Forest and Rangeland Ecosystem Condition Indicators: Identifying National Areas of Opportunity Using Data Envelopment Analysis

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ABSTRACT. This article reports the methodology and results of a data envelopment analysis (DEA) that attempts to identify areas in the country where there is maximum potential for improving the forest and rangeland condition, based on 12 indicator variables. This analysis differs from previous DEA studies in that the primary variables are measures of human activity and indicators of forest and rangeland condition in place of the traditional economic inputs (costs) and outputs. It also involves a different (ecological) production process than traditional DEA analyses, and a statistical preanalysis is developed and applied to homogenize the large and highly diverse landscape where this ecological production process takes place for the purposes of the DEA. It is concluded that, based on this analysis, there are opportunities to improve the forest and rangeland condition without reducing the amount of human activity, but not over large areas, only for some indicators, and typically not for a large number of indicators in the same place. This means that large-scale improvements in environmental condition across many indicators may often not come about without a reduction in human activity. FOR. SCI. 50(4):473–494.

Key Words: Efficiency, frontier analysis, ecological outputs, environmental impacts, resource interactions.

SINCE the early 1990s, there has been a growing interest in developing indicators of ecosystem condition that permit society to gauge whether natural resources are being used in a way that is sustainable (Lubchenco et al. 1991, National Research Council (NRC) 2000). Governments and resource management agencies no longer base responsible resource stewardship on sustained yield, but rather on notions of ecosystem sustainability (Nobel and Dirzo 1997, Wackernagel et al. 2002). This shift is now reflected in numerous international organizations (e.g., the United Nations Commission on Sustainable Development, the International Tropical Timber Organization (ITTO), the Helsinki Process, and the Montréal Process) that are directed to develop indicators of sustainable resource development. The United States (along with Canada, Japan, New Zealand, Australia, Republic of Korea, Chile, Mexico, China, the Russian Federation, Uruguay, and Argentina) has adopted the Montréal Process, with its associated set of indicators, as the common framework for evaluating a country's progress toward sustainable management at the national level (Coulombe 1995). Considerable work is currently going on to obtain baseline measurements of these

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Acknowledgments: This study was supported by funds from the Strategic Planning and Resource Assessment Staff, Washington Office, USDA Forest Service. The authors thank Jim Baldwin for very helpful comments. The usual disclaimer applies.

Manuscript received December 10, 2002, accepted December 16, 2003.

indicators in the United States. Because sustainability limits or standards against which to evaluate indicator measures are lacking (Kates et al. 2001), it is doubtful that any clear conclusions will be forthcoming soon regarding the sustainability of forest management as practiced in the United States. The fundamental thesis of this article is that even in the absence of sustainability standards, indicators can be used to look for areas of opportunity to improve the forest and rangeland condition throughout the United States.

We should clarify immediately that the indicators we use in this article do not match exactly the Montréal Process indicators, but they are similar in intent and concept. We have chosen specific indicators to be consistent in this regard, but we have been constrained by data availability at the national scale. The purpose of this article then is not to use Montréal Process indicators to make a determination of "sustainable" or "not sustainable" (which is not currently feasible), but rather to look for areas in the country where there is maximum potential for improvement, as measured by our forest and rangeland condition indicators (referred to simply as "condition indicators" hereafter). By "areas. . . where there is maximum potential for improvement," we mean that we wish to identify geographic units that are relatively inefficient with regard to condition indicator values, given the level of human/economic activity in those units. If we can identify areas that are currently under the most stress but could be made better simply by managing resource use more efficiently, this would present a noteworthy opportunity for improvement, because environmental impacts (as reflected in our condition indicators) could be reduced without the economic and social costs associated with reducing human activity. In the absence of reference standards, we will define the areas under the most stress as those with the worst indicator values relative to other areas, along the lines of Prendergast et al. (1993). We will address this analytical problem with a method from the Management Science literature called data envelopment analysis (DEA). We will use DEA to determine whether areas currently under the greatest ecosystem stress also represent the areas where the greatest opportunity for improvement exists.

Database

A detailed description of data sources and variables contained in our database is available at www.fs.fed.us/rm/analytics/dea_data_dictionary.html. The database for this study consists of 12 forest and rangeland condition indicators, 13 measures of human activity, and 11 measures of climate and topographic variation that serve as environmental shifters. Because of data availability, only the coterminous United States is included. The database contains observations on each variable by county. There are 3,111 counties in the database.

Data were obtained from numerous sources in formats ranging from highly aggregated county data to micro data with many sample points. Most of the data had to be reformatted or otherwise processed and synthesized to be consistent with the data structure requirements of the analytical approach. In the case of micro data with many sampling points, county observations were obtained by "kriging" to the county centroid (see Cressie 1991, Ripley 1981, and Haining 1990 for a detailed discussion of kriging and geostatistical techniques in general).

In brief, the condition indicators for the analysis are:

HAB	Index of habitat disturbance, the ratio of area of disturbed land to total area
EDG	A measure of total linear edge between natural land cover and human land use
PCH	One minus the ratio of average patch size to the maximum possible
EXT	Proportion of exotic individuals to total individual birds
MOR	Percent mortality in growing stock on timberlands
GRO	One minus the ratio of actual productivity on timberlands to potential productivity
STR	Absolute value of the difference between recent streamflow and historical average
NTG	Total nitrogen measured in surface waters
PHO	Total phosphorous measured in surface waters
PHL	maximum pH in precipitation (which was <7) minus observed pH in precipitation
TRI	Total toxic chemical releases to the environment (air, water, and land)
PAD	One minus the proportion of area that is "protected"

The human activity outputs are:

POP	Human population density
DAM	Dam density
BFC	Beefcow density
PRO	Producer mine density
COL	Coal mine density
WLP	Productive oil and gas well density
TBR	Timber harvest
RDS	Road density, primary highways
VTR	Road density, vehicular trails
RCL	Outdoor recreation participation in land-based activities
RCW	Outdoor recreation participation in water-based activities
RCS	Outdoor recreation participation in snow-based activities
VST	Total farm production expenses

The shifters are:

TMP	Mean annual temperature
TMS	Spatial variation in temperature
SST	Seasonal variation in temperature
AVT	Temporal variation in temperature
PRC	Mean annual precipitation
PRS	Spatial variation in precipitation
SSP	Seasonal variation in precipitation
AVP	Temporal variation in precipitation
VEG	Total vegetation carbon

DEM Mean elevation
DMS Elevation variance

Methods

Data Envelopment Analysis

DEA is a type of frontier analysis of inputs and outputs—it classifies decisionmaking units (DMUs) according to whether they are (relative to each other) on the efficiency frontier or not. Because much of the economic data available nationally are organized by counties, we define the county as the DMU for our analysis. The classic references are Charnes et al. (1978) and Banker et al. (1984). An excellent synthesis is in Seiford and Thrall (1990), and three textbook references are Norman and Stoker (1991), Charnes et al. (1994), and Cooper et al. (2000). Using the jargon in Seiford and Thrall (1990), as we do throughout this section, we will focus on the "input-oriented" forms of DEA (the reasons for this will become obvious later in the article). DEA generates an efficiency score between 0 and 1 for each DMU and assigns a score of 1 to a unit only when comparisons with other units included do not provide evidence of inefficiency in the use of inputs in producing outputs. There are two basic forms of DEA, each one of which is the dual of the other. They provide the same information, and the solution to one can be determined from the shadow prices of the other. The "envelopment" problem will only assign a score less than 1 to a unit if some (any) linear combination of other units included in the analysis could produce the same set of outputs using a smaller set of inputs. The "multiplier" problem will assign a score less than 1 to a unit only if the ratio of its sum of weighted outputs to its sum of weighted inputs is less than some other unit, even when the most favorable weights have been incorporated in its evaluation. Let us look at each version in more detail.

The Envelopment Version

The logic of this version of DEA is that a unit is inefficient if any convex (linear) combination of the other units included in the analysis dominates or envelopes it. The basic measure of efficiency is the ability to produce its outputs with minimum inputs. Thus, a unit or a linear combination of units dominates another one if it can use less of any input without using more of any other input or decreasing any output. Because we want to allow any linear combination of the other units in evaluating each unit, the standard approach is to solve a linear program for each unit (DMU "o"). This linear program is:

$$
\begin{aligned}
\text{Minimize:}\quad & q_o \\
\text{Subject to:}\quad & \sum_j w_j x_{ij} \le q_o x_{io} && \forall\, i \\
& \sum_j w_j y_{rj} \ge y_{ro} && \forall\, r \\
& w_j \ge 0 && \forall\, j
\end{aligned}
$$

where:

i indexes inputs ($i = 1, \ldots, m$)
r indexes outputs ($r = 1, \ldots, s$)
j indexes DMUs ($j = 1, \ldots, n$)
x_{ij} = the amount of input i used by DMU j
y_{rj} = the amount of output r produced by DMU j
w_j = the weight assigned to DMU j (these are the choice variables)
q_o = the DEA efficiency score for DMU "o"

It is important to note that we include DMU "o" in the left-hand sides of the constraints. This ensures that the optimal q cannot be more than 1.

