A Taxonomically Based Ordinal Estimate of Soil Productivity for Landscape-Scale Analyses

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Abstract: In this article, we introduce, evaluate, and apply a new ordinally based soil Productivity Index (PI). The PI uses family-level Soil Taxonomy information, that is, interpretations of features or properties, recognized in Soil Taxonomy, that tend to be associated with low or high soil productivity, to rank soils from 0 (least productive) to 19 (most productive). The index has a wide application generally at landscape scales. Unlike competing indexes, it does not require copious amounts of soil data, for example, pH, organic matter, or cation exchange capacity, in its derivation. Geographic information system applications of the PI, in particular, have great potential. Results confirmed that for 1,000 sites in southern Michigan, the mean PI of cultivated sites is significantly higher (10.94) than that of forested sites (7.77). We also compared the PI with published productivity values for Illinois soils. The positive statistical correlations that resulted confirmed that the PI is an effective measure of productivity for areas that do not have robust productivity data or a wealth of local soil knowledge, as does Illinois. Last, 2009 crop yield data for 11 Midwestern states were used to further evaluate the PI. In a geographic information system, we determined the soils and crops in particular fields and thus were able to ascertain the mean PI value per soil, per crop, per county. Statewide summaries of these data produced statistical correlations among yields of specific crops and PI values that were all positive; many exceeded 0.60. For regionally extensive applications, the PI may be as useful and robust as other indexes that have much more exacting data requirements.

Key words: Soil fertility, crop yield, soil taxonomy, GIS.

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"Fertility," or the inherent ability of soils to provide the necessary environment to growing plants, particularly with regard to nutrients, is an important and yet also a somewhat elusive (and often application-specific) soil property. Alternatively, "soil productivity" refers to the capacity of a soil to produce a certain yield of crops or other plants within a specified system of management (Soil Science Society of America, 2011). Therefore, soil productivity is perhaps the more quantifiable of the two terms and is the focus of this research.

Various publications have focused on soil productivity, deriving fairly accurate estimates of, and correlations among, crop and forest yields for specific soils or soil types (Ortega and Santibanez, 2007). However, most of these studies have restricted use because their accuracy diminishes beyond the specific area of study. Indeed, in many cases, they cannot be used outside of the study area because the productivity estimates are keyed to particular soil series or to specific crops. Alternatively, some studies have shown that productivity is, indeed, mappable across large areas, but only where there exist abundant and detailed data on terrain and soil attributes (Rossel et al., 2010) or where productivity is grouped into only a minimal number of categories (e.g., Jamroz, 2009). Our focus here is to examine productivity at larger (landscape) extents, acknowledging that we are sacrificing high site-specific accuracy assessments of productivity, which have dominated the literature, for greater and more widespread applicability. As a result, our data will be amenable to landscape-scale geographic information system (GIS) applications.

Soil productivity can be easily and rapidly amended by human activities. Thus, no index of productivity can accurately assess current soil productivity where soils have had a long history of cropping, erosion, and/or additions of soil amendments (e.g., Urkurkar et al., 2010). Particularly, irrigation and drainage practices impact soil fertility/productivity and, therefore, any index of productivity is only an estimate; it is always affected by land-use practices, both current and those in the past. Thus, we focus on natural native soil productivity, as expressed in a soil's taxonomic classification and recognize that such an estimate is, at best, a good starting point. We use soil classification nomenclature to derive productivity estimates because most soil classification taxa do not change (at least short-term) because of fertilization, cultivation, or irrigation. We argue that, on a landscape scale, natural soil productivity is mainly affected by exchangeable and reserve nutrient contents, soil tilth, organic carbon contents, clay mineralogy, and presence or absence of a root-impeding layer (e.g., Dick, 1992; Mendonça and Rowell, 1996; Trasar-Cepeda et al., 1998; Ortega and Santibanez, 2007; and Chaer et al., 2009), and that a soil's taxonomic classification is often reflective of some or most of these attributes.

In an earlier article, Schaetzl et al. (2009) developed and presented an ordinal natural soil drainage index (DI), which is intended to reflect long-term soil wetness or the amount of water that a soil can supply to growing plants under natural conditions. The DI's main assumption is that soils in drier climates and with deeper water tables have less plant-usable water. Because the taxonomic nomenclature of a soil often reflects its long-term wetness, the DI is derived, in part, from a soil's taxonomic subgroup classification. Our success in deriving the DI from soil taxonomic classifications was the impetus for our current research effort, designed to index soil productivity, from similar, that is, soil taxonomic, inputs. Ultimately, we envision—and call for—research and applications where the DI and PI are collectively used to derive even better assessments of soil productivity.

COMPARING THE PRODUCTIVITY INDEX WITH OTHER MEASURES AND MODELS OF FERTILITY/PRODUCTIVITY

Two other existing and competing indices of soil productivity are worth discussing here. Recently, the state of Minnesota

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released its Crop Productivity Index (CPI) (Minnesota Geospatial Information Office, 2011). The CPI, data for which are available only for Minnesota, is calculated for each soil component mapping phase from the Cropland Productivity rule in the National Soil Information System, a database used by the Natural Resources Conservation Service (NRCS). Index ratings are ordinal and range from 0 (low productivity soils) to 100 (highest level of productivity). Unlike the PI, which returns the same value for all soils that have the same taxonomic nomenclature, the CPI can change across county boundaries and varies as a function of slope and other factors. Thus, its use is geographically limited.

Another measure of crop productivity potential is the USDA-NRCS National Commodity Crop Productivity Index (NCCPI) (Dobos et al., 2008). The NCCPI is also generated from the National Soil Information System. In the NCCPI, soil properties, landscape features, and climatic characteristics are input to a model that assigns productivity ratings to soils. The overall NCCPI is segmented into submodels, each of which is directed toward the production of a certain crop, for example, wheat, cotton, sorghum, corn, soybeans, and barley. The model ranges from 0.01 (low productivity) to 1.0 (high productivity). Inputs to the model fall into several categories: chemical and physical soil properties, water, soil climate, landscape, positive attributes, and negative attributes (Dobos et al., 2008). Like the PI, the NCCPI has the benefits of being consistent across political boundaries, and it has an advantage if the user is interested in productivity as related to a particular crop.

Although the NCCPI takes into account many more variables that impact crop productivity than does the PI, the complexity of the NCCPI submodels makes creating maps time intensive and less transparent to the public, many of whom will have difficulty accessing all the necessary data. In addition, data inputs to the NCCPI are considerable. State level indexes, like Minnesota's CPI, may have a quite high local value, but present severe challenges for regional- and/or national-scale analyses. And most importantly, before public policy and land value decisions can be made, based on any of these models, they must be validated against actual yield data.

