Topographic Position and Landforms Analysis
Andrew D. Weiss, The Nature Conservancy

The Nature Conservancy
SAVING THE LAST GREAT PLACES ON EARTH

Director: Ecoregional Data Management Team
The Nature Conservancy, Northwest Division
217 Pine St. Suite 1100
Seattle WA 98103
(206) 343-4345 x360
aweiss@tnc.org

Introduction

Many physical and biological processes acting on the landscape are highly correlated with topographic position: a hilltop, valley bottom, exposed ridge, flat plain, upper or lower slope, and so on. Examples of these processes include soil erosion and deposition; hydrological balance and response; wind exposure; and cold air drainage. These biophysical attributes in turn are key predictors of habitat suitability, community composition, and species distribution and abundance.

This poster presents an algorithm, implemented in GRID, for generating a multi-scale Topographic Position Index, classifying this index into slope position and landform types, and using the Topographic Position Index to characterize watersheds.

This work was done as a contractor with U.S. EPA Region 10, working on the Environmental Monitoring and Assessment Program Western Landscape Project (Jones *et al* 2000).

Jones, K. Bruce *et al* 2000. Assessing Landscape Conditions Relative to Water Resources in the Western United States: A Strategic Approach. *Environmental Monitoring and Assessment* 64: 227 – 245.

Study Area

The focus study area encompasses the area around Mt. Hood, Oregon, and the west slope of the Cascades. The EMAP-West Oregon Pilot Area encompasses portions of the Upper Deschutes basin, the Willamette Valley, and the northern Coast Range.

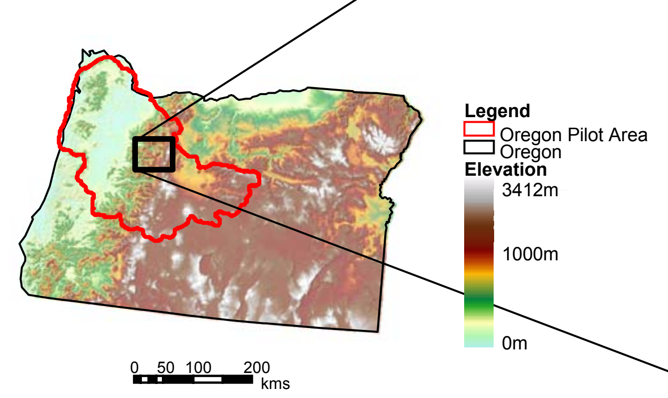
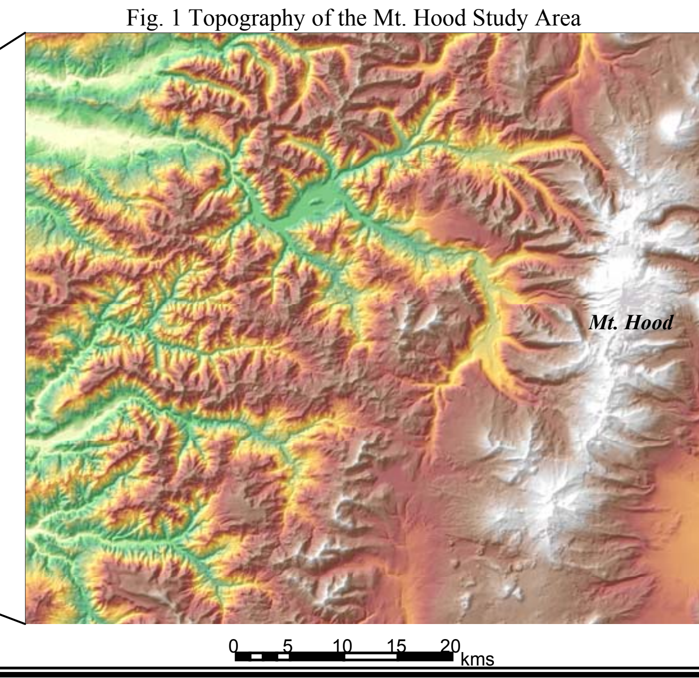


Fig. 1 Topography of the Mt. Hood Study Area



Future Research

1) Using directionally weighted TPI (using multiple wedge-shaped neighborhoods in 4 or 8 directions). How equal these wedges are could help resolve slopes from flat areas from saddles, ridges from hilltops and valleys from depressions. It could also provide the aspect of landforms (direction of a valley or ridge) which could be a great use for mesoclimate and wind/weather exposure.