The Multiplier Version

The basic logic of this version of DEA, which is typically attributed to Farell (1957), is that efficiency can be measured by the ratio of output to input:

$$\text{efficiency} = \text{output/input}$$

where the larger the ratio, the better the efficiency is indicated to be. Now with multiple outputs and/or multiple inputs, it seems reasonable to use a weighted sum of each in this ratio:

$$\text{efficiency} = \text{weighted sum of outputs/weighted sum of inputs}$$

The immediate problem, of course, is to determine the weights for both the numerator and the denominator in this ratio. The logic of the multiplier form of DEA is to let each unit use whatever weights are most advantageous to its own evaluation. As noted earlier, the weakness of this approach is that a unit might be indicated to be efficient more on the basis of the weights chosen than on any real inherent efficiency. The strength, however, is that the designation of inefficiency is robust to the weighting assumptions. In this regard, the DEA result is conservative and tenable.

The usual procedure for determining the multiplier DEA result is, again, to solve a linear program for each unit. To derive this linear program we start with a nonlinear program that:

$$
\begin{aligned}
\text{Maximizes:}\quad & z_o = \sum_r u_r y_{ro} \Big/ \sum_i v_i x_{io} \\
\text{Subject to:}\quad & \sum_r u_r y_{rj} \Big/ \sum_i v_i x_{ij} \le 1 && \forall\, j \\
& u_r,\, v_i \ge 0 && \forall\, r,i
\end{aligned}
$$

where:

v_i = the weight assigned to input i (choice variables)
u_r = the weight assigned to output r (choice variables)
z_o = the DEA efficiency score for DMU "o"

The indexes and parameters are as previously defined.

An equivalent linear program, which is the dual of the linear program given for the envelopment version, is to:

$$\text{Maximize:} \quad z_o = \sum_r u_r y_{ro}$$

$$\text{Subject to:} \quad \sum_i v_i x_{io} = 1$$

$$\sum_r u_r y_{rj} - \sum_i v_i x_{ij} \leq 0 \qquad \forall j$$

$$u_r, v_i \geq 0 \qquad \forall r,i$$

This linear program takes advantage of the fact that the ratio in the objective function in the nonlinear program can be maximized by setting the denominator equal to an arbitrary normalizing constant (one) and maximizing the numerator. The main constraint is linearized by multiplying both sides of the inequality by the denominator of the ratio on the left-hand side in the nonlinear program. This is called the input-oriented form of the multiplier version (Seiford and Thrall 1990) because it is the dual of the input-oriented envelopment model given previously. It is common to constrain the weights to be greater than some arbitrarily small constant, which satisfies the non-negativity constraints in the linear program specified above and also ensures that no output or input is completely ignored in the DEA evaluation. It is also possible to further constrain the weights (which we do not do); this is typically done if the DEA results are not able to distinguish as many inefficient units as the analyst desires. Obviously, constraining the weights affects the generality of any inefficiency designation that emanates from such an analysis.

Notice that in these formulations the inputs and outputs are parameter observations from the DMUs, and the weights are the choice variables solved for in the linear program for each DMU. The weights will solve at different levels in each DMU's linear program.

Variable Returns to Scale

The DEA models presented so far implicitly assume constant returns to scale, such that efficiency is unaffected by the scale of production (e.g., doubling all outputs will exactly require a doubling of all inputs). There is also a version of DEA that allows for variable returns to scale. In this version, the designation of inefficiency is robust to the scaling assumption as well as to the weights assigned. Allowing returns to scale to vary results in fewer units being identifiable as inefficient, so constant returns to scale are sometimes assumed to strengthen the discretionary power of the DEA. The inefficiency designations, however, are more conservative/tenable if variable returns to scale are allowed. Therefore, we used this version of DEA wherever possible.

Using the multiplier version (the dual of the envelopment version), variable returns to scale are allowed in the linear program by adding positive and negative deviational variables (d) (for either increasing or decreasing returns) as follows:

$$\text{Maximize:} \quad z_o = \left(\sum_r u_r y_{ro} + d_1 - d_2 \right) \Big/ \sum_i v_i x_{io}$$

$$\text{Subject to:} \quad \left(\sum_r u_r y_{rj} + d_1 - d_2 \right) \Big/ \sum_i v_i x_{ij} \leq 1 \qquad \forall j$$

$$d_1, d_2, u_r, v_i \geq 0$$

This is converted to a linear program as before to yield:

$$\text{Maximize:} \quad z_o = \sum_r u_r y_{ro} + d_1 - d_2$$

$$\text{Subject to:} \quad \sum_i v_i x_{io} = 1$$

$$\sum_r u_r y_{rj} + d_1 - d_2 - \sum_i v_i x_{ij} \leq 0 \qquad \forall j$$

$$d_1, d_2, u_r, v_i \geq 0$$

This formulation essentially allows each unit to use whatever scale factor (increasing or decreasing) that is most advantageous to it, just as it was allowed to select whatever weights are most advantageous. Again, this assumption is weak in terms of discriminating between efficient and inefficient units, but it is strong in terms of the tenability of the determination that is made on those units found to be inefficient. With either the multiplier or the envelopment approach, automating the DEA process is obviously advantageous because a linear program must be solved for each DMU. We used WARWICK DEA (Thanassoulis and Emrouznejad 1996) for this purpose. This software uses the envelopment version for constant returns to scale and the multiplier version for variable returns to scale (as just described).

Applying DEA to Forest and Rangeland Condition Indicators

The Production/Cost Function Structure

Measures of human activity and indicators of forest and rangeland condition will play the roles of the outputs and inputs (costs), respectively, and these are obviously different than the traditional output and input variables typically included in DEA. Let us define three vectors of variables: $\tilde{H}$ is a vector of human activity measures, including extractive resource outputs such as timber harvest, livestock grazing, recreation use, and mining activity; $\tilde{I}$ is a vector of forest and rangeland condition indicators; and $\tilde{S}$ is a vector of natural environment shifter variables such as topography and climate. If we think of the relationship between these variables as a production process, then a joint production function could be defined. The textbook treatment of joint production would use an implicit-form production function as:

$$0 = f(\tilde{I}, \tilde{H}, \tilde{S}) \tag{1}$$

to relate these three variable vectors. Mittelhammer et al. (1981) show, however, that this approach is limiting because it does not allow any of the variables to be unrelated. In a traditional economic production unit, we expect to be able to fix inputs and then define a locus of output combinations—the product transformation curve—or to fix outputs and then define a locus of input combinations—the isoquant. In ecological systems theory, management actions are viewed as altering the structure and function of the ecosystem, which then results in a particular system response (Barrett et al. 1976, Hall and Day 1977, Allen and Hoekstra 1992). Viewed deterministically, any combination of human activity and shifter variables is associated with a particular set of condition indicator impacts, and the transformation curve between different condition indicators would be a single point. For example, once a certain harvesting schedule is applied, impacts on stream conditions, wildlife habitat conditions, and so forth are determined by the resulting ecosystem structure and function, and the mix of these impacts is not within human control. This would suggest that an appropriate production structure should have the property that:

$$\partial I_i / \partial I_j = 0, \; i \neq j \tag{2}$$

with all H and S held constant. Mittelhammer et al. and others show that such a property is not obtainable with Equation 1. A production structure that has this property would be:

$$I_i = g_i(\tilde{H}, \tilde{S}) \qquad \forall \, i \tag{3}$$

Note that Equation 3 is not a simultaneous system but is still a joint production structure, because the I are simultaneously affected by the H and S variables. If the H and S vectors are fixed, however, only a single I vector results, reflecting the autonomy of the ecosystem, as desired.

This implies that a separate DEA should be performed for each forest and rangeland condition indicator. Because these indicators will be defined as undesirable impacts to be minimized, Equation 3 would best be regarded as a type of cost function. The outputs in our DEA will be the human activity indicators, and the inputs (to be minimized) will be the condition indicators that presumably result from that activity. The natural environmental shifter variables (i.e., topographic and climatic descriptors), on the other hand, are intended to capture inherent differences in ecosystem productivity among DMUs. The next section will discuss a statistical approach to handling these shifter variables in a procedure that will precede the DEA.

