Estimating Upland Watersheds Risk to Increased Sediment Due to Wildfires in the Forests lands of Colorado.

Preliminary Report 5/22/2023

Mary Ellen Miller &
Mike Billmire
3600 Green Court, Suite 100, Ann Arbor, MI, 48105
http://www.mtri.org

Executive Summary

Water in Colorado predominately comes from high-elevation forested watersheds that are facing an ever increasing threat from wildfire and anthropogenic pressure. When wildfires occur, there is a high likelihood of impaired water quality (excess Nitrogen, Carbon and Phosphorous), high sediment loads, increased stream temperatures, and suspended ash particles to transport to either the water intakes or a water storage reservoirs. This can have a detrimental effect on aquatic habitat and fisheries. Determining which upland watersheds have the highest likelihood from a sediment export and water quality perspective, can give water providers and land managers an opportunity to understand the benefit of fuel treatments verses expected increases in sediment and water quality degradation. To combat this high erosion risk, the USDA Forest Service and other land management agencies have initiated fuel reduction programs, but the areas needing treatment far exceed the available funding (Sampson *et al.* 2000). Hence, there is a need to assess and compare the relative priority for fuel reduction treatments on a spatially explicit basis for sensitive watersheds such as source areas for municipal drinking water supplies. In order to meet the needs for fuel planning from a watershed perspective we have developed a spatially explicit erosion risk map for upland forested watersheds in the forests of Colorado.

The three main tasks accomplished were:

1) Predicting potential post-fire severity for the forests and rangelands of Colorado. We used an online modeling tool (https://apps.mtri.org/burnsev/get), which leverages historical soil burn severity maps, fire behavior modeling, terrain indices and machine learning to predict potential post-fire soil burn severity (Fig 1). Predicting post-fire erosion before a wildfire occurs is difficult, this model currently has an overall accuracy of 50%.

2) Predictions of potential post-fire erosion were created using the WEPP Watershed model (Fig 2). Inputs were created from the forecasted soil burn severity using the Rapid Response Erosion Database (RRED; http://rred.mtri.org/rred/, Miller et al. 2016). RRED rapidly generates properly formatted inputs for the Water Erosion Prediction Project (WEPP) model. WEPP is a physically-based soil erosion model developed by an interagency team of scientists to model erosion and runoff from hillslopes and small watersheds (Laflen et al. 1997, Elliot 2004).

3) Potential post-fire erosion predictions for the state of Colorado are available for viewing and downloading on an online interface: https://apps2.mtri.org/erosion.