2) Exploring the use of neighborhood statistics of slope and aspects, or slope/aspect measured at a coarser scale to increase the resolution of landform classifications.

3) Testing TPI and thresholding strategies in a wide variety of different landscapes.

4) Assessing the usefulness of TPI as predictors for landscape level processes and features, and for predictive species/communities models.

5) Compare TPI to the Topographic Convergence Index ln[A/tan(slope)], where A is the upslope contributing area.

6) Exploring higher order topographic position indices, such as a high pass filter on topographic position to highlight the extremes (ridges/valleys) in a neighborhood

Basic Algorithm

The Topographic Position Index (TPI) compares the elevation of each cell in a DEM to the mean elevation of a specified neighborhood around that cell (Fig. 2a). In this example an annulus neighborhood is used, but continuous circles or other shapes could be used. Since the only input required is a digital elevation model, TPI can be readily generated almost anywhere.

Positive TPI values represent locations that are higher than the average of their surroundings, as defined by the neighborhood (ridges). Negative TPI values represent locations that are lower than their surroundings (valleys). TPI values near zero are either flat areas (where the slope is near zero) or areas of constant slope (where the slope of the point is significantly greater than zero).

Topographic position is an inherently scale-dependent phenomenon. As an example, consider a location in a meadow in Yosemite valley. At a fine scale of 100m, the topographic position would be a flat plain. This may be an appropriate scale for looking at soil transport or site water balance. At a scale of several kilometers, this same point is at the bottom of a 1500m deep canyon, which may be more significant for overall hydrology, mesoclimate, wind exposure, or cold air drainage. The ecological characteristics of a site may be affected by TPI at several scales. In a study of vegetation distributions in the Spring Mountains of southern Nevada (Guisan, Weiss, and Weiss 1999) species distribution models show significant relationships to TPI at scales of 300m, 1000m, and 2000m. TPI was generally second most important predictive variable after elevation.

Guisan, A., S. B. Weiss, A. D. Weiss 1999. GLM versus CCA spatial modeling of plant species distribution. *Plant Ecology* 143: 107-122

Fig. 2a: Topographic Position Index

tpi<*scalefactor*> = int((dem - focalmean(dem, annulus, *irad*, *orad*)) + .5)

scalefactor = outer radius in map units
irad = inner radius of annulus in cells
orad = outer radius of annulus in cells

The index is converted to integer for storage efficiency and symbolization

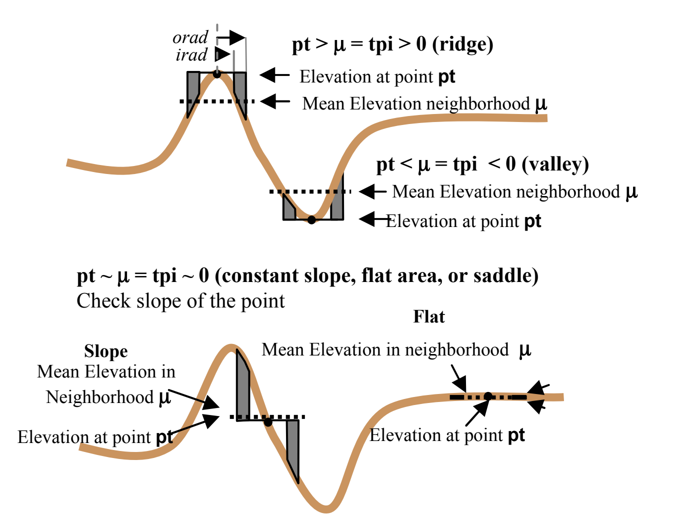


Fig. 2b: tpi300, computed from a 30m DEM with the formula:
tpi300 = int((dem – focalmean(dem, annulus, 5, 10)) + 0.5)
At this scale a dendridic network of both main and lateral ridges and drainages are revealed.