By way of clarification, we stress that the PI, the index of soil productivity we present here, is different from indices derived to assess soil quality. Soil quality concepts generally assess the various soil properties and processes as they affect the soil's ability to function effectively within a healthy ecosystem (Cox, 1995; Patzel et al., 2000; Schoenholtz et al., 2000). Our focus is on natural soil productivity, which, along with soil water content, is an important metric in the determination the soils' ability to produce food and fiber.

Last, we recognize that increased accuracy and predictability could be achieved were we to restrict our analysis to certain soil types or to small areas or even field scales, as, for example, the CPI does. However, our purpose is to present an index that will be widely applicable on mainly large (regional, statewide, etc.) scales and yet has sufficient categories so as to be discriminating enough for many kinds of landscape/productivity/fertility applications often within GIS frameworks.

MATERIALS AND METHODS

Derivation

We initially attempted to group all soils in the USDA-NRCS taxonomic database based on what we viewed as key aspects of fertility or potential productivity using data from the NRCS laboratory data Web site (http://ssldata.nrcs.usda.gov/). We chose the following data categories because they generally correlate with productivity and because they are routinely determined for soil samples sent into the laboratory: (i) cation exchange capacity (CEC) categories (superactive, subactive, semiactive, active, histic, and low); (ii) CEC activity at pH7, divided by the percent clay and weighted for the solum; (iii) organic matter content of the uppermost mineral horizon; (iv) organic matter content at the 50-cm depth; (v) pH categories (noncalcareous, nonacid, acid, dysic, euic, and calcareous); and (vi) whether or not the soil has a root-impeding lithic layer within the control section, that is, Lithic subgroups. After acquiring these data (where possible, some pedons lack the complete data set) for 18,073 pedons, we realized that the data were from a highly nonrandom sample of U.S. soils. Many more subgroups were missing from the NRCS laboratory data set than we had anticipated, and, more importantly, the data are skewed toward pedons that often are, we believe, atypical of central taxonomic concepts. That is, field soil mappers are much more likely to send in samples from pedons that are atypical and for which they cannot ascertain its taxonomic classification than they are for pedons that represent a taxa's central concept. Thus, we chose not to derive the PI using these data and moved on to a second approach.

The procedure we used to derive the PI, given the lack of robust soils laboratory data, was similar to the method used by Schaetzl et al. (2009) in developing the DI. For the PI to have widespread applicability, especially within a GIS, we tied it to taxonomic subgroups within Soil Taxonomy (Soil Survey Staff, 1999) and limited the categories to ordinal values. Unlike the DI categorization, which spans a large range from 0 (dry) to 99 (wet), we knew that we would have less ability to discriminate soil productivity using only taxonomic information. Thus, our goal was for the final PI value to span the range 0 to 19 (one fifth as long as the DI). We used the following variables to guide our initial assessments of productivity among the 12 soil orders: (i) organic matter content, (ii) CEC, and (iii) clay mineralogy, as well as our knowledge of general land use on each of the orders. For example, Oxisols with low CEC values because of oxide and 1:1 clay minerals and low organic matter contents received the lowest base PI value of 3 (Table 1). Similarly, Histosols are highly fertile, if drained, because of their organic matter content and high CEC values, and thus they merited the highest base PI value of 14 (Table 1). Soil orders that are routinely intensively cultivated and, thus, have shown a long history of successful cultivation and productivity, for example, Mollisols, Vertisols, and Histosols, were assigned base PI values nearer the high (fertile) end of the range.

Next, we assigned modifier values to each suborder, Great Group and subgroup, when these entries implied changes (more or less) in overall productivity relative to the base value. The rationale for each of these modifiers is briefly listed in Tables 2, 3, and 4. For subgroups with more than one modifier, for example, Humic Psammentic Dystrudepts, values for each modifier were used in combination, that is, summed, when calculating a final PI. In all, we developed PI values for the more than 2,450 taxonomic subgroups recognized in Soil Taxonomy (Soil Survey Staff, 1999).

Last, we modified the PI by adjusting for texture based on texture family classification. Because Psamments and "psamm" modifiers merit a -2 value (Tables 2, 3, 4), we assigned a value of -2 to soils in sandy texture families (Fig. 1). Silty soils tend to have the best tilth and soil-water relationships for plant growth, and thus we assigned soils in silty texture families a modifier value of +2. Other modifier values are shown in Fig. 1. Modifying the PI for texture also helps accommodate for tilth—an

TABLE 1. Base PI Values for the 12 Soil Orders

Soil Order	Base Productivity Index Value	Justification
Histosols	14	Organic soils, highly fertile when drained
Mollisols	13	Highest organic matter contents of all mineral soils
Vertisols	12	Also very high in organic matter
Andisols	11	Minimally weathered and rich in short-range–order minerals; many are rich in organic matter
Alfisols	10	Generally low in organic matter, but many are quite fertile
Inceptisols	9	Like Alfisols, but usually less fertile
Gelisols	8	Generally fertile soils, but severely compromised because of cold climate
Spodosols	7	Acid soils of minimal productivity, although some have notable amounts of organic matter
Entisols	6	Minimally developed soils, usually low in organic matter
Aridisols	5	Can be fertile but severely compromised by dry climate
Ultisols	4	Low-activity clays limit productivity
Oxisols	3	Oxide and low-activity clays greatly limit productivity

important part of productivity for cultivated crops; fine-textured clays and silty clays have their PI values lowered, as do excessively sandy soils. Alternatively, silty and loamy soils—typically the ones that have excellent tilth—have slightly higher PI values. A complete spreadsheet of PI values for all current soil textural families mapped in the United States is available for download at www.drainageindex.msu.edu.

Verification

The next step in our research plan was to examine how well PI values correlated spatially and statistically with data on (i) land use; (ii) crop growth, yields, and production; (iii) tree growth; and (iv) other productivity indices. We viewed this analysis as a means of verification of the use, efficacy, and predictive power of the index.

We assumed that areas with higher PI values would more often be farmed and that forested areas are often uncultivated because the soils there are less fertile; our experience in the Great Lakes region strongly supports this assumption. To examine this relationship quantitatively, however, we randomly assigned 1,000 data points across Michigan's Lower Peninsula in a GIS (Fig. 2). These points were overlain onto two files: SSURGO (Soil Survey Geographic) soil data from the NRCS (Soil Survey Staff, 2011) and 2009 land use (USDA-NASS, 2011a). At each point, we determined the PI value of the soil from the SSURGO database as well as land use (and field crop, where applicable) from the land-use database. The PI data for cultivated, forested, and "all other" land-use categories were compiled and compared using a standard t test with the assumption that variances are not equal among the populations.