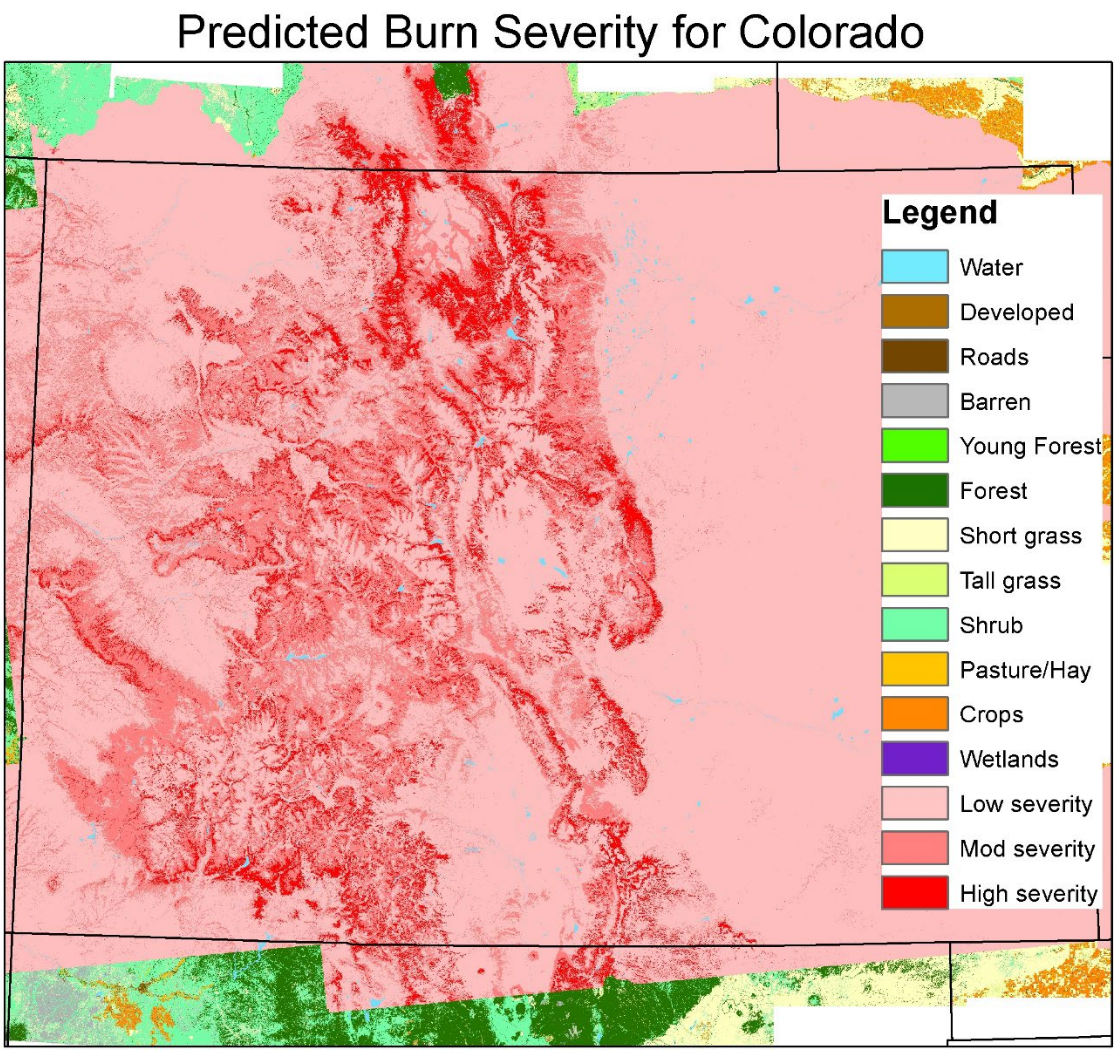

Figure 1. Predicted burn severity for the state of Colorado.

Burnsev is an online burn severity model created at Michigan Tech Research Institute to forecast burn severity in the continental US, https://apps.mtri.org/burnsev/get. Users select historical fires for an Area of Interest, the model interface then uses the fire behavior model FlamMap, FIRESEV data layers, historical fire data and the machine learning algorithm Random Forests to create a prediction of potential burn severity. We found that overall accuracy of predictions were highest if users select historical training fires from a collections of soil burn severity maps. Average accuracy of a collection of ten case fire was 50% using soil burn severity (SBS) maps for training. The original burn severity model has been updated from 62 to 352 SBS fires and is currently being improved upon with new data layers.