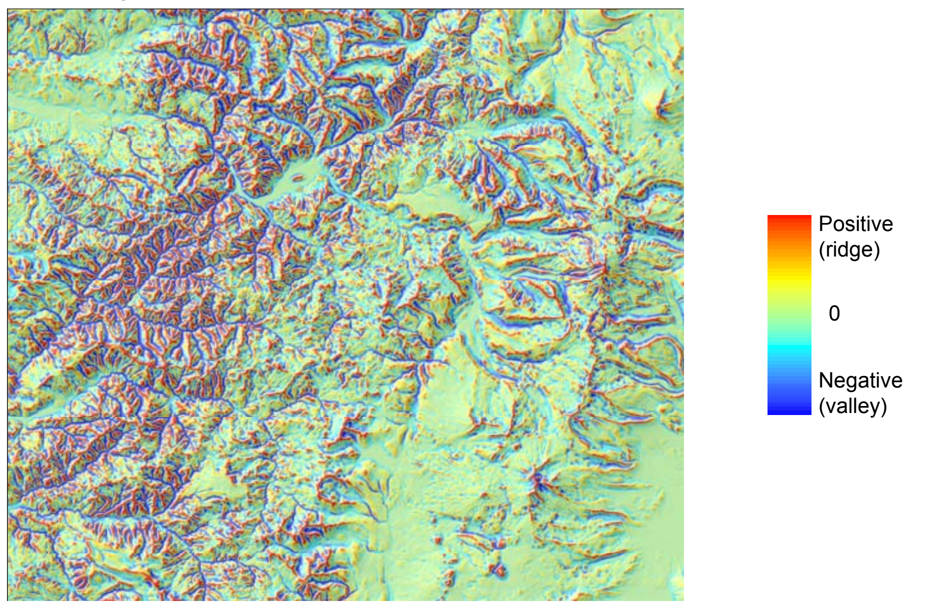
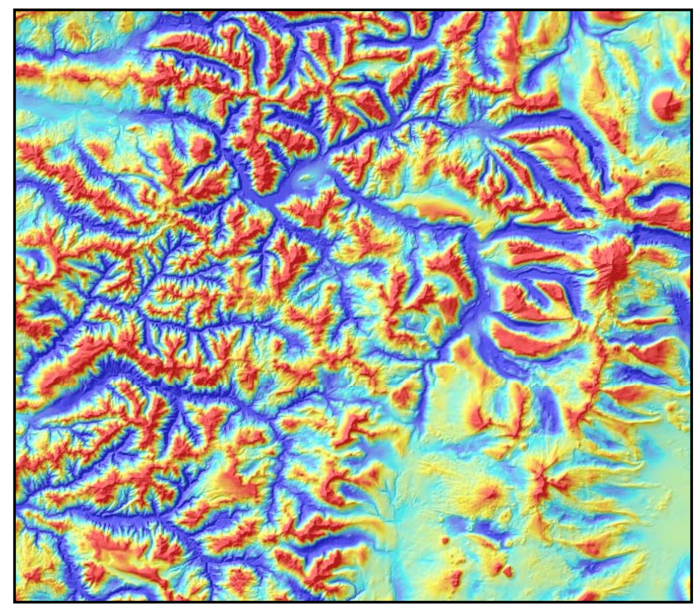


Fig. 2c: tpi2000, computed from a 30m DEM with the formula:
tpi2000 = int((dem – focalmean(dem, annulus, 62, 67)) + 0.5)
At his scale the major ridge lines and drainages are highlighted. Smaller lateral features disappear.



Slope Position

By thresholding the continuous TPI values at a given scale, and checking the slope for values near zero, landscapes can be classified into discrete slope position classes (Fig. 3a).

Using tpi300 (Fig. 3b), many individual ridge lines and valleys are delineated at a fine scale, including lateral drainages in the major valleys, and the bottoms of the major canyons are classified as flat areas. At tpi2000, the classification shows the major landforms (Fig. 3c): mountains, major ridge lines, and the major valleys and canyons. Smaller lateral features disappear, and canyons bottoms are now classified as valleys.

Defining the thresholds needs to take into account several factors: the specific landscape (a ridge in Kansas is different than a ridge in central Colorado); the scale of the index; and the particular problem being addressed. Selected features particularly important to a specific analysis could be extracted by adjusting class breakpoints, and incorporating additional metrics, such as the variance of elevation or slope in the neighborhood of the target cell.