TABLE 2. Suborder PI Modifiers*

Suborder Modifier Name	Change Made to Base PI Value	Justification	Soil Orders Affected
And-	+2	Andic properties imply increased productivity	Inceptisols
Gel-	+2	Gelic properties imply increased organic matter	Spodosols and Inceptisols
Hist-	+2	Histic properties imply increased organic matter	Gelisols
Hum-	+2	Increased amounts of organic matter	Spodosols
Anthr-	+1	Manuring and other human influences likely increase the overall productivity	Inceptisols
Arg-	+1	Illuvial clay in B horizon probably increases CEC and water-holding ability	Aridisols
Calc-	+1	Calcium is an essential nutrient; these soils have an abundance	Aridisols
Fluv-	+1	Soils in floodplains frequently get influxes of fresh humus-rich sediment	Entisols
Rend-	+1	High amounts of Ca, an essential nutrient; high pH levels in subsoil	Mollisols
Umb-	+1	Increased amounts of organic matter	Inceptisols
Vitr-	+1	Glassy mineral assemblage promotes nutrient storage and exchange	Andisols
Dur-	−1	Duripan restricts rooting depth	Aridisols
Psamm-	−2	Sandiness limits CEC and water-holding capacity	Entisols

*Modifiers not shown here have no effect on the base PI value.

TABLE 3. Great Group PI Modifiers*

Great Group Modifier Name†	Change Made to Base PI Value	Justification
And- Gel- Hist- Hum-	+2	See Table 2
Eutr-	+2	Definition implies high productivity and pH
Moll-	+2	Increased amounts of organic matter
Plagg-	+2	Implies long-continued manuring and mixing
Anthr- Arg- Calc- Calci- Fluv- *Umbr*- Vitr-	+1	See Table 2
Melan-	+1	Implies darker colors and increased amounts of organic matter
Somb-	+1	Implies subsoil organic matter accumulations
Verm-	+1	Worm activity is commonly associated with fertile soils of good tilth and high organic matter contents
Dur-	−1	See Table 2
Acr-	−1	Abnormally low CEC in Oxisols
Fragi- Fragloss-	−1	Fragipan restricts rooting depth and implies low pH
Hal-	−1	High amounts of sodium inhibit most types of plant growth
Kand- Kan-	−1	Kandic horizon is inherently low in productivity and CEC
Natr- Na-	−1	High amounts of sodium inhibit most types of plant growth
Pale-	−1	Implies old age and long-term weathering and pedogenesis
Petr-	−1	Petrocalcic horizon restrict rooting depth
Plac-	−1	Placic horizon implies acidic conditions and restricted rooting
Plinth-	−1	Plinthite is inherently infertile and often restricts rooting
Sal-	−1	High amounts of soluble salts inhibit most types of plant growth
Sphagn-	−1	Highly acidic Histosols
Sulf-	−1	Highly acidic materials within the solum
Dur- Psamm-	−2	See Table 2
Dystr-	−2	Definition implies low productivity and pH
Nadur-	−2	Combination of Natric (−1) and Duripan (−1)
Quartz-	−2	Quartz-rich sands are inherently infertile

*Modifiers not shown here have no effect on the base PI value.

†Names in italics are obsolete terms used in versions of Soil Taxonomy that were published before 1999. We included them in our system so older soil names could also be fit to the PI.

This analysis should determine whether the more fertile (read: cultivated) soils have higher PI values than do soils on forested sites. Because our land-use shapefile also contained data on crops, we were also able to compile data on the mean PI values for soils cultivated to various crops as of 2009.

In addition, PI values were compared with and correlated to soil productivity values for the state of Illinois, as published in Odell and Oschwald (1970). This Cooperative Extension Service publication lists productivity indexes for most soil series in Illinois. For each soil series in Illinois, we statistically correlated each of the following variables (reported as crop yields): (i) grain crops, basic management; (ii) forage crops basic management; and (iii) annual timber growth per acre (deciduous) with the PI for the same soil. The former data are reported by soil series, whereas the PI is determined by taxonomic subgroup as modified by texture family.

Last, we correlated the PI with crop yield data for Pennsylvania, Ohio, Tennessee, Kentucky, Indiana, Michigan, Illinois, Wisconsin, Iowa, Missouri, and Minnesota. These states were chosen to minimize the impact of irrigation on yields, as would commonly be the case in the western United States or the Great Plains. (The PI assumes that soils are not irrigated.) We accomplished this task by first obtaining data on mean countywide crop yields, as reported by the USDA National Agriculture Statistics Service for the year 2009 (USDA-NASS, 2011b). Generally, we only used data for the major crops produced in each of these states (Table 6). To correlate PI data with crop yield, we determined the PI values of all land parcels in the county that had that crop in that year and then summarized these data by county using zonal statistics in ESRI ArcMap 9.3 to calculate a countywide mean PI (for all parcels that had each particular crop). Crop coverages were obtained from 2009 land-use data, specifically, the crop data layer (USDA-NASS, 2011a). These crop specific, mean, county-level PI values were then compared with the county yield values reported by USDA-NASS (2011b) using Spearman's rank correlation coefficient (R_s). We also calculated linear regression relationships and output scatterplots of the data to further examine these relationships. Summary data were calculated by crop and by state, as well as for corn, wheat, and soybeans, for the 11 states combined.

Application

Mapping PI values was a key part of this research; maps can indicate the use and efficacy of the index, as they have done for the DI (Schaetzl et al., 2009). To that end, we joined our PI data values to various statewide SSURGO soil grids. The grids were created by rasterizing county-scale SSURGO files from the NRCS soil data mart (http://soildatamart.nrcs.usda.gov/), seaming them together into a statewide mosaic, and then resampling them to create a larger national-extent grid file. The PI