With the problem structure defined this way, the DEA measures efficiency in terms of a county's forest and rangeland condition relative to its level of human activity. A county's level of direct investment in mitigating the impacts of human activity on forest and rangeland condition might influence that measurement. We have no data on mitigation investments, and even if we did, allocative efficiency might be very difficult to distinguish from direct mitigation efforts. Thus, we must assume that investment in impact mitigation is constant across all counties, so that differences in DEA scores are attributable to differences in efficiency. If this assumption is not met, then a county that is indicated to be inefficient might be so because of either inferior allocative efficiency or because of a relatively low level of direct investment in mitigation. In the latter case, an opportunity for improving the forest and rangeland condition is still suggested by a low DEA score because mitigation investments are indicated to be lower than in other similar counties, but the opportunity may require additional investment to be realized.

Accounting for Topographic and Climatic Shifters

Production in forest and rangeland ecosystems takes place on heterogeneous landscapes with heterogeneous climate conditions as compared with the spatially limited traditional economic production units (even a farm). An important assumption in DEA is that the DMUs are homogeneous except as accounted for by the inputs and outputs included. We address this assumption in two ways. First, we stratified the coterminous United States into three "ecoregions" based on boundaries from Bailey (1995). These ecoregions, which we demarcate on all the figures below, are large enough to preserve the geographic scale of the problem, but counties (DMUs) are more homogeneous at this scale with respect to inherent ecosystem properties. Moreover, counties within ecoregions are much more consistent in size when compared with the coterminous United States as a whole.

Second, we use statistical procedures to account for within stratum (ecoregion) variation in environmental characteristics among DMUs. Although county heterogeneity is reduced with the ecoregional stratification, environmental characteristics within these broad strata still vary in ways that affect the level of ecosystem productivity. Also, it is very important to correctly specify the inputs and outputs. Environmental shifters that affect DMUs must typically be included as either inputs or outputs. Anything that the DMU would wish to maximize is an output and anything that it would wish to minimize is an input. In our study, the environmental shifters are climate and topographic characteristics (including the variability of those characteristics) within each county. It is rather difficult to determine whether these factors are inputs or outputs for our DEA analysis, and in fact they may function one way for certain condition indicators and another way for other indicators. For this reason, we will treat the environmental shifters in a statistical manner, preceding the DEA.

In simple terms, the underlying model for each indicator I is:

$$I = f(\tilde{H}, \tilde{S}) + e$$

$$e = q + s$$

where:

f = the "environmental cost function" for the average efficiency DMU
$\tilde{H}$ = the vector of human activity variables
$\tilde{S}$ = the vector of climate and topographic shifters
e = the total residual error with mean zero.
q = the efficiency/inefficiency factor (with mean zero)
s = the normal residual with mean zero

For the DEA analysis, the desired model would have the effect of the climate and topographic shifters ($\tilde{S}$) purged, so that the DMUs are as homogeneous as possible. Thus, we implement the following procedure.

First we regress:

$$I_{ih} = \hat{B}_{i0} + \sum_{j=1}^{J} \hat{B}_{ij} S_{jh} + \hat{g}_{ih} \quad (4)$$

for each indicator i (h indexes the observations [counties], j indexes the shifters, $\hat{g}_{ih}$ is the estimated residual, and the $\hat{B}$'s are estimators). We do not include the human activity variables in the regression to maximize the amount of variation in the indicators that is accounted for by the shifters. Note that the residual, g_{ih}, can be partitioned into a normally distributed random error term (s), a term associated with the efficiency/inefficiency of resource use (q), and a term associated with the unspecified (intentionally) human activity variables. We must necessarily assume that the total residual in this equation meets the standard assumptions of normality with mean zero. Then, using the estimated Equation 4, we predict:

$$I^*_{ih} = \hat{B}_{i0} + \sum_{j=1}^{J} \hat{B}_{ij} \bar{S}_j + \hat{g}_{ih}$$

for each indicator i, where the $\bar{S}$ vector includes the means of each ($j=1, \ldots, J$) shifter across all county observations (indexed by h). This predicts the forest and rangeland condition indicator that would be observed if each county's environmental shifters were at their mean levels. Note again that the estimate of the residual, $\hat{g}_{ih}$, is included in this equation so that the "adjusted" indicator I^*_{ih} retains the effect of the human activity variables, the efficiency/inefficiency factor, and (unavoidably) the random error residual from the original data. Finally, we perform the DEA using I^*_{ih} rather than the original I_{ih} observations. Naturally, the original $\tilde{H}$ observations are used in the DEA.

The underlying model should be contrasted with the Stochastic Frontier Model (introduced by Aigner et al. [1977]; see Carter and Cubbage [1994] for a forestry example), where it is desired to estimate that the frontier function and the efficiency/inefficiency factor is thus asymmetric (e.g., half-normal). For the purposes of our preanalysis to the DEA, f is not a frontier,but is a central-tendency function. The effect of efficiency/inefficiency is thus assumed to be symmetrical, with both positive and negative effects around the mean level of efficiency (zero). In our analysis, the frontier is then identified with DEA, using the I^*_{ih} as just described.

Preliminary testing strongly indicated spatial autocorrelation in our data set (as one might expect). Thus, when estimating Equation 4, we deviated from the usual assumption of ordinary least squares, that residuals g_{ih} are uncorrelated. Instead, we assumed that the covariance between any two residuals was a function of their distance apart and described by the spherical spatial covariance model (Littell et al. 1996):

$$Cov(g_{ik}, g_{il}) = \sigma^2 [1 - 1.5(d_{kl}/\rho) + 0.5(d_{kl}/\rho)^3] 1(d_{kl} < \rho) \quad (5)$$

where g_{ik} and g_{il} are the residuals for any two observations, d_{kl} is the Euclidean distance between the two observations, and $1(d_{kl} < \rho)$ equals 1 when $d_{kl} < \rho$ and 0 otherwise. The variance of g_{ih} that is unaffected by spatial correlation is σ^2. This σ^2 is called the sill in spatial statistics terminology, and ρ is called the range, the distance beyond which observations are assumed to be uncorrelated. Using the spherical covariance assumption in Equation 5, Equation 4, ρ, and σ^2 were estimated using restricted maximum likelihood with SAS Proc Mixed (Littell et al. 1996, SAS Institute 2001).

To account for the variation in county size within each ecoregion, we weighted each observation in this estimation by $n(a/T)$, where n is the total number of counties in the ecoregion, a is the area in the county, and T is the total area of all counties in the ecoregion. This avoids, for example, giving undue weight to smaller (more numerous) counties.

In all of the estimations of Equation 4, we included all shifters axiomatically. We did this for two reasons. First, we wanted to account for the potential effect of all shifters, and second, variable selection within the spatially adjusted regression is difficult because no automated procedures are available. Including all shifter variables, of course, risks the inclusion of insignificant variables and the implied overspecification of the equation. To test for this effect, we selected one indicator and two regions and compared the predicted values of the equation with all shifter variables to a "parsimonious" model where the Akaike information criterion (Burnham and Anderson 1998) was used with standard ordinary least squares to choose between models with all possible variable combinations. In both cases, the actual model estimation included the spatial autocorrelation adjustment. There were minimal differences between predictions based on the full models compared with those of the parsimonious models. Therefore, we expect any effects of overspecification on predictions to be quite small.

Results

A total of 36 models (12 condition indicators in 3 ecoregions), as specified in Equation 4, were fit to adjust each condition indicator for heterogeneity among DMUs within ecoregions. Recall that our intent with this pre-DEA analysis was to remove variation in condition indicators that could be attributed to inherent ecosystem properties. It is important to emphasize that the DEA was performed separately for each ecoregion, so that all efficiency results for any given county are relative to the other counties in its ecoregion. We were able to allow variable returns to scale in all cases except for the PHL and TRI indicators, where we had to restrict the DEA to constant returns to scale. The implications of this assumption were discussed previously. We present the DEA results for each indicator in the Appendix. Here, we will focus on overlays across indicators.