One repeatable method of creating classes, used in Fig. 3b and 3c, is to use standard deviation units. In this example, classes 2 and 5 are de-emphasized:

Class	Description	Breakpoints
1	ridge	> + 1 STDEV
2	upper slope	> 0.5 STDV =< 1 STDV
3	middle slope	> -0.5 STDV, < 0.5 STDV, slope > 5 deg
4	flats slope	>= -0.5 STDV, =< 0.5 STDV , slope <= 5 deg
5	lower slopes	>= -1.0 STDEV, < 0.5 STDV
6	valleys	< -1.0 STDV

Fig. 3a: TPI and slope position

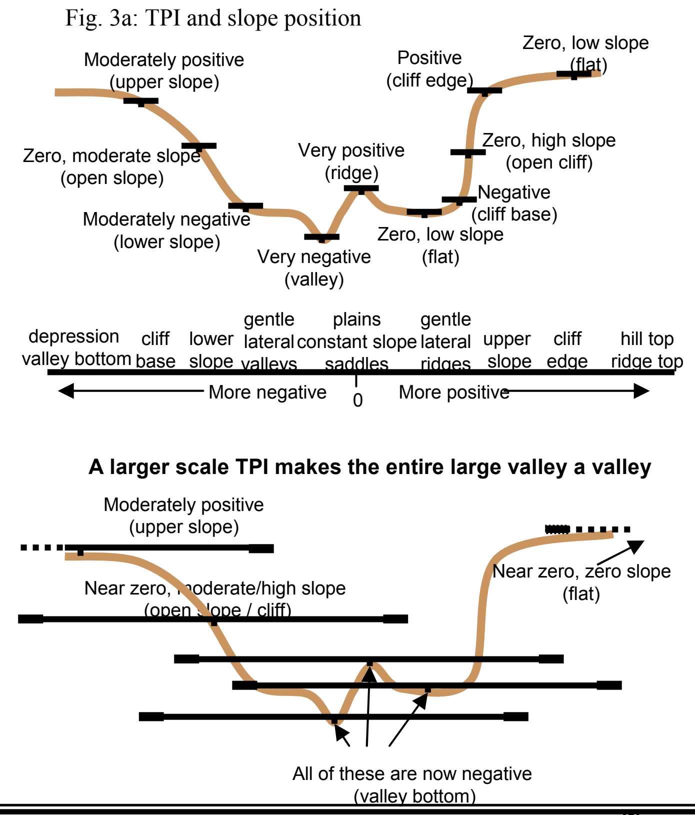


Fig. 3b – tpi300 thresholded by standard deviation units into 6 slope position classes

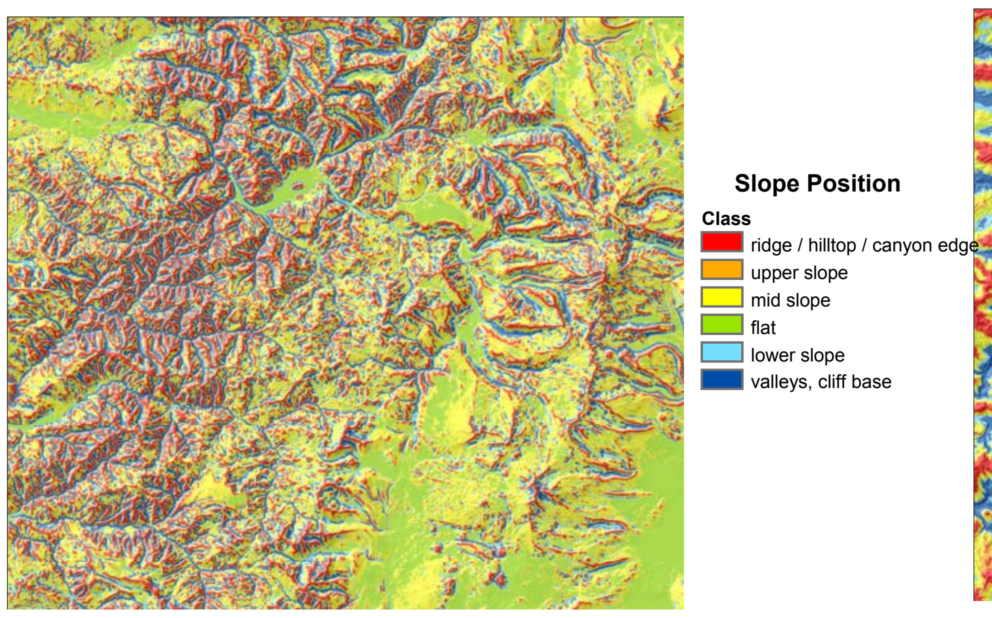
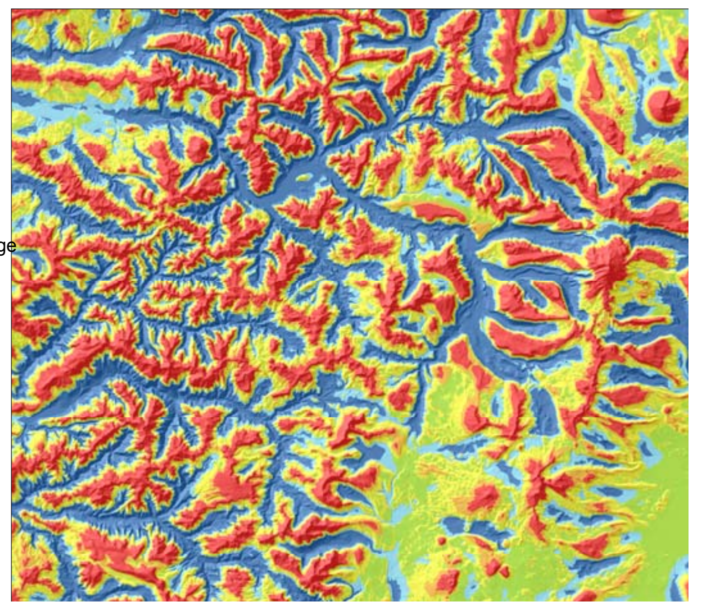