TABLE 4. Subgroup PI Modifiers*

Subgroup Modifier Name†	Change Made to Base PI Value	Justification
Andaqueptic Andeptic Andic Aquandic Haploxerandic Udandic Ustandic Ustivitrandic Vitrandic Vitric Vitritorrandic Vitrixerandic	+2	See Table 2 (Vitr-) and Table 3 (And-)
Aquollic Borollic Calcixerollic Hapludollic Haploxerollic (in Aridisols) Haplustollic Mollic Rendollic Udollic Ustollic Xerollic	+2	See Table 3 (Moll-) and Table 2 (Rend-)
Calciargidic Calcic Calcidic *Calciorthidic Haplocalcidic*	+2	See Table 2 (Calc- and Arg-)
Plagganthreptic	+2	See Table 3 (Plagg-)
Pachic	+2	Thick A horizon with more organic matter than is typical
Humic Humaqueptic	+2	Increased amounts of organic matter
Histic Ruptic-Histic	+2	Increased amounts of organic matter
Aquertic Ruptic-Vertic Udertic Ustertic Vertic	+2	Vertic characteristics indicate enhanced CEC and increased organic matter content
Alfic Aqualfic Argiaquic *Argic Argidic Boralfic Haplargidic Haploxeralfic* Ruptic-Alfic Ruptic-Argic *Udalfic* Ustalfic Xeralfic	+1	Illuvial clay in B horizon probably increases CEC and water-holding ability; see also Table 2 (Arg-)
Anthraquic Anthropic	+1	Increased amounts of organic matter and P
Cumulic	+1	Thicker A horizon and probably increased organic matter
Fluvaquentic Fluventic Torrifluventic Udifluventic *Ustifluventic*	+1	See Table 2
Lamellic	+1	Lamellae enhance nutrient-holding capacities in sandy soils
Sombric	+1	See Table 3
Thapto-Histic	+1	Buried organic materials provide nutrients to growing plants
Umbric	+1	See Table 2
Vermic	+1	See Table 3
Durixerollic	−1	Combination of Duric (−1) and Mollic (+2).
Acraquoxic Acrudoxic Acrustoxic Albaquultic Aquultic *Orthoxic* Oxic Ruptic-Ultic Torroxic Udoxic Ultic Ustoxic	−1	Oxic/kandic mineralogy implies low CEC
Alic	−1	High amounts of aluminum reduce productivity
Arenic	−1	Sandy, generally infertile soils
Duric Duridic Durinodic Durorthidic Haploduridic Petronodic	−1	See Table 2
Fragiaquic Fragic	−1	See Table 3
Halic	−1	See Table 3
Kandic Kanhaplic	−1	See Table 3
Natric	−1	See Table 3
Placic	−1	See Table 3
Plinthaquic Plinthic	−1	See Table 3
Ruptic-Lithic Ruptic-Lithic-Entic *Ruptic-Lithic-Xerochreptic*	−1	Shallow bedrock limits rooting volume, but not as extreme as Lithic (−2) subgroups
Salic Salidic *Salorthidic*	−1	See Table 3
Sodic	−1	High amounts of sodium inhibit most types of plant growth
Sphagnic	−1	See Table 3
Sulfaqueptic Sulfic Sulfuric	−1	See Table 3
Dystric	−2	See Table 3
Grossarenic	−2	Thick sands at surface imply reduced productivity and low CEC
Lithic	−2	Shallow bedrock reduces rooting volume
Petrocalcic Petrocalcidic	−2	Petrocalcic horizon is a rooting impediment, like bedrock
Petroferric	−2	Shallow iron pan reduces rooting volume
Petrogypsic	−2	Petrogypsic horizon is a rooting impediment, like bedrock
Psammentic Torripsammentic *Psammaquentic Quartzipsammentic*	−2	See Table 2

*Modifiers not shown here have no effect on the Base PI value.

†Names in italics are obsolete terms used in versions of Soil Taxonomy that were published before 1999. We included them in our system so older soil names could also be fit to the PI.

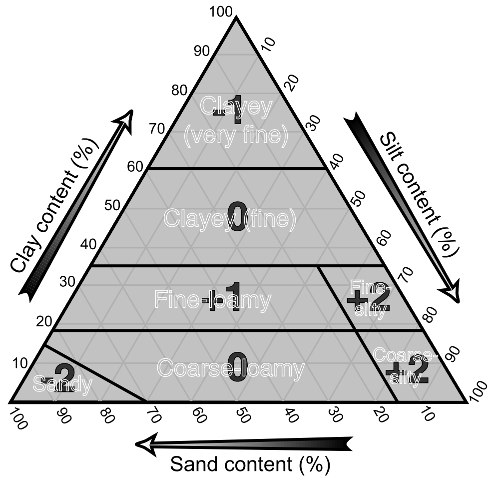

FIG. 1. A standard USDA textural triangle showing the PI modifiers used for the various texture families.

TABLE 5. Mean PI Values for Sites of Different Crops and Land Uses in Lower Michigan as of 2009*

Crop or Land Use	Mean PI	S.D.
All field crops	10.94	2.36
Alfalfa	10.35	2.10
Corn	10.85	2.35
Dry edible beans	12.25	2.12
Potatoes	10.33	2.52
Soybeans	11.27	2.06
Sugar beets	14.00	0.00
Winter wheat	10.43	3.38
All forest	7.77	3.21
Deciduous forest	8.17	3.15
Evergreen forest	5.87	2.90
Mixed forest	6.18	2.75

*Based on the sample of 1,000 random points (see above).

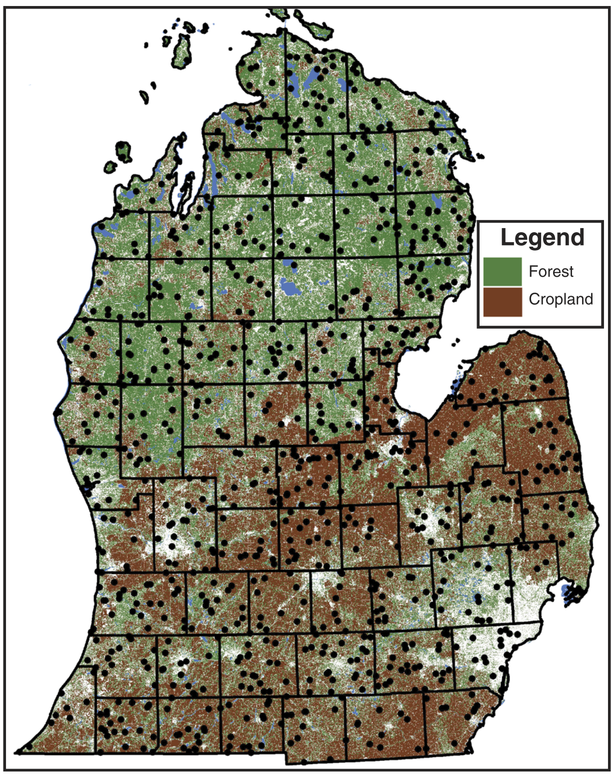

FIG. 2. Map of Lower Michigan showing land use as of 2009 and the locations of the 1,000 points at which we determined PI values. Blue areas are water bodies; white areas are classified as ''other'' or, more commonly, urban land uses.