Overlays of Individual Indicator Maps

An overlay of all 12 current condition hotspot maps (Figures 5a–16a in the Appendix) indicates that most counties are associated with ≥1 indicator hotspot (Figure 1). A total of only 15.1% of the area in the country is free from

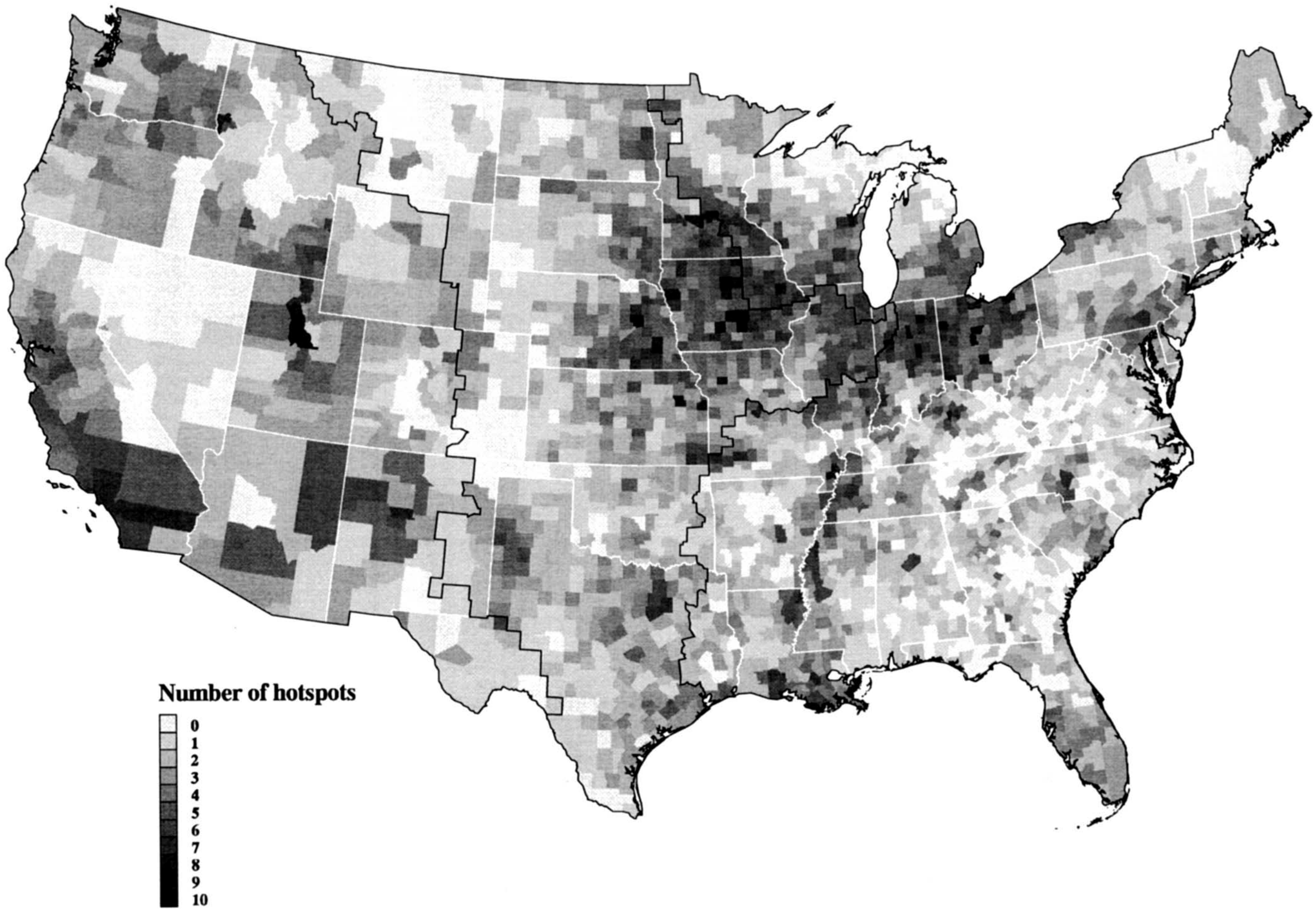

Figure 1. Overlay of Figures 5a–16a: Current condition hotspots.

any current condition hotspot, and there are clearly areas of the country where many current condition hotspots co-occur. The till plains in and around Iowa and extending into part of the Great Lakes region is the largest and most obvious area of current condition hotspot concentration. There are also concentrations in the Southwest (including southern California), the interior West (especially around Salt Lake City), the southern Mississippi River Valley, the Gulf Coast, and southern New England. The highest coincidence of current condition hotspots tends to occur in areas that are either intensively used for agriculture or have experienced significant human population growth.

Figure 2 presents an overlay of the counties with low efficiency scores from the DEA results (Figures 5b–16b in the Appendix). Again, it is important to remember that these efficiency scores are low relative to other counties in their ecoregion, not relative to the country as a whole. There appears to be some noteworthy similarities between these results for the different indicators. New England (especially Maine), the Mid-Atlantic Coast, the Gulf Coast, the southern Mississippi River Valley, the Great Lakes region, the Southwest, and the northern interior West all repeatedly have lower efficiency scores in the DEA. These similarities will be explored further in the Discussion.

It is important to point out that low efficiency scores can occur where the resource or environment is not under stress—it may be that environmental efficiency is low because minimal motivation exists to be more efficient. The areas that we are most interested in are the coincidence of current condition hotspots and areas with low efficiency scores—the opportunity hotspots. And the coincidence of multiple opportunity hotspots would suggest areas where we can make improvements across a number of our forest and rangeland condition indicators. The overlay of all the opportunity hotspots is presented in Figure 3 (Figures 5d–16d in the Appendix). Because the spatial extent of opportunity hotspots was low relative to the total ecoregion area, it is not surprising that many counties are devoid of any opportunity hotspots (27.6% of the area of the coterminous United States). Furthermore, incidence of overlap among indicators is much lower with opportunity hotspots when compared with low efficiency areas—a maximum of six opportunity hotspots co-occur within any county. Among counties with one or more opportunity hotspots, most (86.5% of the opportunity hotspot area) occur singly or jointly with only one other indicator. Still, despite this low incidence of overlap, there are identifiable areas where the overlap is concentrated. Most of the areas of low efficiency score concentration identified from Figure 2 are still represented here, including parts of New England and the Great

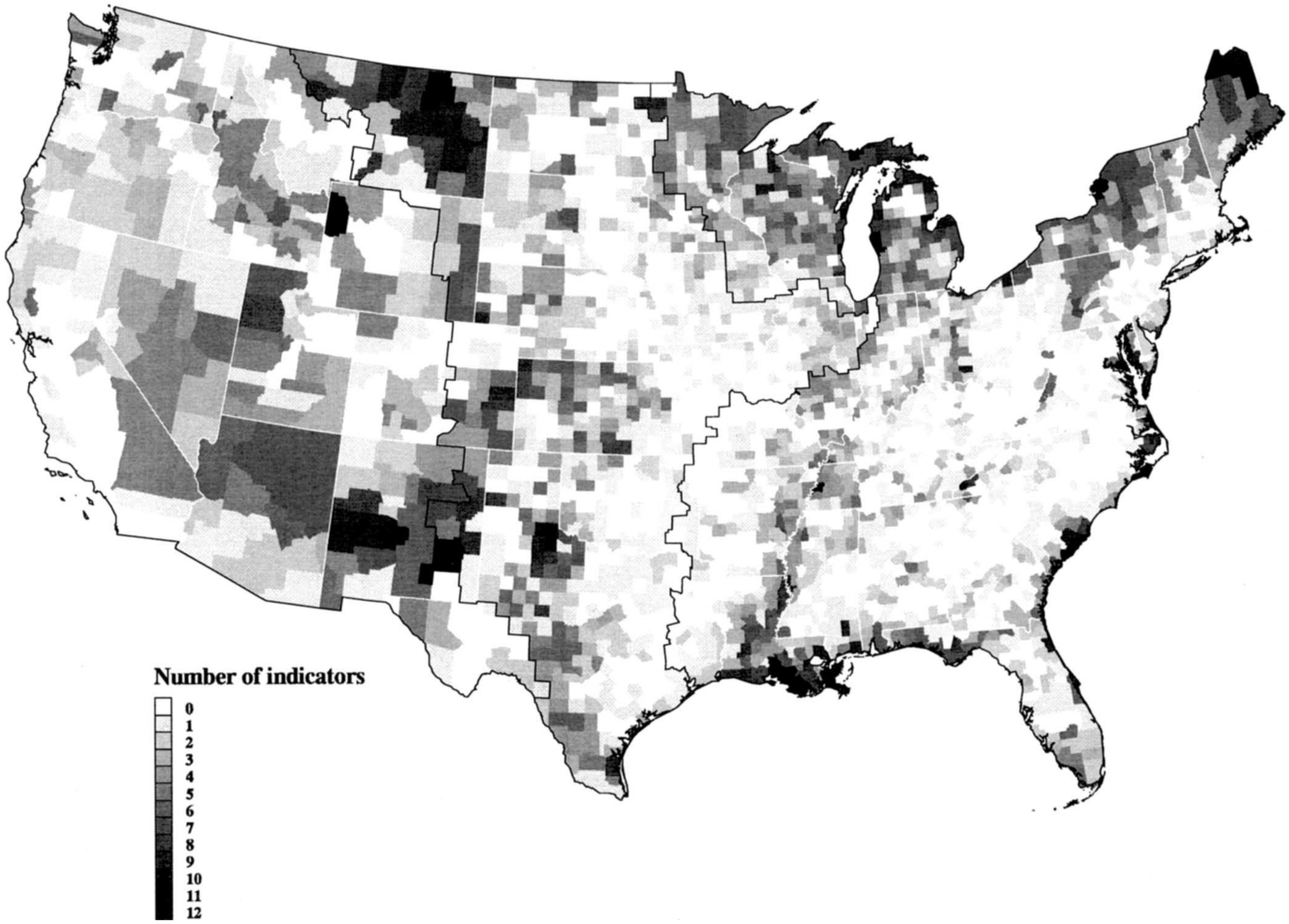

Figure 2. Overlay of Figures 5b–16b: Indicators with relatively low efficiency scores.

