Ducey, M.J.: Zheng, D.; Heath, L.S. 2009. Creating compatible maps from remotely sensed and forest inventory data using radial basis functions. In: Proceedings of Extending Forest Inventory and Monitoring Over Space and Time, 19-22 May, 2009; Quebec City, Quebec. http://blue.for.msu.edu/meeting/proceed.php.

Creating Compatible Maps from Remotely Sensed and Forest Inventory Data Using Radial Basis Functions

M.J. Ducey[1], D. Zheng[2], and L.S. Heath[3]

[1] Department of Natural Resources and the Environment, University of New Hampshire, 310 Nesmith Hall, Durham, New Hampshire, 03824 U.S.A. (603) 862-4429; mjducey@cisunix.unh.edu

[2] Department of Natural Resources and the Environment, University of New Hampshire, 310 Nesmith Hall, Durham, New Hampshire, 03824 U.S.A. (603) 868-7696; daolan.zheng@unh.edu

[3] USDA Forest Service, Northern Research Station, 271 Mast Road, Durham, New Hampshire, 03824 U.S.A. (603) 868-7612; lheath@fs.fed.us

Introduction

Forest inventory designs, especially those used at national scales, are usually capable of producing design-unbiased or model-unbiased estimates of forest attributes (such as timber volume or total aboveground carbon) over large areas. However, they typically lack the resolution to produce reliable, fine-grained estimates. By contrast, maps derived from remotely-sensed data contain a great deal of fine-grained information of varying and perhaps unknown reliability, and often fail to match the reliable large-area estimates produced by the statistically-designed forest inventories.

This challenge and its conceptual solution are similar to those presented by Iles (2009) through the concept of "total balanced" estimates. If inventory data provide unbiased estimates of the total of an attribute for one or more sub-areas, and if mapped information is adjusted to match the inventory-estimated totals (or means) for those sub-areas ("total balancing"), then the mapped information inherits the properties of unbiasedness from the inventory data. It also inherits properties related to the sampling variance (such as the standard error of the sample estimate). Cieszewski et al. (2003) provide a qualitative and conceptual framework for total balancing using data from the U.S. Forest Service, Forest Inventory and Analysis (FIA) program.

Unfortunately, putting the relatively simple idea of total balancing into practice can raise some technical challenges. A straightforward approach is to use a ratio map: pixels or polygons within an inventory subunit are multiplied by the ratio of the inventory estimate to the original map estimate for that subunit. Ratio maps have been employed successfully to ensure compatibility between inventory estimates and remote sensing-derived maps (Zheng et al. 2004, 2008). However, the ratio map approach typically creates artificial discontinuities in the final map at the boundaries of the inventory subunits. This can lead to complications for further analyses (especially spatial analyses) and perceptual rejection of the map by end users.

In this study, we explore a new approach to ensure compatibility between inventory estimates and remote sensing-derived maps using networks of radial basis functions (RBFs). Exact compatibility is ensured,

and because adjustment is smooth, there are no artificial discontinuities in the resulting map.

Methods

In the radial basis function (RBF) network approach, we seek to construct an adjusted map **Z** as the product of our original map **X** with an adjustment map **U**:

$$\mathbf{Z} = \mathbf{U} \cdot \mathbf{X}$$

where $\cdot$ denotes Hadamard (element-by-element) multiplication. We assume for the purposes of this presentation that the means of **X** and **Z** are equal over the area of interest; this is easy to guarantee by preadjustment of **X**. **U** in turn is constructed as the weighted sum of Gaussian RBFs $\mathbf{W}_j$, j=1..J, each characterized by its geographic center and bandwidth:

$$\mathbf{U} = 1 + \Sigma_j b_j \mathbf{W}_j$$

Holding the centers and bandwidths of the RBFs as temporarily fixed, we can treat the weights b_j as a set of parameters to be estimated.

Parameter estimation is reasonably straightforward. Each inventory estimate for a sub-area of the map provides a constraint on the weights that can be written as a linear equation:

$$\Sigma_k \delta_{ik} z_k = Y_i$$

where δ_{ik} is an indicator function equal to 1 if the kth pixel is in the ith sub-area, and Y_i is the inventory estimate for the ith sub-area. In general, we will employ a network of RBFs with more RBF nodes than inventory sub-areas, so the contraints taken together represent an underdetermined linear system. The Moore-Penrose pseudoinverse provides the minimum-length solution, yielding a set of weights that will provide an exact but reasonably smooth solution for a given set of node centers and bandwidths.