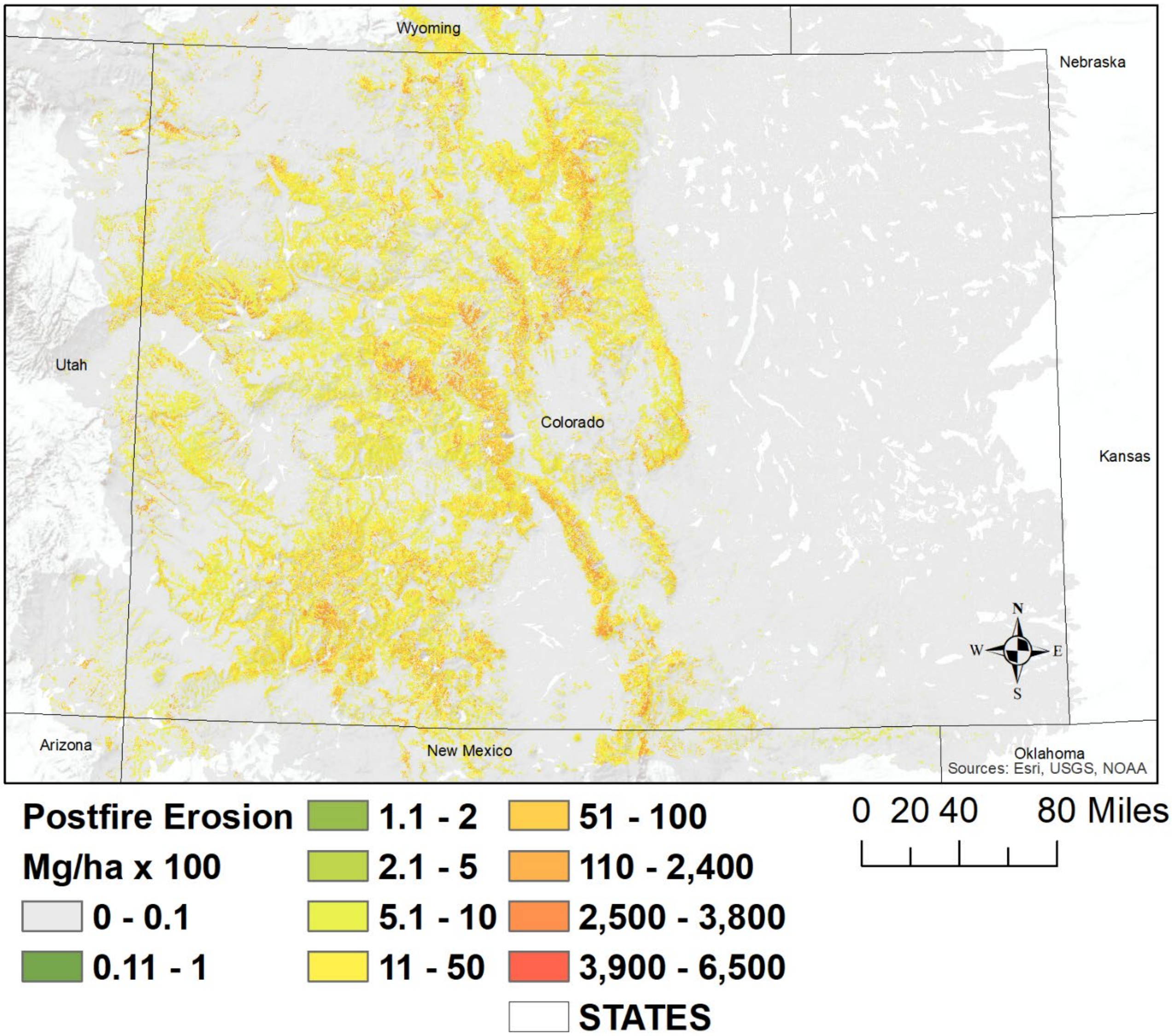

Figure 2. Predicted post-fire erosion for the state of Colorado.

Models

We used multiple models and tools to predict soil burn severity and post-fire erosion risk for the state of Colorado (Fig 3). The first step in the modeling process was to forecast potential burn severity using the BurnSev tool (Fig 4). This online model was created by combining Random Forest, FIRESEV modeling inputs and FlamMap, a fire behavior model. The soil burn severity predictions were then uploaded into the Rapid Response Erosion Database (RRED, Miller et al., 2016) to create spatial model inputs for WEPP, the Water Erosion Prediction Project. The primary inputs for WEPP include a digital elevation model (DEM), climate data, soil maps, and land cover/land management information. Climate files were created using a stochastic weather generator Cligen (Nicks et al. 1995). To model mountainous terrain the climate files were adjusted using Rock:Clime which modifies monthly precipitation for a selected climate station based on elevation and PRISM data (Parameter-elevation Regressions on Independent Slopes Model, Daly et al. 2004). In order to predict average first year post-fire erosion rates a 50 year climate was used with soils and land cover kept at first year conditions. The final map is in units of Mg ha^{-1} yr^{-1}; results were multiplied by 100 and converted to integer format to reduce file size and allow for more rapid display.