Lakes region, the southern Mississippi River Valley, the Gulf Coast, and the Southwest (including parts of Utah). The opportunity hotspots will be analyzed further in the Discussion.

One final observation that may strengthen the credibility of our analysis a bit is that the areas identified as having low efficiency scores do show some spatial contiguity across the ecoregion boundaries we used. The Texas–New Mexico concentrations of these areas cut across two ecoregions, as do the Wyoming–Montana areas. Because the analysis was done separately for each ecoregion, this suggests that the results are not merely an artifact of the ecoregion definition and that these areas have low efficiency scores relative to the counties in more than one ecoregion. The analyses in different ecoregions tend to corroborate each other in these cases (though weakly so). In other cases, such as the Great Lakes region, the low efficiency area identified is limited to a single ecoregion and seems to partially follow the ecoregion boundary.

Discussion

Three key questions emerged from studying the maps presented in the Results, which require further analysis. We will address each one individually as follows.

Question 1— Do the areas with relatively low efficiency scores (see Figures 5b–16b in the Appendix and Figure 2) tend to be spatially contiguous, and are these DEA results for different indicators similar in their degree of spatial contiguity? This question is important because it tells us whether there tends to be large, clearly identifiable low efficiency areas or if they tend to be diffused and less systematic. We quantify the degree of spatial contiguity (the tendency for low efficiency counties to be adjacent to one another) for each indicator based on Moran's I statistic (Upton and Fingleton 1985). In estimating Moran's I, we restricted our spatial neighborhood to the four nearest counties and weighted each observation based on the ratio of its area to the area of the coterminous US. We chose to weight the observations in this manner so that the measure of spatial contiguity was not dominated by the pattern among small (and thus more numerous) counties.

The spatial contiguity of areas with relatively low efficiency scores varies across condition indicators (Table 1). Four condition indicators (EXT, ECG, PCH, and NTG) tended to occur in a highly aggregated fashion ($I > 0.5$); three (MOR, GRO, and STR) had a highly diffuse pattern ($I < 0.15$) characterized by many isolated counties; and the remainder (HAB, PAD, PHO, PHL, and TRI) were characterized by a mixture of aggregated and diffuse patterns that

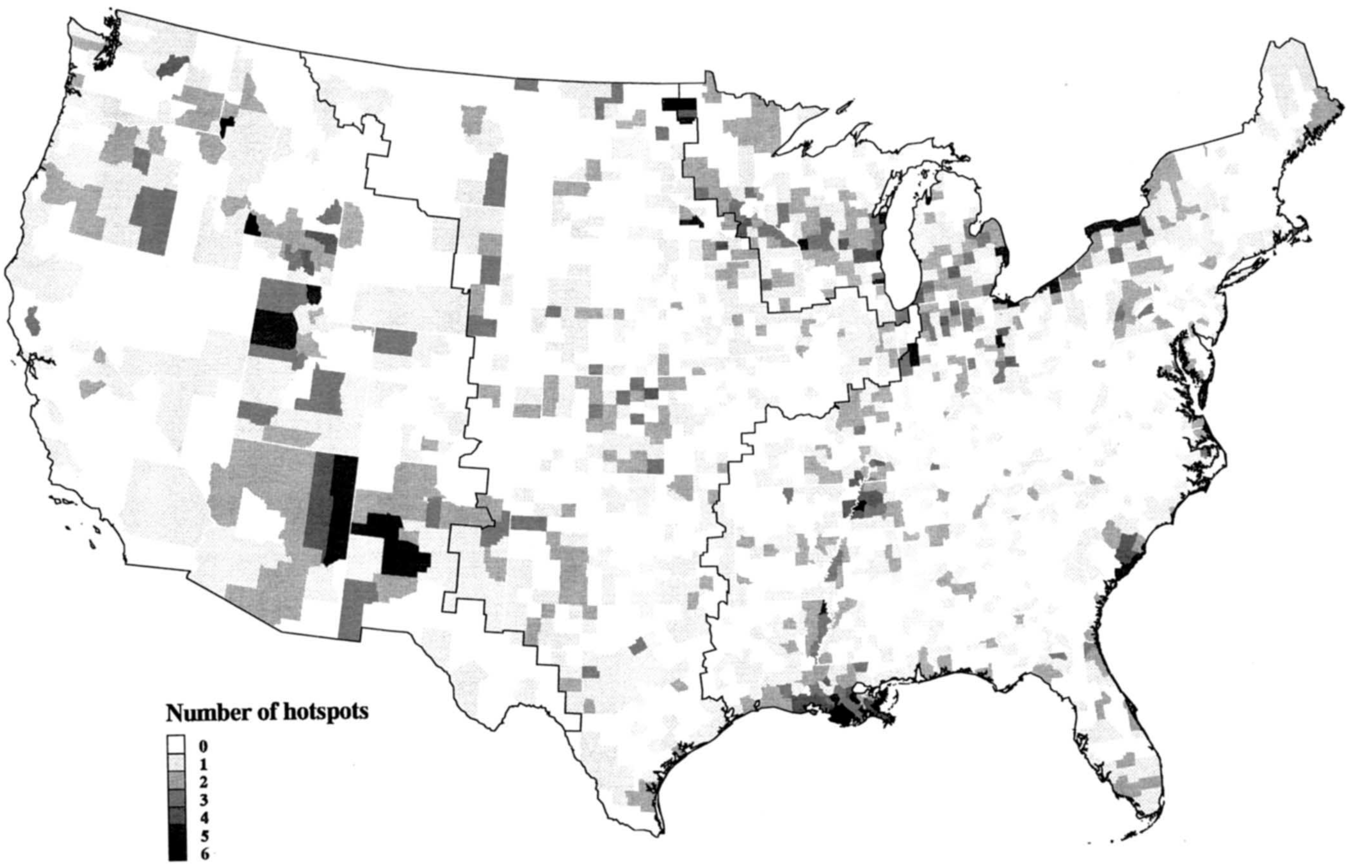

Figure 3. Overlay of Figures 5d–16d: Opportunity hotspots.

tended to vary by ecoregion (see Figures 5 and 13–16 in the Appendix). The next question is related to this one and will be cross-referenced.

Question 2—Do the areas with relatively low efficiency scores have similar geographic patterns of occurrence across condition indicators? The patterns displayed in Figure 2 identify places where areas with low efficiency scores are coincident, but it does not tell us whether there are similar geographic patterns of occurrence of these lower DEA scores across multiple indicators. We described the tendency for similar co-occurrence using cluster analysis on binary data, where presence (one) or absence (zero) of low efficiency scores was determined across all counties and indicators. We used an unweighted average linkage cluster method based on Jaccard's coefficient of similarity (McGarigal et al. 2000). We chose Jaccard's coefficient because it focuses on the pattern of presences (and ignores the pattern of joint absences) in quantifying the degree of similarity across low efficiency areas.

The results from the cluster analysis suggest that there are four basic groups of indicators that behave in a geographically similarly way (Figure 4). The first cluster comprises PAD, PHL, EXT, EDG, HAB, PCH, and PHO and appears to be grouping indicators that had relatively high spatial contiguity (see Table 1; $I > 0.45$ for six of the seven indicators). Many of these indicators also are related in a mechanistically logical fashion. Land use disturbance (HAB) is known to affect the arrangement of native habitats on the landscape (EDG, PCH) (Saunders et al. 1991). Furthermore, the disturbance and arrangement of native habitats directly affects the distribution and abundance of native wildlife (Rapport et al. 1985). Therefore, it is not surprising that the low efficiency areas for exotic birds (EXT) covaried with HAB, EDG, and PCH. A second cluster is associated with timber growth, mortality, and nitrogen levels (GRO, MOR, and NTG). This pattern of association is somewhat surprising given the Moran's *I* results presented in Table 1. GRO and MOR were among those indicators whose low efficiency areas occurred diffusely across the landscape ($I < 0.15$), whereas NTG was among those that showed a strong pattern of spatial aggregation ($I = 0.51$). The final two indicator clusters are not clusters at all but are single indicators that occurred across the landscape in a geographically unique way. Low efficiency areas for TRI and STR were both fairly diffuse in their occurrence ($I = 0.34$ and 0.10, respectively), and the occurrence of their low efficiency areas did not covary in any substantive way with any other indicators. Overall, there is reason to believe that there is systematic similarity between many (but not all) of the DEA low efficiency results.