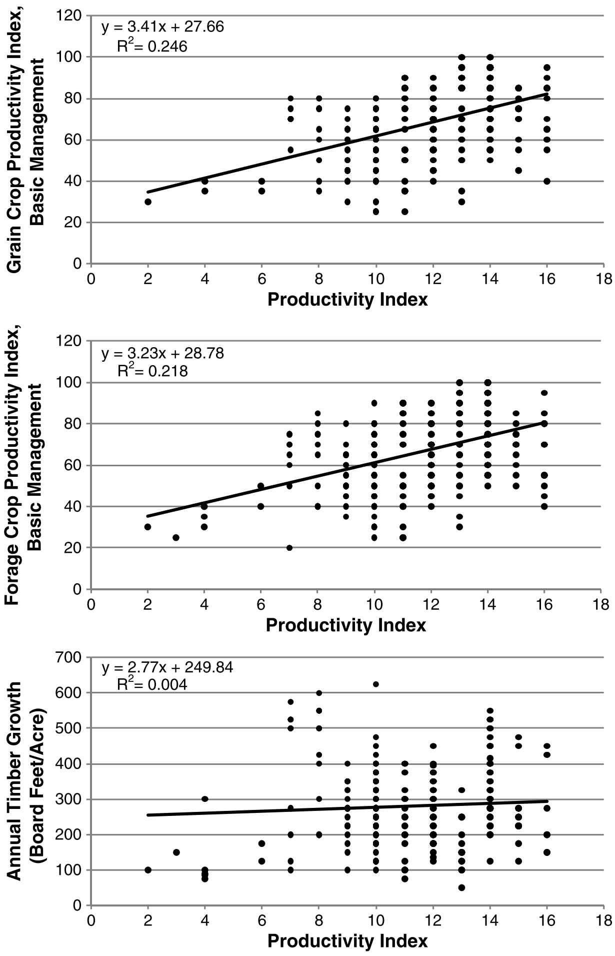

FIG. 3. Scatterplots showing the relationships between productivity indexes of grain and forage crops, as well as timber growth, versus PI, for soils in Illinois.

TABLE 6. Spearman Rank Correlation Coefficient (R_s) Values for Relationships Between Mean County PI and Mean County Crop Yields (2009) by State

	R_s Value From Linear Regression Equation				
State	**Corn**	**Soybeans**	**Winter Wheat**	**Oats**	**Other Crops**
Iowa	0.28	0.24	—	0.36	
Illinois	0.73	0.75	0.78	—	
Indiana	0.57	0.59	0.62	—	
Kentucky	0.38	0.15	0.19	—	
Michigan	0.50	0.30	0.46	0.25	0.02 (sugar beets)
Minnesota	0.29	0.23	—	0.80	0.24 (sugar beets)
Missouri	0.18	0.21	0.06	—	
Ohio	0.54	0.45	0.67	—	
Pennsylvania	0.12	0.18	0.47	0.06	
Tennessee	0.30	0.05	0.20	—	
Wisconsin	0.55	0.78	0.60	0.31	0.68 (alfalfa)
All states combined	0.57	0.31	0.23		

values for each soil taxonomic subgroup were joined to these files in a GIS using the MUKEY attribute, enabling us to map and examine PI values across landscapes.

RESULTS AND DISCUSSION

Land Use Versus PI

Of our 1,000 randomly located points within the Lower Peninsula of Michigan, 236 fell on cropped land, whereas 319 were on forested parcels (Fig. 1). Our statistical and GIS analyses clearly showed that soils with higher PI values are more often farmed to row or forage crops than they are forested. The mean PI value for the cropped land was much higher (10.94) than for forested land (7.77) (Table 5). Using a *t* test and assuming unequal variances, this difference was highly significant at $P < 0.0001$. Standard deviation values were also quite low for the land-use categories (Table 5), illustrating not only the efficacy of the PI but also the clarity of local knowledge that farmers possess about which soils are best for particular crops. These data indicate that the PI values do mimic productivity in a general sense, and that, at least in Lower Michigan, land owners are preferentially farming the more fertile soils. Table 5 further illustrates that some of the more nutrient-demanding crops had mean PI values that exceeded 10.00, and that, as expected, PI values for evergreen coniferous forest were the lowest of any land-use category.

Soil Productivity Values Versus PI

We used data on productivity (grain crops, forage crops, and timber growth), as determined for more than 350 soil series in Illinois by Odell and Oschwald (1970) to further evaluate the accuracy and efficacy of the PI. The PI values were calculated for the same soil series that Odell and Oschwald (1970) used, and the data compared statistically. Recall that the PI of Odell and Oschwald (1970)—determined to series—should be more accurate in terms of prediction than the PI, which is only determined to texture family.

Results show that the PI correlates extremely well with the PI of Odell and Oschwald (1970) (Fig. 3). Correlations were better for grain crops than for tree growth probably because the latter are drawing on soil resources and affected by soil conditions much farther below the surface than are traditionally examined by soil mappers, for example, Host et al. (1988). A

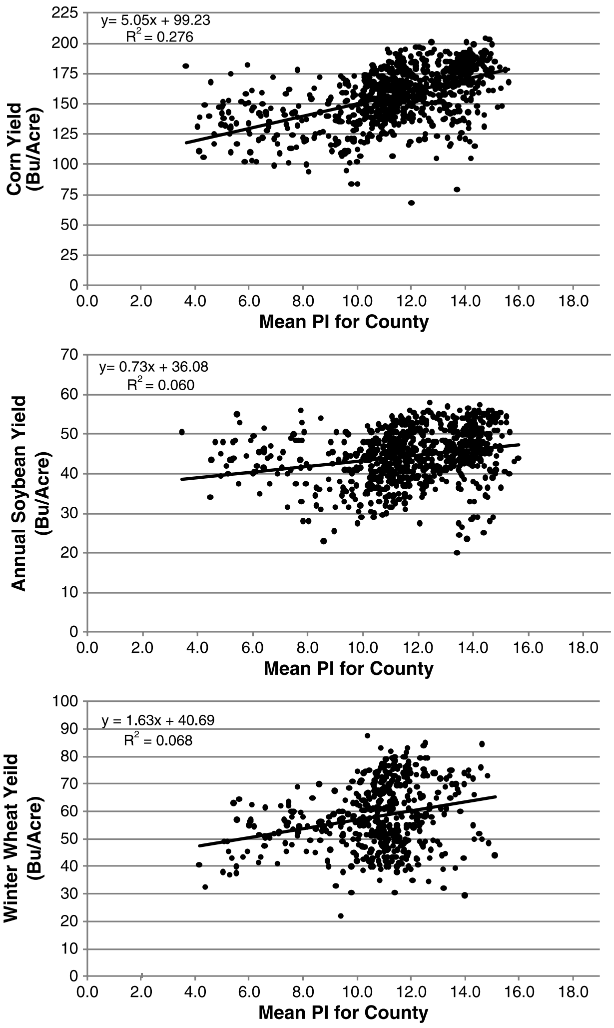

FIG. 4. Scatterplots showing the relationships between countywide crop yields (2009, corn, soybeans, and winter wheat) and mean PI values for all parcels in each county that were planted to that crop in 2009.

second source of error in the timber growth data may involve abnormally wet soils. The PI does not take soil wetness or water table effects into consideration, and thus extremely wet soils may rate high in the PI but be poor for tree growth. This caveat is less of a factor for the growth of traditional crops; if soils are too wet for a particular crop, they are typically drained.