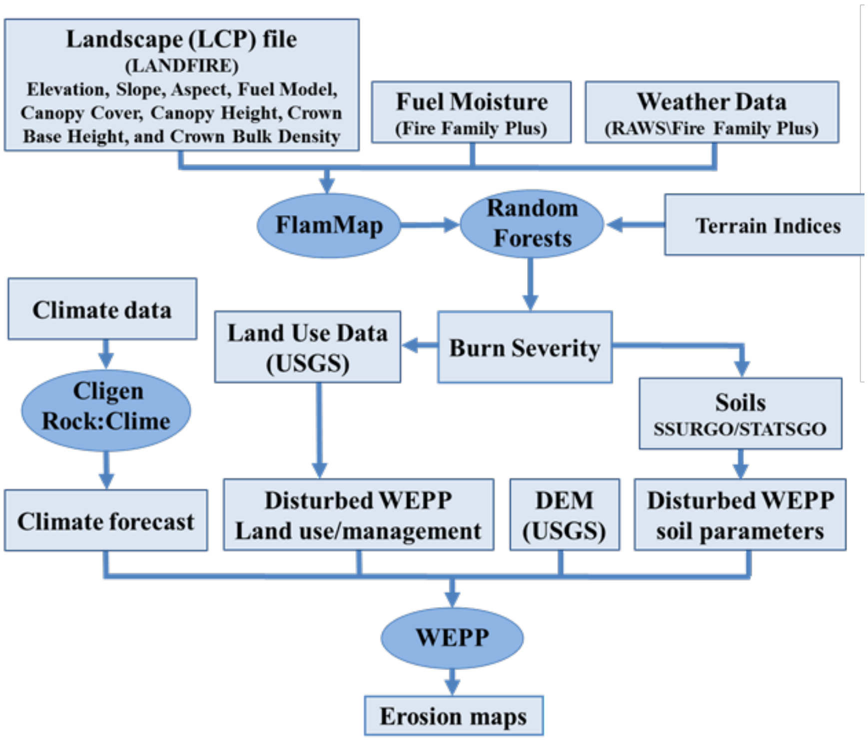

Figure *3*. Modeling flowchart depicting FlamMap and WEPP inputs\outputs and coupling (Buckley et al., 2014).

FlamMap

FlamMap is a spatial fire behavior model that uses land cover, topography, and fuel characteristics data from the LANDFIRE database along with fuel moisture and weather data (Finney, 2006). The required spatial inputs include elevation, slope, aspect, fuel model, canopy cover, canopy height, crown base height, and crown bulk density (Stratton, 2006). Initial fuel moistures are required for each fuel type and wind data are required as well. Wind information can be entered either as a spatial layer or as a fixed constant to apply to all the raster cells. The basic fire behavior outputs include fireline intensity, flame length, rate of spread, heat per unit area, and crown fire activity (Finney, 2006). Land managers currently use FlamMap as a planning tool to predict the effectiveness of different fuel treatment scenarios (Gercke and Stewart, 2006; Stratton, 2004). FlamMap model input and output are used in the Burn Severity Prediction tool.

WEPP

The WEPP model is a process-based soil erosion model that has been developed by an interagency team of scientists (Laflen et al., 1997). WEPP technology includes two versions, a hillslope version to estimate the distribution of erosion on a hillslope, and a watershed version that links hillslopes with channels and in-stream structures to estimate sediment delivery from small watersheds. The surface hydrology component of the WEPP model uses climate, soils, topography, and vegetation input files to predict infiltration, runoff volume, and peak discharge for each simulated storm. WEPP then uses these inputs and predictions to calculate both rill and interrill erosion as well as sediment deposition (Flanagan and Nearing, 1995). Disturbed WEPP (Elliot, 2004) is an online interface for WEPP designed to facilitate the use of WEPP in forested areas. Disturbed WEPP input files can be used to simulate a variety of forest conditions and management scenarios, including the effects of fuel treatments and wildfire (Soto and Diaz-Fierros, 1998; Larsen and MacDonald, 2007; Spigel and Robichaud, 2007). Recent improvements to the WEPP model have been undertaken specifically to improve predictions of water flow and sediment discharge from forested watersheds.