Question 3—Do the areas with relatively low efficiency scores tend to systematically co-occur with the current condition hotspots, or are the opportunity hotspots identified in Figure 3 just random coincidences? Having studied the nature of the low efficiency areas in the previous two questions, the central question for the article is whether the

Table 1. Summary statistics of spatial contiguity (Moran's *I*) of low-efficiency DEA scores and tests for independence (2 × 3 contingency table) between current condition hotspots and DEA efficiency classes.

		National			Eastern			Central			Western		
Condition indicators	Moran's *I*	Low efficiency adjusted residual[a]	High efficiency adjusted residual[a]	Chi-square statistic[b]	Low efficiency adjusted residual	High efficiency adjusted residual	Chi-square statistic	Low efficiency adjusted residual	High efficiency adjusted residual	Chi-square statistic	Low efficiency adjusted residual	High efficiency adjusted residual	Chi-square statistic
HAB	0.46	**−9.8**[c]	**−2.6**	**120.8**	**−7.2**	**−4.4**	**90.4**	**−7.5**	−0.7	**62.2**	−1.2	**2.4**	**6.3**
EDG	0.59	**9.4**[d]	**−6.7**	**108.9**	**3.2**	**−3.5**	**18.1**	**9.3**	**−5.5**	**97.2**	**6.4**	**−2.7**	**42.2**
PCH	0.56	**−2.5**[e]	**−8.0**	**83.4**	**−2.3**	**−6.0**	**49.1**	**−5.7**	**−5.0**	**72.8**	**6.4**	−1.9	**40.5**
EXT	0.57	**2.3**	**−5.1**	**26.9**	**8.5**	**−8.6**	**119.4**	**−6.4**	1.7	**41.2**	−2.0	−0.9	**6.3**
MOR	0.11	**12.9**	**−7.2**	**184.6**	**5.9**	**−6.4**	**59.8**	**11.4**	−1.4	**130.5**	**8.8**	**−4.5**	**85.0**
GRO	0.14	**14.5**	**−4.8**	**211.8**	**11.6**	**−4.2**	**135.6**	**6.4**	−1.2	**41.4**	**4.5**	**−2.8**	**23.9**
STR	0.10	**26.8**	**−5.9**	**722.6**	**21.0**	**−3.0**	**447.3**	**14.3**	**−3.9**	**205.5**	**8.5**	**−4.0**	**74.5**
NTG	0.51	**22.2**	**−10.5**	**518.8**	**22.5**	**−9.5**	**521.2**	**6.7**	**−5.0**	**56.9**	1.6	−1.3	3.5
PHO	0.35	0.2	**−9.3**	**93.1**	−0.4	**−7.2**	**56.5**	**−2.6**	**−4.8**	**40.3**	**6.3**	**−3.5**	**40.5**
PHL	0.46	−0.4	**−2.7**	**8.4**	**2.4**	**−4.2**	**19.8**	**−5.1**	**2.6**	**29.0**	1.6	**−2.5**	**7.1**
TRI	0.34	**19.1**	**−8.4**	**372.7**	**20.3**	**−9.7**	**422.3**	**3.3**	0.3	**12.7**	**4.9**	**−3.9**	**30.5**
PAD	0.49	−1.5	2.0	5.1	−3.3	**3.4**	**18.1**	1.8	−0.8	3.6	0.3	0.0	0.1

[a] The adjusted residuals test for extreme cell values.
[b] The chi-square statistic tests for overall independence.
[c] Bolded values are significant at $p \leq 0.05$.
[d] Underlined positive adjusted residuals indicate greater than expected coincidence.
[e] Non-underlined negative values indicate greater than expected avoidance between current condition hotspot counties and counties with either low efficiency or high efficiency scores.

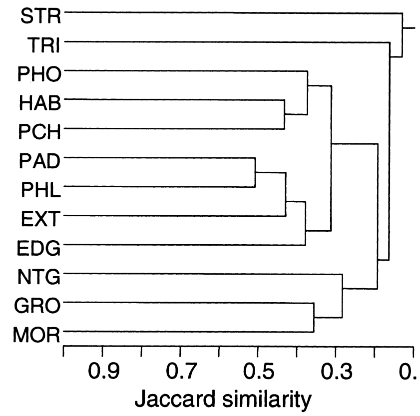

Figure 4. Dendrogram of among-condition-indicator similarity in county-level occurrence of low efficiency hotspots. Four clusters were defined based on Jaccard similarity.

opportunity hotspots are significant or just coincidences that should be expected to occur randomly. To address this question, we analyzed the frequency of counties in a 2 × 3 contingency table. The rows of the table partitioned counties into current condition hotspot and nonhotspot sets. The columns of the table partitioned counties into low efficiency, high efficiency, and moderate efficiency scores. The chi-square statistic indicated whether there was evidence that the current condition hotspot for each indicator was independent of DEA efficiency. Furthermore, to interpret any pattern of independence, we examined the adjusted residuals for each cell of the contingency table for extreme values (Mosteller and Parunak 1985) that would indicate greater than expected coincidence or avoidance between current condition hotspots and DEA efficiency scores. Adjusted residuals are approximately distributed as standard normal deviates (Haberman 1973). Positive residuals indicate coincidence, and negative values indicate avoidance. To account for multiple comparisons when testing individuals cells, we implemented a Bonferroni adjustment that multiplied the *p*-value (two-tailed) associated with the standard deviate by $(r–1)(c–1)$, where r and c represent the number of rows and columns in the contingency table, respectively (Mosteller and Parunak 1985).

We were most interested in whether the count of counties comprising the opportunity hotspots (i.e., the counties that are both a current condition hotspot and have a low efficiency score) is greater than can be attributed to random chance. Such a pattern would indicate that areas under the greatest ecosystem stress also represent the areas where the greatest improvement can be attained by managing impacts of resource use more efficiently (i.e., human activity would not need to be reduced to observe a lower environmental impact). We also tested for coincidence or avoidance between current condition hotspots and high efficiency scores. Evidence for coincidence in this latter test would indicate that those areas under the greatest ecosystem stress could only be improved by a reduction in human activity because efficiency is already high. Because the adjusted residuals for the moderate scores are not easily interpreted with respect to Question 3, we do not report them.

The chi-square statistics indicate that, in general, the overall occurrence of current condition hotspots is not independent of the three DEA efficiency classes at the national and regional scales (Table 1). The two indicators that are exceptions to this pattern are PAD (nationally and in the central and western regions) and NTG (in the western region).

The most striking result is the lack of coincidence between the current condition hotspots and the areas with the highest DEA efficiency scores. Only three indicators—PAD in the eastern region, PHL in the central region, and HAB in the western region—showed a significant pattern of co-occurrence. All other indicators, both nationally and regionally, showed a significant pattern of avoidance or a level of deviation that was not different from that attributable to random chance.

Significant coincidence between current condition hotspots and low DEA efficiency scores was indicated for 7 of the 12 indicators at the national level. Only two of the indicators had a significant pattern of avoidance (PCH and HAB), and PAD, PHO, and PHL were not significantly different from a random level of coincidence. Similar conclusions can be drawn for the eastern region, and generally similar results are exhibited for the other two regions. Thus, the opportunity hotspots are statistically significant for a majority of the indicators at the national and regional scale.