Fig. 3c – tpi2000 thresholded by standard deviation units into 6 slope position classes

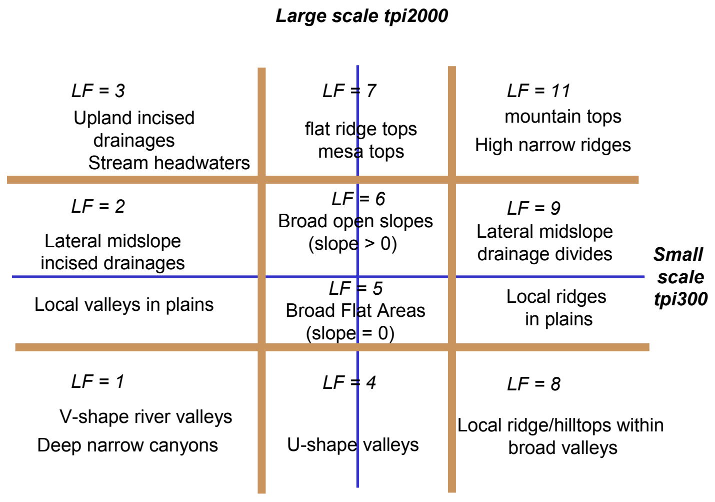


Landforms

Combining TPI at a small and large scale allows a variety of nested landforms to be distinguished (fig. 4a). As a general rule, because elevation tends to be spatially autocorrelated, the range of TPI values increases with scale. One method to address this problem is to standardize the TPI grids to mean = 0 and stdev = 1 (this should only be done if the means of the original TPI grids are 'reasonably' close to zero). This lets the same basic equations to be used to classify any scale combinations of TPI grids.

The exact breakpoints among classes can be manually chosen to optimize the classification for a particular landscape and problem. As in slope position classifications, additional topographic metrics, such as variances of elevation, slope, or aspect within the neighborhoods, may help delineate landforms more accurately, and extract different types of features.