Solution smoothness can be evaluated as the sum of squared values of the finite-difference approximation to the Laplacian. The overall smoothness of the solution can be improved (while guaranteeing non-negativity) by greedy stochastic search: the center and bandwidth for a randomly selected node are perturbed, the new network weights are obtained, smoothness is evaluated, and if the new network represents an improvement it is retained. This process is repeated until no further improvement in the solution occurs after a reasonable number of attempts.

We evaluated this approach using the raw (unadjusted) forest aboveground biomass (AGB) map for the state of Maine, USA of Zheng et al. (2008), shown in Figure 1. The county totals as estimated from FIA data and from the unadjusted map are shown in Figure 2. There are 32 county sub-areas within the state; for this paper, we employed an RBF network with 128 nodes. The initial assignment of node locations was systematic.

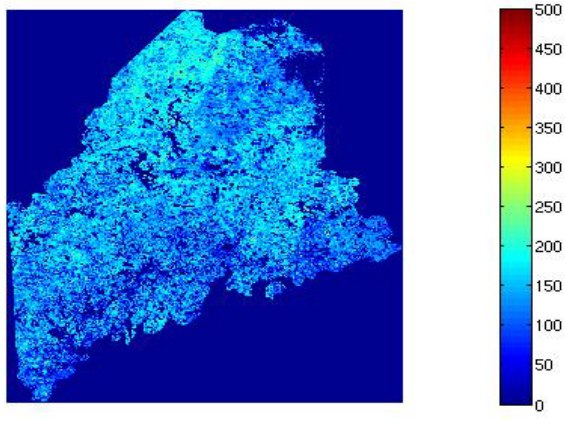

Figure 1. Unadjusted map of aboveground biomass density (Mg/ha) from Zheng et al. (2008).

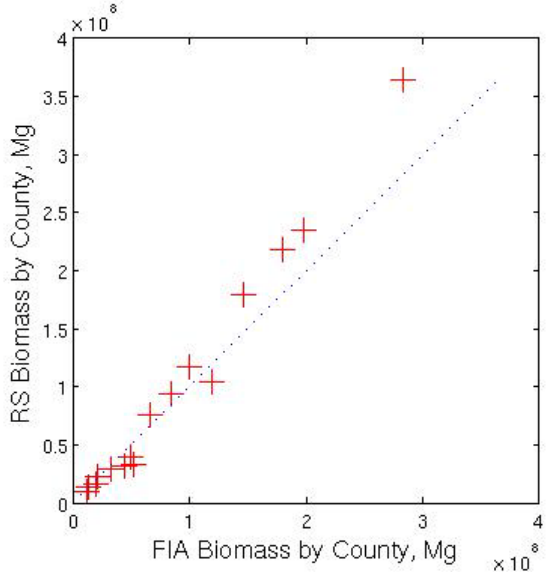

Figure 2. Forest aboveground biomass by county for the state of Maine, as estimated from FIA plot data and from the unadjusted map of Zheng et al. (2008).

Results and Discussion

The adjustment factor map **U**, and the adjusted map **Z** using the initial network configuration represented immediately useful solutions. All of the constraints represented by county-level FIA estimates were satisfied exactly. **U** revealed a clear pattern for the unadjusted map to underestimate biomass in the southern and central portions of the state, and to overestimate in the northern and downeast portions as compared to the FIA point data. However, the adjustment was smooth and showed no discontinuities at county borders.

Figure 3 shows the configuration of the network after convergence of the greedy stochastic search algorithm. Several of the nodes have been moved "offshore" or otherwise out of the area of interest, suggesting that 128

nodes may be more than is necessary to adjust this particular map. Other nodes have been clustered near areas of more intense adjustment, to provide for a smoother solution. The resulting adjustment factor map **U** is shown in Figure 4, while the final adjusted biomass map **Z** is shown in Figure 5. The results are generally consistent with those from the initial network configuration but the extent, magnitude, and smoothness of the adjustment are different.

