.2-0.5), no change (0.6-3.9), small increase (4.0-8.0), and large increase (>8.0).  Not all species models are equal - we therefore need to know about the "**model reliability**" of each modelled species. It is important to keep in mind that model reliability is generally higher for common species than for rare species. To do so, we evaluated and combined five model output variables into a single rating: 1) a pseudo-R2 obtained from the RandomForest model, 2) a Fuzzy Kappa comparing the imputed RF map to the FIA-derived map, 3) a true skill statistic of the imputed RF, after removing records with very high coefficient of variation (CV), 4) the deviance of the CV among 30 regression trees via bagging, and 5) the stability of the top five variables from 30 regression trees. When model reliability is low, less certainty exists for the model results. We therefore rate for each species, the reliability of the DISTRIB-II model into three classes - high, medium and low - taking into account several model performance factors (see [Peters et al. 2019](https://www.nrs.fs.fed.us/pubs/58353)).  An important caveat when interpreting our DISTRIB model is that we are predicting potential suitable habitat by year 2100 – **not** where the species will be. See [Peters et al. 2019](https://www.nrs.fs.fed.us/pubs/58353) and [Iverson et al. 2019](https://www.nrs.fs.fed.us/pubs/57857) for details of the DISTRIB-II modelling approach.  **Caveats to DISTRIB-II** (or any species distribution model). This summary, modified from [Janowiak et al. 2014](https://www.nrs.fs.fed.us/pubs/46393), provides a discussion as to limitations of this kind of modeling.  Species distribution models establish a statistical relationship between the current distribution of a species or a community and climate, habitat, or other environmental variables. This relationship is used to model how the range of the species will shift as climate change affects those attributes. These models are less computationally expensive than process models, so they can typically provide projections for the suitable habitat of many species over a large area. There are some caveats that users should be aware of when using them, however.4 These models use a species’ realized niche instead of its fundamental niche. The realized niche is the actual habitat a species occupies given interactions with other species (e.g., predation, disease, and competition), limitations on dispersal, and the existence of suitable climates.5 A species’ fundamental niche, in contrast, is the full set of habitats a species potentially could occupy. Given that a species’ fundamental niche may be greater than its realized niche, SDMs may underestimate current niche size and future suitable habitat. In addition, species distributions in the future might be constrained by competition, disease, and predation in ways that do not currently occur. If so, SDMs could overestimate the amount of suitable habitat in the future. Furthermore, fragmentation or other physical barriers to migration may create obstacles for species otherwise poised to occupy new habitat. Therefore, a given species might not actually be able to enter the assessment area in the future, even if Tree Atlas projects it will gain suitable habitat. Additionally, SDMs like Tree Atlas do not project that existing trees will die if suitable habitat moves out of an area; rather, this is an indication that they will be living farther outside their ideal range and will be exposed to more climate-related stress. Lastly, SDMs may have difficulty in accurately extrapolating into projected climates with no current analog.6, 7  Although useful for projecting future changes, both process models and SDMs share some important limitations. They assume that species will not adapt evolutionarily to changes in climate. This assumption may be true for species with long generation times (such as trees), but some short-lived species may be able to adapt even while climate is rapidly changing. The inputs to the forest impact models for current distribution of trees, site characteristics, and downscaled GCM projections are all based on estimates, each with its own uncertainty. No single model can include all possible variables, so there are important inputs that will likely be excluded from individual models. These include: population genetics—diversity and also specific traits like cold hardiness or disease resistance, interspecies interactions including competition and facilitation, disturbance dynamics such as fire and fire suppression, pest and pathogen dynamics, dispersal modes and capacities, niche breadth, extreme events such as droughts and storms, and more. Given these limitations, it is important for all model results to pass through a filter of local expertise to ensure that results match with reality on the ground.  **SHIFT Model**  DISTRIB-II predicts future suitable habitats, but these habitats may not be colonized in this century depending on the speed that a tree species can migrate and the fragmented nature of the landscapes (as depicting in caveats, above). This is where SHIFT, a spatially explicit simulation model steps in, to calculate the likelihood of colonization based on the abundance of a tree species within its current range (source region), the habitat quality of the landscape beyond the source range boundary (sink) and the distance between occupied and unoccupied areas, for a range of historical migration rates (~ 10 km to > 100 km/century). SHIFT thus calculates the likelihood of colonization, for each 1x1 km cell, for suitable sink habitats over an approximately 100-year time period consisting of multiple generations, depending on the tree species.  