Fig 4a: Combining TPI at 2 scales to develop landform classes



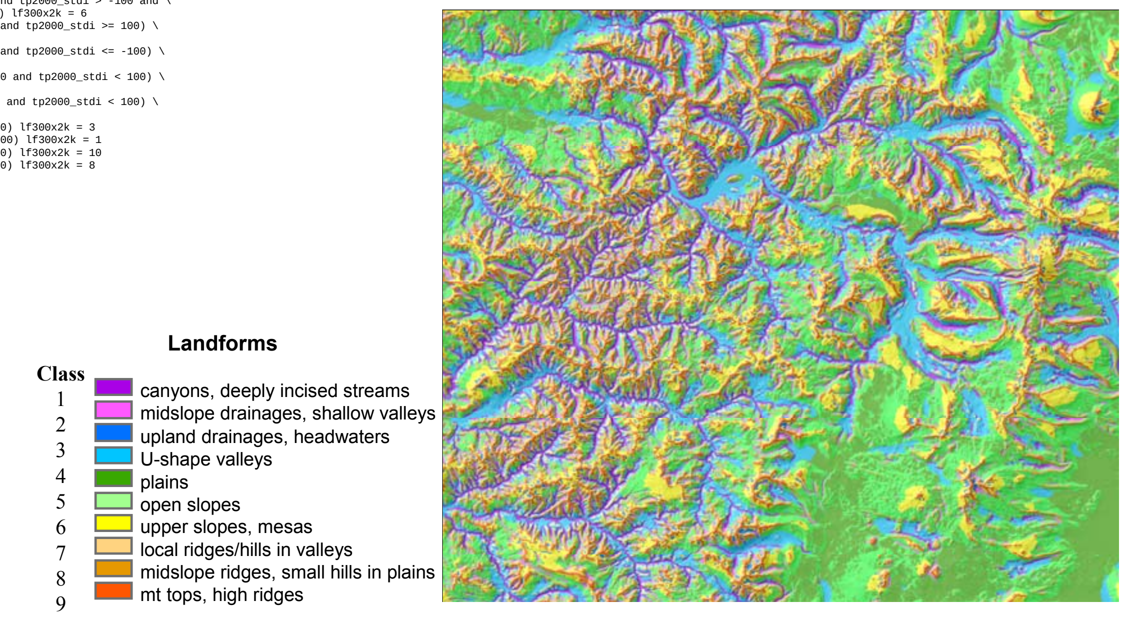
/* First, standardize the TPI grids using the formula:
/* tpi<sf>_stdi = int((((tpi<sf> – mean) / stdv) * 100) + 0.5)

```
tp300_stdi = int((((tp300i - 0.399) / 7.566) * 100) + .5)
tp2000_stdi = int((((tp2000i - 0.346) / 89.435) * 100) + .5)
```

/* Then classify the plane in Fig 4a by 1 stdv units (= 100 grid value units), and check /* the slope for the central zone:

```
if (tp300_stdi > -100 and tp300_stdi < 100 and tp2000_stdi > -100 and \
          tp2000_stdi < 100 and slopei_deg <= 5) lf300x2k = 5
else if (tp300_stdi > -100 and tp300_stdi < 100 and tp2000_stdi > -100 and \
          tp2000_stdi < 100 and slopei_deg >= 6) lf300x2k = 6
else if  (tp300_stdi > -100 and tp300_stdi < 100 and tp2000_stdi >= 100) \
    lf300x2k = 7
else if  (tp300_stdi > -100 and tp300_stdi < 100 and tp2000_stdi <= -100) \
    lf300x2k = 4
else if (tp300_stdi <= -100 and tp2000_stdi > -100 and tp2000_stdi < 100) \
    lf300x2k = 2
else if (tp300_stdi >= 100 and tp2000_stdi > -100 and tp2000_stdi < 100) \
    lf300x2k = 9
else if (tp300_stdi <= -100 and tp2000_stdi >= 100) lf300x2k = 3
else if (tp300_stdi <= -100 and tp2000_stdi <= -100) lf300x2k = 1
else if (tp300_stdi >= 100 and tp2000_stdi  >= 100) lf300x2k = 10
else if (tp300_stdi >= 100 and tp2000_stdi <= -100) lf300x2k = 8
 endif
```

Fig 4b: The Mt. Hood region classified into 10 landform classes.



Watershed Metrics

Watersheds can be characterized by extracting the TPI values underneath streams or within a buffer around streams, and then taking the mean value within each watershed unit. The example at right overlays streams from the Pacific Northwest River Reach Files over tpi2000, then computes the mean value within USGS 5[th] level Hydrologic Units.

Watersheds with higher (more negative) mean values have a high proportion of streams that are in relatively deeper and narrower drainages, with narrowness defined by the spatial scale of the index. At the scale of 300m (fig. 5c), the metric reflects the degree that the stream channel is incised, and the narrowness of the valley. At the scale of 2000m (fig 5d) the metric reflects the broader valley morphology and the relative relief of streams and their surrounding topography. This can be seen in the lower Willamette valley, where the tpi300 metric shows streams to be more incised (light blue) than further up the valley. At tpi2000 these same watersheds move into the lowest quintile.