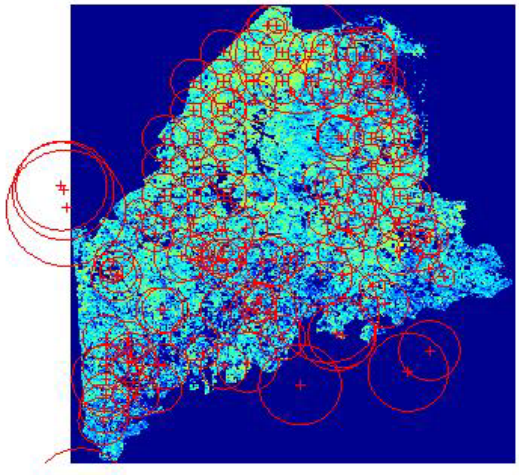

Figure 3. Final configuration of the RBF network after greedy stochastic search.

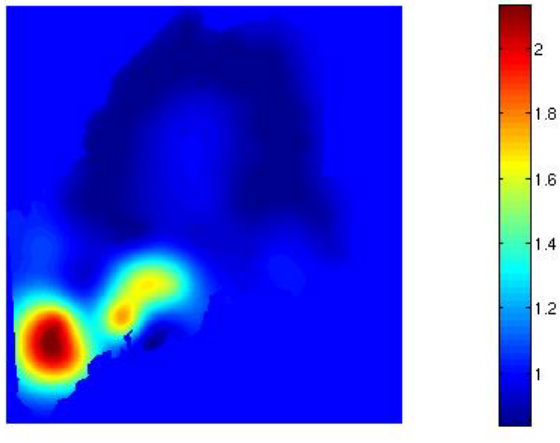

Figure 4. Adjustment map **U** (unitless; a value of 1 indicates no change) for the final network configuration.

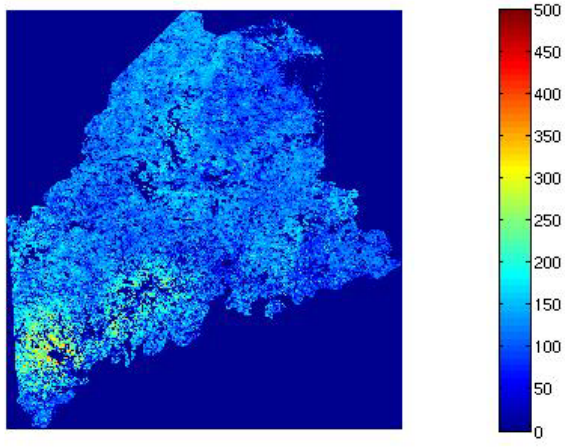

Figure 5. Adjusted aboveground biomass density map (Mg/ha) for the final network configuration.

Conclusions

Radial basis function networks provide a computationally feasible approach for ensuring consistency between remote sensing-derived maps and unbiased estimates derived from inventory data. Additional work, not shown here, suggests that the results are reasonably stable across a range of network complexity, and are generally reproducible despite the nature of the stochastic search algorithm employed here. Further evaluation will focus on whether the adjustment improves accuracy at the pixel scale, on the utility of the **U** map for diagnosing and interpreting challenges of the input map and inventory data, and on the usefulness of the method for larger areas with possible spatial trends in addition to local variability.

Literature Cited

Cieszewksi, C.J., K. Iles, R.C. Lowe, and M. Zasada. 2003. Proof of concept for an approach to a finer resolution inventory. pp. 69-74 in 2003 Proceedings of the Fifth Annual Forest Inventory and Analysis Symposium. USDA Forest Service, Gen. Tech. Rep. WO-69.

Iles, K. 2009. “Total-Balancing” an inventory: A method for unbiased inventories using highly biased non-sample data at variable scales. Math. Comp. For. Nat. Res. Sci. 1: 10-13.

Zheng, D., S.D. Prince, and T. Hame. 2004. Estimating net primary production of boreal forests in Finland and Sweden from field data and remote sensing. J. Veg. Sci. 15: 161–170.

Zheng, D.L., L.S. Heath, and M.J. Ducey. 2008. Spatial distribution of forest aboveground biomass estimated from remote sensing and forest inventory data in New England, USA. Journal of Applied Remote Sensing 2: 021502 (online).