Conclusion

In this article, we have reported those areas of the country where environmental stress was high (current condition hotspots) and where natural resources were apparently being managed inefficiently (indicated by low scores in the DEA). A comparison of geographic maps that identified counties with relatively low efficiency scores seemed to indicate that some indicators were distributed in a similar fashion across the coterminous United States. Based on a statistical analysis of spatial contiguity measures and indicator coincidence, we found evidence supporting significant similarity in the low efficiency areas among different indicators. Throughout the individual indicator results, however, the opportunity hotspots did not seem to be spatially extensive. When we analyzed the opportunity hotspots statistically, we concluded that a slim majority of indicators demonstrated significant areas of opportunity—where the environment is currently under stress and where efficiency in managing environmental impacts is relatively low. When we looked across indicators, the overlap of these opportunity hotspots was not extensive. This suggests that there are opportunities to improve the environmental condition without reducing the amount of human activity but not over large areas, only for some indicators, and typically not for a large number of indicators in the same place. Looking at Figure 3 (along with Figures 5d–16d) reinforces the conclusion that large, clearly identifiable opportunity hotspots that apply to a large number of indicators are relatively rare. This means that large-scale improvements in environmental condition across many indicators will not likely be realized without a reduction in human activity. As stated at the beginning of this article, the objective was to see if there are opportunities to improve the environmental condition without the economic and social costs associated with reducing human activity, simply by being more efficient with regard to how we manage environmental impacts. Our results suggest that there are such opportunities, but that they are not widespread and are not highly contiguous. As noted earlier, if our assumption of homogeneous investment in mitigation of environmental impacts is not met, then these opportunity hotspots may actually indicate counties that have relatively low investment in mitigation efforts. In this case, they would represent opportunities to improve the forest and rangeland condition by bringing the level of mitigation up to that of similar counties.

Naturally, further investigation on a microscale is called for before any definitive conclusion would be appropriate. In a sense, this study provides hypotheses for these microscale studies. This study is an initial investigation at a gross scale with only a few indicators and many empirical limitations. It is exploratory, and all results are tentative. Clearly, much more work is called for in the general area of identifying areas of opportunity for improving the condition of forest and rangelands. The purpose of this study is to suggest candidates for further study. In that regard, it can function as a type of triage for large-scale planning efforts.

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Appendix: Individual Indicator Results

For each indicator, we display the geographic results in four maps: (a) a map of those counties with the worst 20% (based on area) of the indicator value in each ecoregion, referred to as the "current condition hotspots"; (b) a map of those counties with the lowest 20% (based on area) of the DEA efficiency scores in each ecoregion; (c) a map of those counties with the highest 20% (based on area) of the DEA efficiency scores in each ecoregion; and (d) a map that displays the spatial intersection of the current condition hotspots (map a) and the areas with lower efficiency scores (map b). The fourth map identifies those counties where current conditions are relatively stressed and where opportunities may exist for improvements. We refer to these counties as "opportunity hotspots."

Index of Habitat Disturbance (HAB)

One of the simplest indicators of ecosystem condition is the amount of native habitat remaining in a given geographic area (Rapport et al. 1985, NRC 2000). Conversion of native habitats to human-dominated land uses directly affects the capacity of ecological systems to provide the goods and services that humans derive from those systems (Dailey 1997, Vitousek et al. 1997). This indicator is often referred to as an index of anthropogenic disturbance (O'Neill et al. 1988, 1997) and is measured as the proportion of each DMU in an intensive land-use class (urban land, surface mine, or agriculture).

The current condition hotspots for HAB (Figure 5a) reflect areas where much of the land has been converted to human-dominated land uses (especially agricultural activity). These are highly aggregated and show a clear spatial pattern, especially in the Great Lakes region, the upper Midwest, the East Coast, interior West, California, and the Pacific Northwest. There is limited spatial overlap between the current condition hotspots and the areas with low efficiency scores in the DEA (Figure 5b). Because the low efficiency areas in Figure 5b show a spatial pattern that is almost orthogonal to the pattern in Figure 5a, the opportunity hotspots are nearly vacuous (Figure 5d). This would suggest that HAB is an indicator without any large, distinct opportunity hotspots. The areas of high efficiency scores in the DEA analysis (Figure 5c) are scattered across the country with no clear spatial pattern and with minimal coincidence with the current hotspots in Figure 5a. This is a common result among all condition indicators.

Edge (EDG)

As the amount of native habitat is reduced, there comes a point when the arrangement of that habitat becomes critically important to maintaining ecosystems (Saunders et al. 1991, Muradian 2001). Edge effects are thought to be a predominant factor affecting the structure and function of ecological systems (Harrison and Bruna 1999). Although most of the empirical literature has focused on documenting edge effects at local scales, there is accumulating evidence that the influence of edges can be wide-ranging, affecting ecosystem properties over broad geographic regions (Laurance 2000).

Current condition hotspots for the amount of edge between native habitats and human-dominated land uses are generally scattered across the country (Figure 6a). Areas with low efficiency scores from the DEA results (Figure 6b) are more coherent, especially in the Northeast and Great Lakes region, Florida, the Midwest, the interior West, and to a lesser degree in the far West. The areas with high efficiency scores (Figure 6c) are more dispersed but with gaps in the Northeast and Southwest. They have minimal coincidence with the current condition hotspots in Figure 6a.

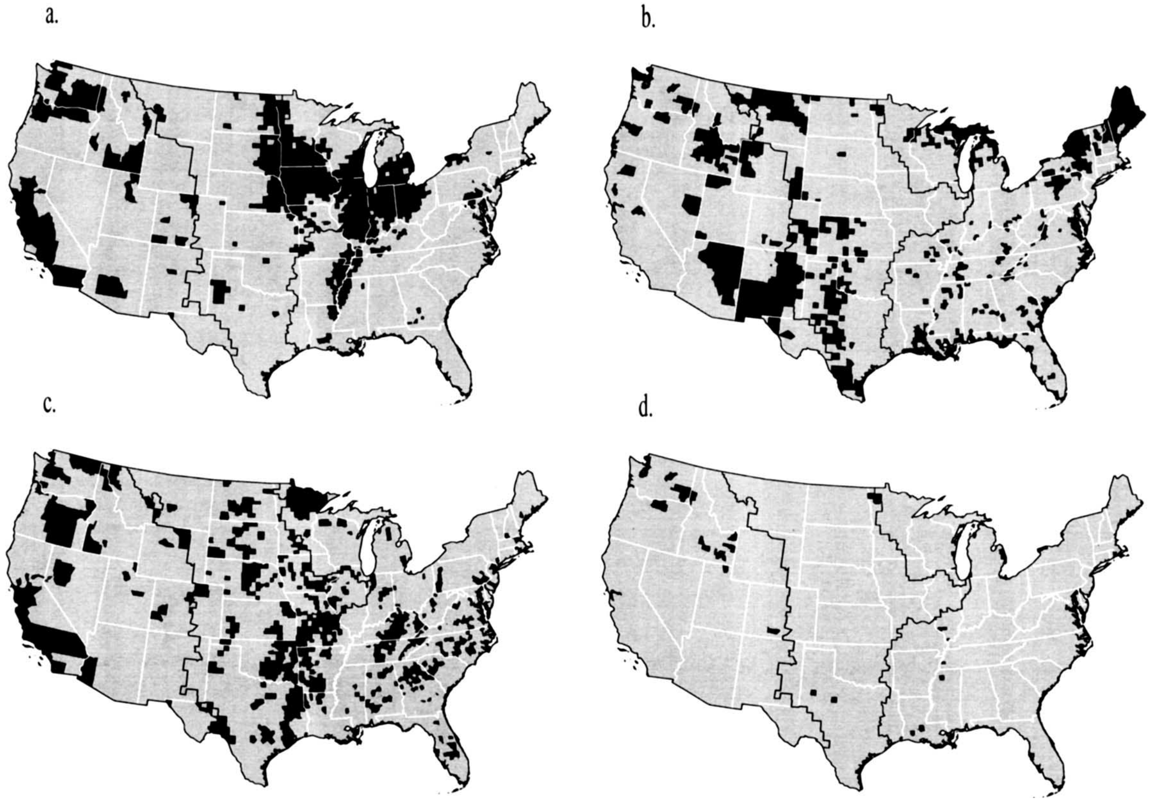

Figure 5. Maps of (a) current condition hotspots, (b) areas with relatively low efficiency scores, (c) areas with relatively high efficiency scores, and (d) coincidence of current condition hotspots with areas of relatively low efficiency for HAB.