Random Forest

The machine learning algorithm, Random Forest, has been used to develop predictions of future high burn severity by utilizing topographic indices, vegetation and climate data (Holden et al, 2009; Dillon et al, 2011). Random Forests is an ensemble classifier consisting of multiple decision trees generated from a random subset of training data and inputs (Breiman, 2001). Each tree is created from an independent "bootstrap" sample consisting of two-thirds of the training data. Once the forest of decision trees is created, an individual pixel's classification is determined by which class receives the most "votes" from each decision tree. The Fire Severity Mapping System project (FIRESEV) utilized Random Forests and over 7,000 fires from the MTBS dataset to generate spatial gridded predictions of potential high severity for the Western US (https://www.frames.gov/partner-sites/firesev/firesev-home/; Dillon et al. 2011). FIRESEV provides predictions of the likelihood of a pixel burning at high severity by providing information on the number of classification trees that predicted a pixel would burn at high severity. Classification accuracies for the random forest algorithm used in FIRESEV ranged from 68-84% (Dillon et al. 2011).

The strengths of the Random Forest algorithm include handling datasets with a small number of observations and a large number of attributes, more powerful than a single classifier, well suited to parallel processing, and insensitive to non-predictive inputs. Additionally, the algorithm can easily handle missing attributes as a subset of the decision trees that were built without the use of the missing attributes can be used to classify the compromised data. The main drawback to the algorithm is it is not intuitive and the model is very sensitive to inaccurate training data (Liaw and Wiener, 2002).

BurnSev an Online Burn Severity Prediction Tool

Random Forests was built into a new online interface for forecasting burn severity using historical burn severity maps https://apps.mtri.org/burnsev/get. The application predicts burn severity of a user-selected area using both Random Forests and FlamMap. The interface requires the user to either enter spatial coordinates or draw a bounding box rectangle on a web map, at which point the nearest MTBS and Soil Burn Severity (SBS) maps are queried from the application's database. The user selects the fires they wish to use in the analysis and the program will extract input layers for sets of low, medium, and high burn severity pixels and use these to predict burn severity of the selected area. FlamMap model inputs and outputs along with topographic indices from the FIRESEV project are used to create training data. When we tested the programming interface for our new online tool on a set of ten test fires the resulting accuracy was only 33%. When we selected only SBS maps for training the results were much better with an average accuracy of 50%. The tool has been updated with additional SBS maps and the default setting is set to use SBS maps.