Crop Yields Versus PI

For all 11 states and 4+ crops, Spearman rank correlation coefficients, calculated for the relationships between crop yields and PI values, were always positive (Table 6). Likewise, compiled data for all 11 states, shown as scatterplots in Fig. 4, also show excellent relationships between yields of corn, soybean, and winter wheat with countywide mean PI values of soils that were planted to that crop in 2009. Given the variation that can be expected to occur in management practices, for example, soil amendments, irrigation, as well as the natural climate variability that existed across these five states in 2009, these results are extremely promising. Indeed, many of the outliers in the scatterplots are for soils with low PI values but generally high yields (Fig. 4) probably because of aggressive management practices that the PI is unable to control for. Data and correlations for individual crops in specific states are even more impressive (Fig. 5; Table 6).

Mapping Applications

To display productivity values in landscape-scale applications, we used a GIS to map PI values at various scales. The color ramp we chose to use for the PI displayed "intuitive" and contrasting colors along the PI 0-to-19 scale. Named "partial spectrum" in ArcGIS, this color symbology ranges from yellow for low PI values (most infertile soils) through orange, red, purple, and then blue (most fertile soils). Applying this color ramp to a soil map mosaic of 11 Midwestern states, derived using SSURGO-level county soil data, resulted in a map of soil productivity across the region (Fig. 6). Many of these patterns would not have been obvious before this study, whereas others are more obvious; for the latter, the PI gave these patterns additional spatial detail. In this map (Fig. 6), areas of high productivity, for example, the loess-covered Mollisol-dominated plains of Iowa, central Illinois, and southeastern Minnesota, show up clearly. Yellow and light-orange areas of lower productivity

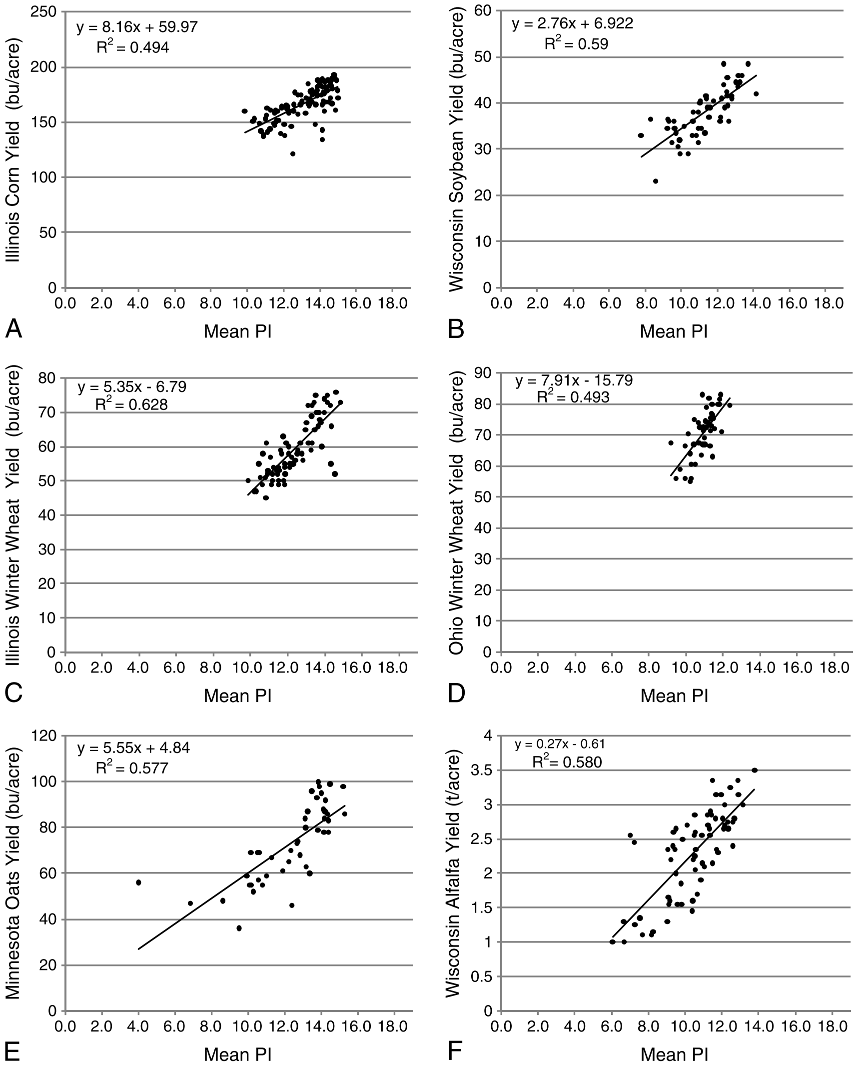

FIG. 5. Scatterplots showing the relationships between countywide yields for selected crops and states and mean PI values for all parcels in each county that were planted to that crop in 2009.