The SHIFT model simulates long distance dispersal via a fat-tailed inverse power function under current fragmented landscapes ([Iverson et al., 2004](https://www.nrs.fs.fed.us/pubs/6913)). It can evaluate multiple species in a macro-ecological context, under a range of paleoecological rates of spread in current fragmented landscapes using simple but robust techniques that do not rely on many parameters. SHIFT calculates the likelihood of colonization based on the abundance of the species and habitat quality of 1 km2 cells in the eastern United States. Each cell informs the model of the location, initial abundance of the species, and the habitat quality (principally by forest or non-forest).  To inform the cells within the source region of the actual distribution of abundance, we used importance values (IVs), a relative measure of abundance based on the basal area and number of stems of the overstory and understory trees ([Iverson et al., 2008](https://www.nrs.fs.fed.us/pubs/3412)). Suitable cells are opportunistically colonized throughout the current range of the species and beyond – therefore, colonization can happen even within the gaps in the current distribution (infilling) as well as throughout the outer margins at range boundaries (migrating).  The spatial arrangement of habitat quality within cells is based on the National Land Cover Data (NLCD), from which we classify the 1 km2 cell as forest or non-forest based on the analysis of the percent forest in each cell. We generously define a cell as a colonizable sink if it were 10% or more forested. Colonization of initially unoccupied cells is estimated as a function of recipient cell forest availability and the sum of the likelihood of each occupied cell sending a propagule to that cell. For each cell not currently occupied, the model estimates the likelihood that each unoccupied cell will become colonized over a period of 100 years (which depends on the number of generations the species requires to achieve 100 years). SHIFT is a ‘fat-tailed’ dispersal model that allows rare long-distance dispersal events up to 500 km beyond the source cells and assumes the release of climatic restrictions to tree growth. Although the 500 km is arguably an overly generous window where the colonization can occur, the inverse power function makes the likelihood of colonization decay rapidly from the species front. We use the 500 km window to account for those rare, long-dispersal events over historical periods that can potentially seed colonizations far from the source.  Our approach uses historical information on rates of past migration events as a guide for future potential migration. Our framework has the advantage of taking into account the structure of the landscape, via fragmentation of habitat quality, which can influence both demography and dispersal distances.  ***SHIFT model***  SHIFT calculates the likelihood of an unoccupied cell becoming colonized during each generation (one model iteration), as a function of habitat quality (in occupied cells and potentially future occupied cells), abundance of the species, and a search distance function as follows:  where P(i,j) is the likelihood of an unoccupied cell being colonized; Q(i,j) and Q(k,n) are habitat quality of unoccupied cell (i,j) and occupied cell (k,n) respectively, (based on the percentage of forest cover of each 1 km2 cell according to the NLCD landcover map; F(k,n), an abundance parameter, is the current estimated importance value (IV) for the migrating specified cell (k,n); (which can be represented as D(i,j; k,n)) is the distance between unoccupied cell (i,j) and an occupied cell (k,n) within the search-window distance; x is the dispersal component; and C is a calibration constant. The likelihood of colonization for each unoccupied cell is summed across all n occupied cells at each generation. To add stochasticity, a random number (RN) is drawn from an even distribution (0–1) and compared with the likelihood of colonization to determine if the cell will get colonized (i.e., if RN <= P). The value of C is derived independently for each species through trial runs to achieve migration rates ranging from approximately ~10 to >100 km per century (depending on criteria of model runs) of that species under high forest availability (80% cover, representing nearly fully forested conditions, which more closely approximate Holocene conditions), but with the current level of species abundance.  The value of x, the dispersal exponent, determines the rate at which seed dispersal declines with distance. As an exponent of D(i,j; k,n) in the denominator, x decreases colonization with distance as an inverse power function; that is, increasing x leads to decreasing long-distance dispersal while decreasing x increases long distance dispersal. Each 100-year run was replicated 100 times so that each run corresponded to a 1% chance of colonization. See ([Prasad et al. 2013](https://www.nrs.fs.fed.us/pubs/43705) and [Prasad et al. 2016](https://www.nrs.fs.fed.us/pubs/50748)) for further details on the SHIFT model.  **MODFACs (Modification Factors)**  The DISTRIB-II and the SHIFT models cannot take into account the multitude of biological and disturbance factors affecting species distribution (insect outbreaks, fire, etc). We therefore use a scoring system based on the available literature to account for these factors. Our scoring system gauges the effect of 9 biological and 12 disturbance components in modifying the interpretations of the species response outcomes from the DISTRIB-II and SHIFT models. This framework also addresses species model uncertainties in light of climate change. Forest managers and other end users who have expertise locally can modify the tabular scoring system locally or regionally, to obtain customized outputs and inform management relevant decisions. See [Matthews (2011)](https://www.nrs.fs.fed.us/pubs/38643) for details. An example for red maple, a highly adaptable species, achieving the highest score of 8.5 is shown in Figure 6.  ModFacs for Red Maple  **Figure 6**. Example for red maple (Acer rubrum), showing 9 biological and 12 disturbance factors considered in the modification factors to achieve an adaptability score. The score of 8.5 is highest of all species, indicating red maple is the most adaptable to a changing climate.  The combination of the biological scores and the disturbance scores forms the basis of an Adaptability score (Figure 7). Higher relative biological and disturbance scores yield higher adaptability. Simple translation of -3 to 3 scores to 0-6 and connection to the hypotenuse trendline from corner to corner yields a low score of 1.7 for balsam fir and a high score of 8.7 for red maple.    **Figure 7**. Disturbance and biological ModFacs scores for 134 tree species, with selected species identified. Increasing adaptability to climate change is predicted for species tending to the upper right quadrant of the graph.  **DISTRIB+SHIFT**  The future suitable habitats, or habitat quality (HQ) predicted by DISTRIB-II (~ 2100) are intersected with SHIFT likelihood of colonization (CL) over ~100 years, to estimate the likelihood of colonization of these future sink habitats around 2100 (Figure 8). This typically shows that only a small percentage of the sink habitats (i.e., beyond the current range boundary) that are available to the tree species has any chance (>2%) of colonization. Using this approach, we can evaluate multiple tree species for their capability to cope with a changing climate and assess potentials for infilling or migrating species in an assisted migration approach for valuable forest tree species that may not be able to keep pace with rapid climate change (see Iverson et al., in review for explanations).  **Figure 8.** Flowchart depicting workflow for outputs of DISTRIB-II (Habitat Quality, HQ), SHIFT (Colonization Likelihood, CL), and adaptability (MODFACS, Adap) to produce Capability and candidate species for Infill ( the number of species that can be considered likely to expand under an RCP, and thus higher candidates for infill planting), Likely (the species was not found in FIA plots, but there is a relatively high probability that the species exists in the unit), or Migrate (the number of species with at least some chance of migrating naturally into each unit, and thus higher candidates for artificial migration). HQCL is the combination of habitat quality (HQ) and colonization likelihood (CL). %OccCol pertains to the percentage of the unit that is either already occupied or with at least a 50% probability of becoming potentially occupied (according to SHIFT) within 100 years. %50Col (or %2Col) pertains to the percentage of the unit not already occupied that has at least a 50% (or 2%) probability of getting colonized within 100 years.  This atlas provides the first instance where the SHIFT model is implemented for most of the species we model. Figure 9 shows the DISTRIB-II output and SHIFT model intersected for eastern hemlock (*Tsuga canadensis*). It illustrates the nature of DISTRIB-II and SHIFT and how they are combined to produce potential colonization likelihood by 2100. Notice that only a small percentage of the future sink habitats have any chance of getting colonized, but that there is infilling and migration in future.    **Figure 8.** Process flow to merge HQ and CL for eastern hemlock. (a) current importance value of hemlock as determined by FIA data; (b) habitat quality (HQ), reclassed into low, medium, high HQ; (c) colonization likelihood (CL), reclassed into low, medium, high CL; (d) combination of (a), (b), and (c), yielding locations with null to high CL on top of low to medium HQ, as well as currently occupied cells; (infill inset) detail of locations where infilling is primary; (migrate inset) detail of locations where migrating is primary.  **Regional species management**  We have used the outputs of the multi-stage approach, mainly [DISTRIB](#DISTRIB_Model)-II and [MODFACs](#MODFACs) to assess management options for different regions. See [(Swanston 2011)](https://www.nrs.fs.fed.us/pubs/38255) for details on regional assessment. Vulnerability assessments have been conducted, using tree atlas data, for the following regions across the eastern US: Mid-Atlantic, Central Appalachians, Central Hardwoods, Minnesota, Michigan, Northern Wisconsin and Western Upper Michigan, New England and northern New York. These are all available at <https://forestadaptation.org/assess/ecosystem-vulnerability>.  **Citations:**  Prasad, A.M., L.R. Iverson, and A. Liaw 2006. [Newer classification and regression tree techniques: bagging and random forests for ecological prediction. Ecosystems](http://www.nrs.fs.fed.us/pubs/8071), **9**:181–199.  Prasad, A. M., J. Gardiner, L. Iverson, S. Matthews, and M. Peters. 2013. [Exploring tree species colonization potentials using a spatially explicit simulation model: implications for four oaks under climate change](http://www.nrs.fs.fed.us/pubs/43705/). Global Change Biology 19: 2196–2208.  Prasad, AM, Iverson LR, Matthews SM, Peters M. 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