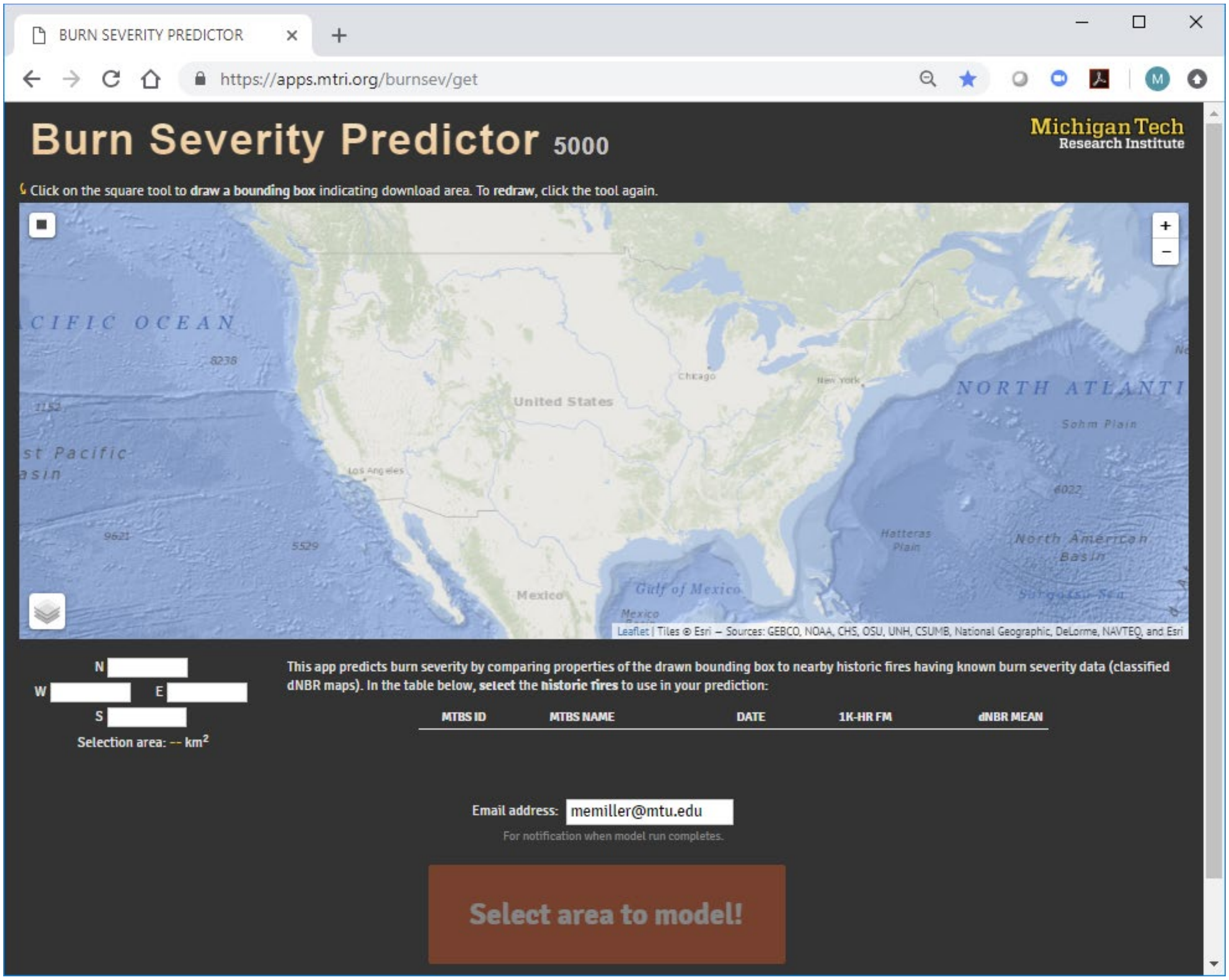

Figure 4. New online graphical user interface to allow land managers to predict potential burn severity for their area of interest using historical burn severity maps and machine learning. https://apps.mtri.org/burnsev/get.

References

Breiman, L. (2001). Random Forests. Machine Learning, 45, 5-32.

Breiman, L. (1996). Bagging predictors. Machine Learning 26(2), 123–140.

Buckley M, Beck N, Bowden P, Miller ME, Hill B, Luce C, Elliot WJ, Enstice N, Podolak K, Winford E, Smith SL, Bokach M, Reichert M, Edelson D, Gaither J (2014) Mokelumne watershed avoided cost analysis: Why Sierra fuel treatments make economic sense. Report prepared for the Sierra Nevada Conservancy, The Nature Conservancy, and USDA, Forest Service. (Sierra Nevada Conservancy, Auburn, CA) Available at: http://www.sierranevadaconservancy.ca.gov/mokelumne [Verified 22 June 2014]

Daly C, Gibson WP, Doggett M, Smith J, Taylor G (2004) Up-to-date monthly climate maps for the conterminous Unites States. Proc., 14th AMS Conf. on Applied Climatology, 84th AMS Annual Meeting Combined Preprints, Amer. Meteorological Soc., Seattle, WA, January 13-16, 2004, Paper P5.1, CD_ROM.