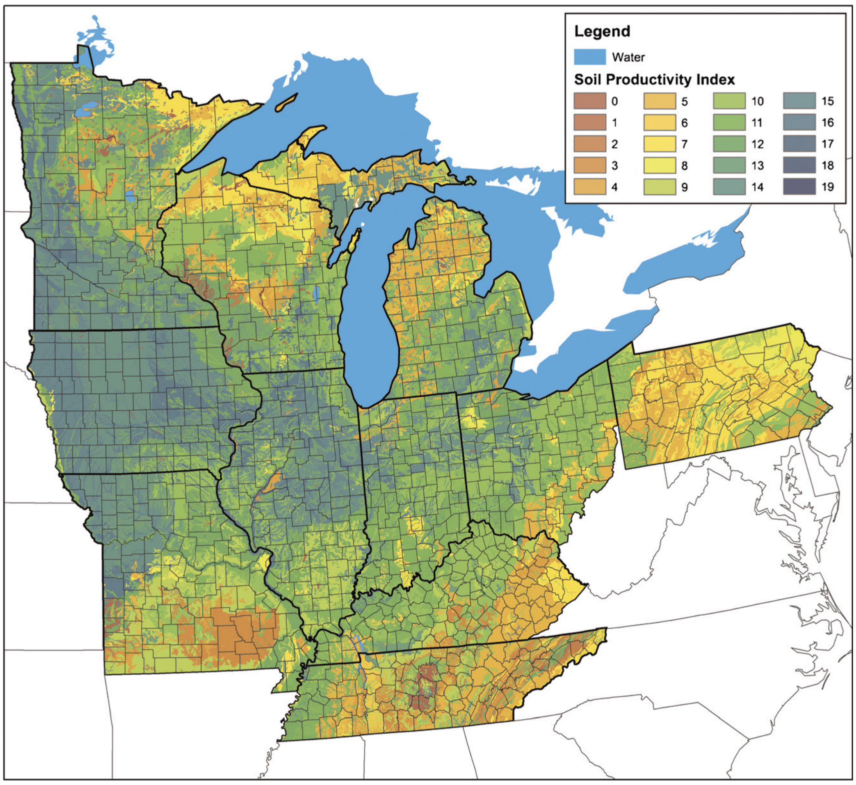

FIG. 6. Map of soil productivity, based on the PI, for 11 Midwestern states.

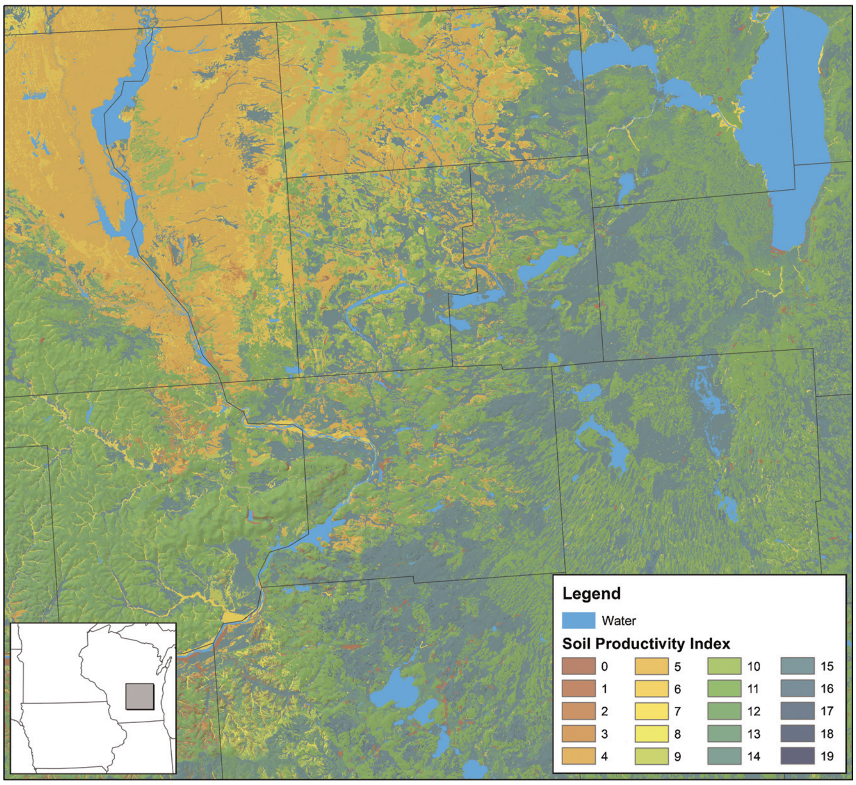

FIG. 7. Soil productivity map of south-central Wisconsin.

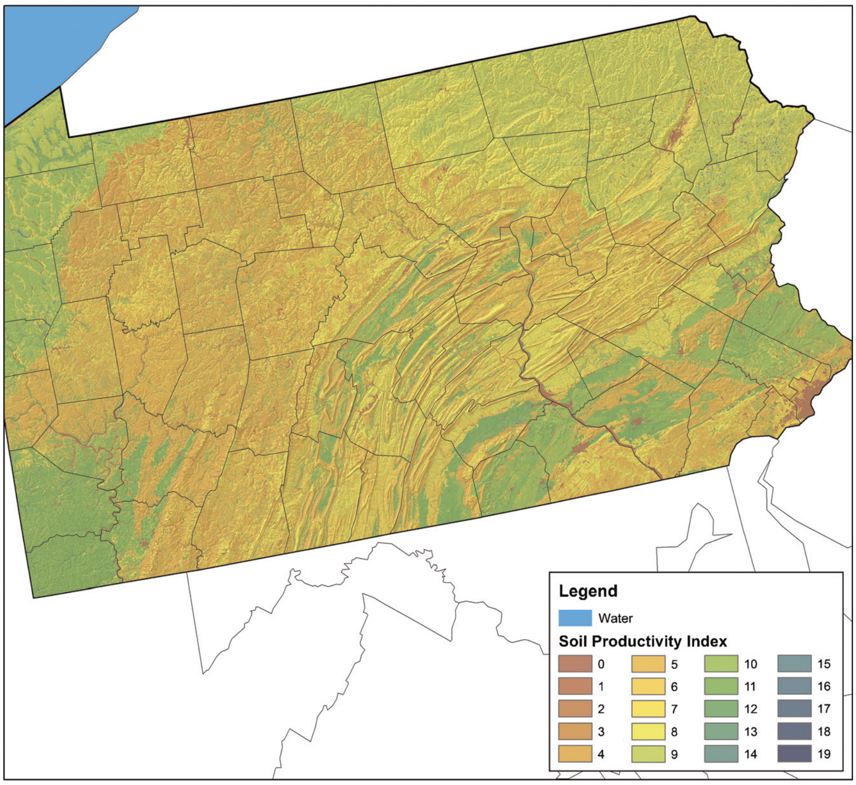

FIG. 8. Soil productivity map showing most of Pennsylvania.