As the scale increases, HUCs in the middle Coast Range move from the top quintile (red) to the middle quintiles. This reflects the lower relief of the mountains in this area. In the southern Cascades, HUCs that were in the middle quintiles at 300m are in the top quintile at 2000m, which reflects the high degree of relief in this region, the wide valleys on the west slope of the Cascades, and the presence of several volcanic peaks on the east size.

As an indicator, which might expect that HUCs in the top quintiles at 300m to be more sensitive to near-stream deforestation, grazing, and human impacts. HUCs in the top quintiles at 2000m might be more sensitive to drainage wide deforestation and land use, and would likely have a stronger response to extreme weather and snowmelt events.

Fig. 5a: Streams (1:100k PNW Reach files) overlaid on tpi2000, with USGS Level 5 Hydrologic Unit boundaries

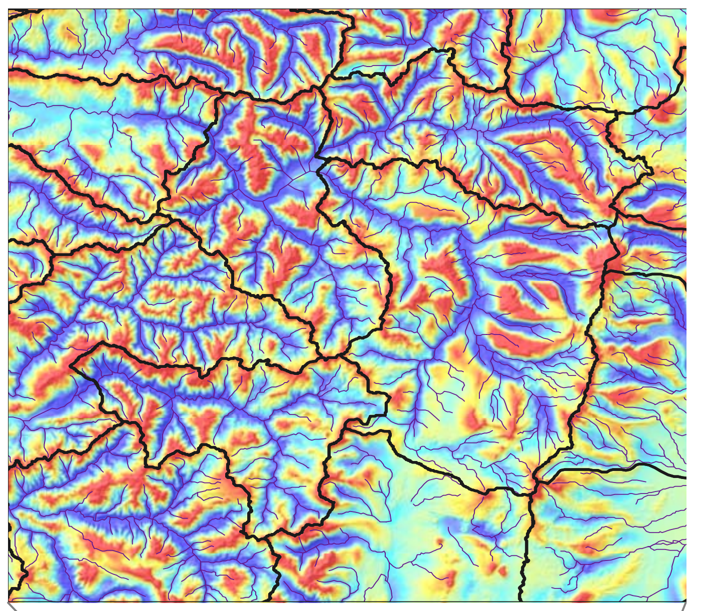


Fig. 5b: Topography of the Western EMAP Oregon Pilot Area, with 5[th] level watersheds.

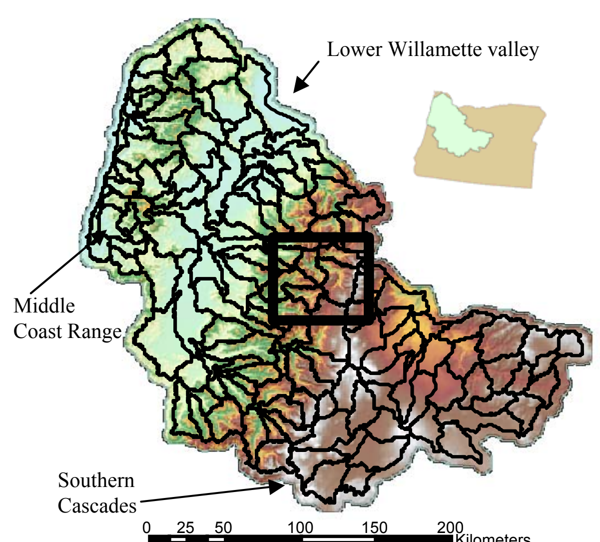


Fig. 5c: Watershed Metrics for tpi300, Quintile classification

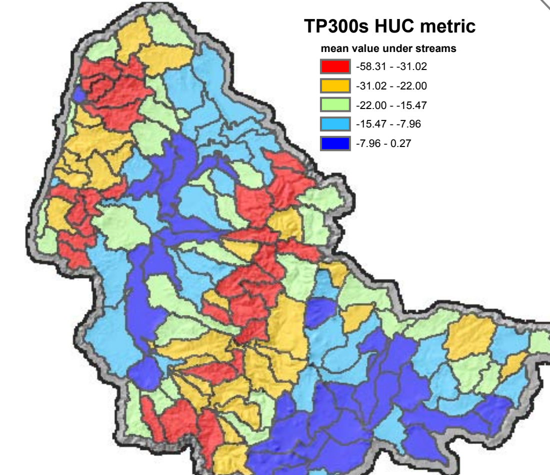


Fig. 5d: Watershed Metrics for tpi300, Quintile classification