Dillon, G.K., Holden, Z.A., Morgan, P., Crimmins, M.A., Heyerdahl, E.K. and Luce, C.H. (2011). Both topography and climate affected forest and woodland burn severity in two regions of the western US, 1984 to 2006. Ecosphere, 2, 1-33.

Elliot, W.J. (2004) WEPP Internet interfaces for forest erosion prediction. Journal of the American Water Resources Assoc. 40(2):299-309.

Finney, MA 2006. An overview of FlamMap modeling capabilities. In: P.L. Andrews, B.W. Butler (comps.). Fuels Management – How to measure success: Conference Proceedings. RMRS-P-41. p 213-219.

Flanagan, D.C., Frankenberger, J.R., Cochrane, T.A., Renschler, C.S., Elliot, W.J. (2013) Geospatial application of the Water Erosion Prediction Project (WEPP). *Trans. ASABE* 56(2), 591–601.

Frankenberger, J.R., Dun, S., Flanagan, D.C., Wu, J.Q., Elliot, J.W. (2011) Development of a GIS interface for WEPP model application to Great Lakes forested watersheds, Paper No. 11139. Presented at the International Symposium on Erosion and Landscape Evolution, 18–21 September, 2011, Anchorage, AL. St. Joseph, MI: Am. *Soc. Ag & Bio Engrs*. 8 p.

Gercke, D.M., Stewart, S.A. (2006) Strategic placement of treatments (SPOTS): maximizing the effectiveness of fuel and vegetation treatments on problem fire behavior and effects. In Proceedings of the 1st Fire Behavior and Fuels Conference: Fuels Management—How to Measure Success.

Laflen, J.M., Elliot, W.J., Flanagan, D.C., Meyer, C.R., Nearing, M.A. (1997) WEPP—Predicting water erosion using a process-based model. *J. Soil Water Conserv*. 52(2), 96–102.

Liaw A. and M. Wiener (2002). Classification and Regression by randomForest. R News 2(3), 18--22.

Miller, M.E., MacDonald, L.H., Robichaud, P.R., Elliot, J.W. (2011) Predicting post-fire hillslope erosion in forest lands of the western United State. *Int. J. of Wildland Fire* 20(8), 982–999.

Miller, M.E., Elliot, W.J., Billmire, M., Robichaud, P.R., and Endsley, K. (2016). Rapid-response tools and datasets for post-fire remediation: linking remote sensing and process-based hydrological models. International Journal of Wildland Fire, 25, 1061-1073.

Nicks AD, Lane LJ, Gander GA (1995) 'Weather generator', pp. 2.1-2.22 In 'USDA-Water Erosion Prediction Project Hillslope Profile and Watershed Model Documentation', Flanagan DC, Nearing MA, Eds, USDA Agricultural Research Service (West Lafayette, Indiana)

Robichaud PR, Lewis SA, Laes DYM, Hudak AT, Kodaly RF, Zamudio JA (2007). Post-fire soil burn severity mapping with hyperspectral image unmixing. Remote Sensing of Environment 108(4), 467–480. doi:10.1016/J.RSE.2006.11.027

Robichaud, P.R., S.A. Lewis, R.E. Brown and L.E. Ashmun (2009). Emergency post-fire rehabilitation treatment effects on burned area ecology and long-term restoration. Fire Ecology Special Issue 5(1): 115-128.

Spigel, K. M., & Robichaud, P. R. (2007) First year post fire erosion rates in Bitterroot National Forest, Montana. *Hydrological Processes*, *21*(8), 998-1005.

Stratton, R.D. (2004) Assessing the effectiveness of landscape fuel treatments on fire growth and behavior. *J. Forest.* 102(7), 32–40.

Stratton, R. D. (2006) Guidance on spatial wildland fire analysis: models, tools, and techniques. United States Department of Agriculture, Forest Service, Rocky Mountain Research Station.

Soto, B., Díaz-Fierros, F. (1998) Runoff and soil erosion from areas of burnt scrub: comparison of experimental results with those predicted by the WEPP model. *Catena* 31(4), 257–270.