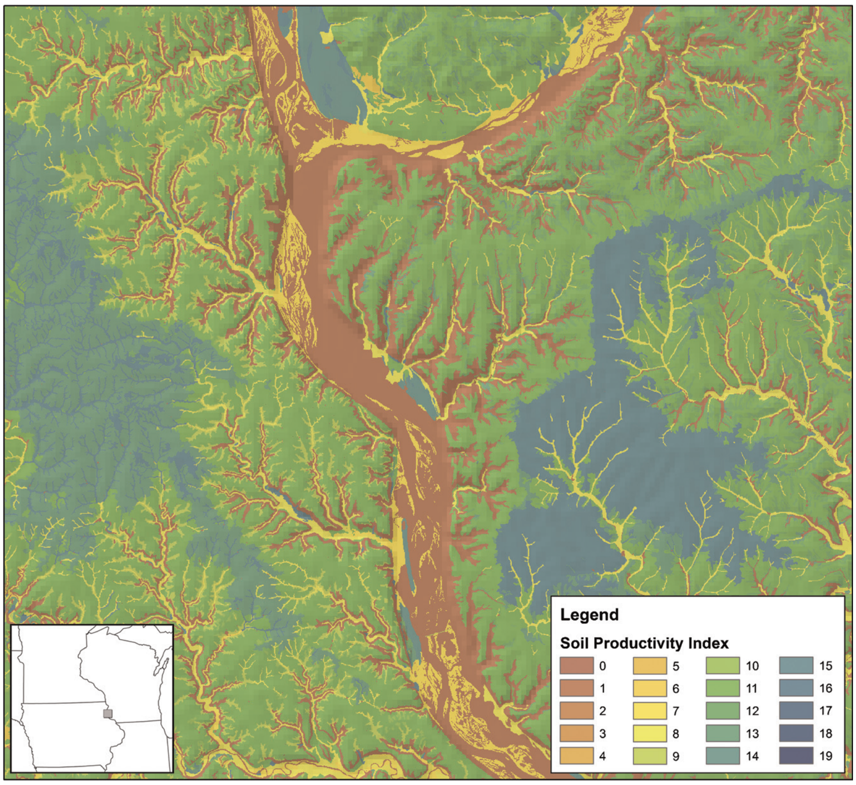

FIG. 9. Soil productivity map of the Wisconsin-Iowa border area near the confluence of the Wisconsin and Mississippi rivers.

are also obvious, for example, for the Central Sand Plains of Wisconsin (Hole, 1976; Clayton and Attig, 1989), the High Plains sandy province of northern Lower Michigan (Schaetzl and Weisenborn, 2004; Schaetzl et al., under review), the Cumberland/Allegheny Plateau regions in Kentucky and Pennsylvania, and the Ozark Plateau of Missouri.

On closer inspection, via larger scale maps, the efficacy and applicability of the PI become even more apparent; we cite a few examples here. In south-central Wisconsin (Fig. 7), soil PI values vary widely. Sandy Psammaquents and Udipsaments dominate the Central Sand Plains, where PI values typically are 4 (yellow). Fertile silty Argiudolls formed in loess show up in Fig. 7 as deep purple (PI = 17). Intermediate sites, depicted in various shades of red, are Hapludalfs (PI = 11 or 12). The light oranges of Psammentic Hapludalfs (PI = 8) are visible at a few locations in the north-central part of the map. Our experience in this area suggests that these values and map colors mimic the natural soil productivity of the area quite well.

An examination of the PI map for western Pennsylvania is also extremely enlightening. The glaciated sections of the state, occupying the northeastern and northwestern corners of the map have higher productivity values than does the unglaciated Appalachian Plateau region to the south (Fig. 8). The deeper red colors in the northwestern part of the map are fine-loamy Fragiaquepts with PI values of 9. Slightly more fertile fine-loamy Fragiaqualfs (PI = 10) are common on landscapes to the immediate south; these soils are shown in purple-red colors. In the northeastern part of the map, the glaciated plateau region shows lower productivity values; many orange hues are apparent. Here, loamy-skeletal Dystrudepts (PI = 7) and coarse-loamy Fragiudepts (PI = 8) dominate the uplands. The bright yellows of the Appalachian Plateau occupy much of the central part of the map. Most of the soils here are fine Endoaquults (PI = 4), fine-loamy Fragiudults (PI =4), loamy-skeletal Dystrudepts (PI = 7), and fine-loamy Hapludults (PI = 5). The bright pink colors evident in some of the valleys of the Ridge and Valley province are fine Typic Hapludalfs and fine-loamy Ultic Hapludalfs (PI = 10); they stand apart because of their limestone parent materials. It is clear that the variation in productivity, largely influenced by parent materials in this case, is captured quite well by the PI.

Our last example shows that the PI holds up at even medium and large scales. Figure 9 shows the area near the confluence of the Wisconsin and Mississippi rivers in southwestern Wisconsin and eastern Iowa. This unglaciated area is bedrock controlled and deeply dissected. Loess mantles the flattest uplands, where it exceeds 2 to 3 m in thickness (Leigh and Knox, 1994; Scull and Schaetzl, 2011; Syverson et al., 2011). Productivity variation across this landscape is great but, nonetheless, is predictable and follows cropping patterns remarkably well. The most fertile soils are on the broad loess-capped uplands, where fine-silty Argiudolls with PI values of 16 are found (purple polygons). On steeper slopes, the PI drops to 12 and the map color changes to cyan, where fine-silty Hapludalfs are mapped on thin loess. Note that, in both Iowa and Wisconsin, intermediate taxonomic intergrade soils (Mollic Hapludalfs; PI = 14) are mapped between the two soils mentioned above. The PI captures this intermediate soil's intermediate productivity value, and the GIS map portrays it exceedingly well. Steep stony rock land in deep narrow valleys is yellow on the map and has a PI of 0. The red areas on the Mississippi floodplain and terraces, often at the mouths of major tributary valleys, are fine-silty Fluvaquents with PI values of 9. Backswamp areas in the Wisconsin River valley are orange; there are areas of Fluvaquents with PI values of 6. This example confirms that the PI is useful for portraying soil productivity at even large scales, as long as the soil map from which it is derived is an accurate representation of the landscape.

CONCLUSIONS

In this article, we introduce a new index of soil productivity. Unlike other indexes that have similar goals, ours is widely applicable because the only inputs to the index are taxonomic soil classification data. Because most counties in the United States have been mapped at large scale by the NRCS, and these maps are widely available in digital form, determining and mapping the PI values of soil landscapes is potentially available to everyone for everywhere that has a soil map.

We have posted a PI "join file" to the following website: *http://www.drainageindex.msu.edu.* This site serves as a clearinghouse for GIS join files for both the DI (Schaetzl et al., 2009) and the PI. A download of the join file from this Web site enables GIS users to link their soil data in a GIS using the MUKEY field in the attribute table to our internal DI and PI tables.

We acknowledge that PI values may not exactly correlate to the precise productivity of a particular field or site because of site-specific management practices and because Soil Taxonomy was not created specifically to mimic productivity. Nonetheless, our data clearly show that correlations between the PI and various measures of soil productivity and crop yields are strong and, thus, potentially useful in various types of landscape-scale research.

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