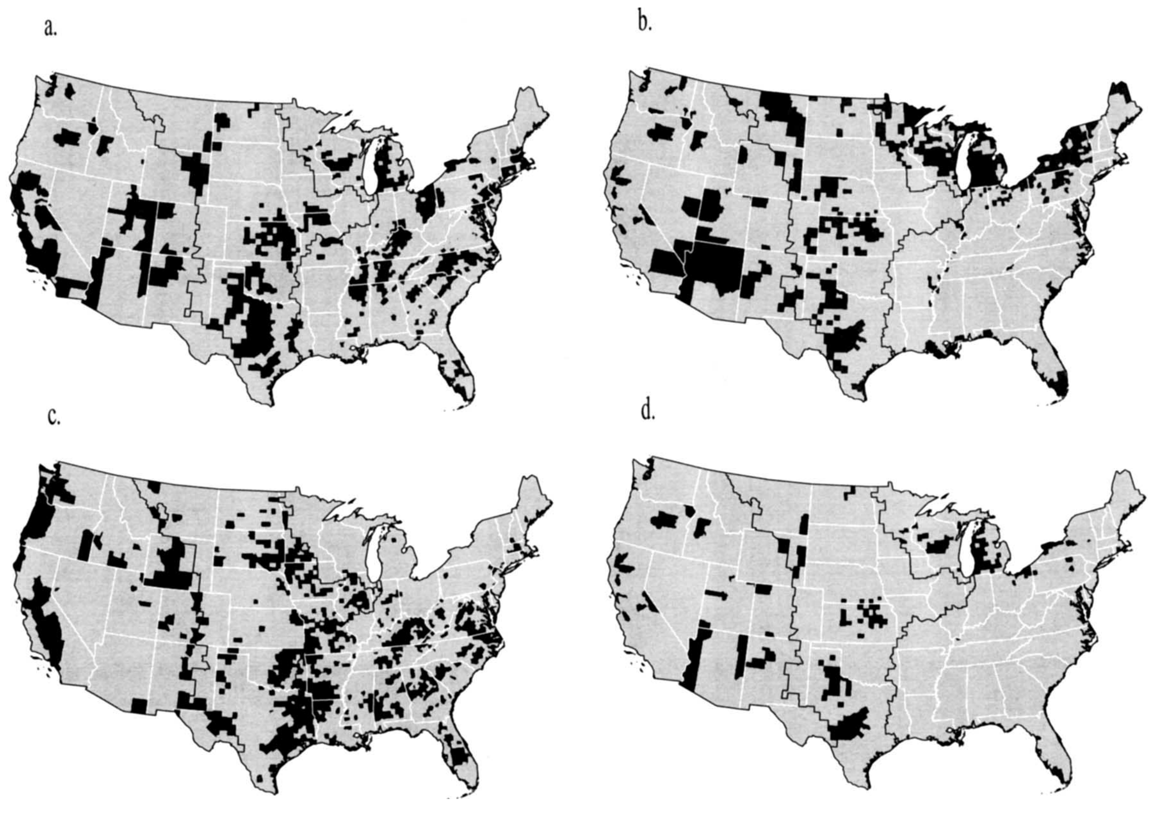

Figure 6. Maps of (a) current condition hotspots, (b) areas with relatively low efficiency scores, (c) areas with relatively high efficiency scores, and (d) coincidence of current condition hotspots with areas of relatively low efficiency for EDG.

The opportunity hotspots (Figure 6d) occur in the Great Lakes region, the Great Plains, the interior West, and the far West.

Patch Size (PCH)

Another attribute of habitat arrangement that affects ecosystem structure and function is the size of patches on a landscape. One of the most obvious, and nearly ever present, effects of habitat destruction is a reduction in average patch size (Bender et al. 1998). Reductions in the average size of patches can compound the effects associated with a loss of habitat (Flather and Bevers 2002) stemming from a reduced capacity to support biological diversity, altered disturbance regimes, and subtle changes to microclimate. (Saunders et al. 1991).

Current concentrations of low average patch size for native habitats are fairly clustered, especially in the upper Midwest (Figure 7a). Peninsular Florida, the Gulf Coast, the interior West, and the central California valleys and mountains also exhibit noticeable current condition hotspot areas. Areas with low efficiency scores from the DEA results (Figure 7b) are also fairly coherent but are not highly correlated with the areas in Figure 7a. The exceptions are shown as the only opportunity hotspots in Figure 7d, primarily in the interior West and along the western Gulf Coast. The areas with high efficiency scores in the DEA results (Figure 7c) are relatively scattered (though with some cohesion just west of the southern Mississippi River Valley). They have minimal coincidence with the current hotspots in Figure 7a.

Exotic Breeding Birds (EXT)

A common observation in the ecosystem stress literature is that as resource development intensifies there is typically an increase in the abundance of exotic (non-native) species that tolerate human activity (Rapport et al. 1985, Pimentel et al. 2000). The number of exotic individuals compared with the total number of individuals within some taxonomic group has been proposed as a useful indicator of ecosystem health (NRC 2000) and has been used recently with bird monitoring data as a broad-scale indicator of ecosystem condition (Hof et al. 1999, Sieg et al. 1999).

The proportion of exotic species comprising the bird community is especially prominent throughout the upper Midwest (Figure 8a). There are a number of smaller isolated current condition hotspots in the Mid-Atlantic region, the Great Plains, the intermountain West, southern California, and the Pacific Northwest. The DEA results (Figure 8b) show areas with lower efficiency scores along the East Coast, in western New England, the Great Lakes region, the intermountain West, and scattered throughout the Great Plains. The Gulf Coast and the Pacific Northwest also have small areas indicated. These areas appear to occur where agriculture or human settlement has converted native lands to intensive human uses. The areas with the highest efficiency scores, given in Figure 8c, are fairly well dispersed

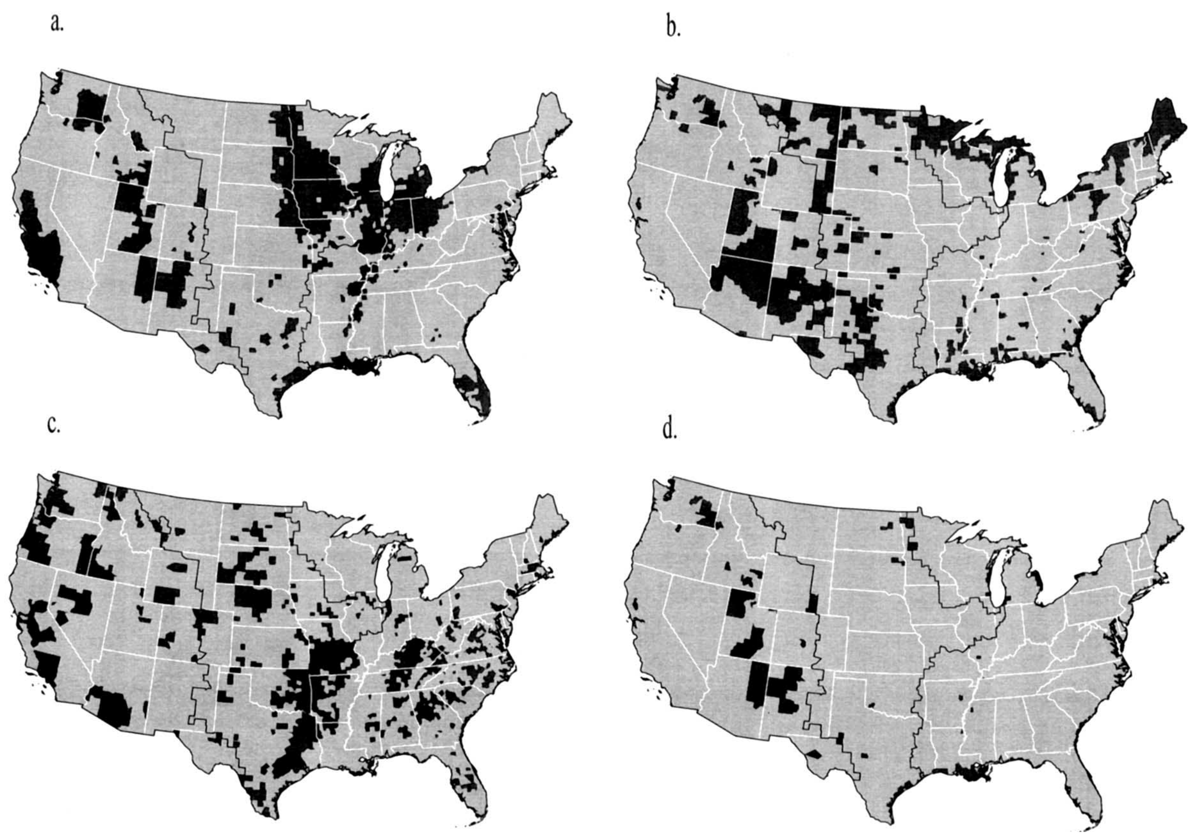

Figure 7. Maps of (a) current condition hotspots, (b) areas with relatively low efficiency scores, (c) areas with relatively high efficiency scores, and (d) coincidence of current condition hotspots with areas of relatively low efficiency for PCH.

Figure 8. Maps of (a) current condition hotspots, (b) areas with relatively low efficiency scores, (c) areas with relatively high efficiency scores, and (d) coincidence of current condition hotspots with areas of relatively low efficiency for EXT.

across the country. The high efficiency areas in Figure 8c do not overlap heavily with the current condition hotspots in Figure 8a. There is some limited spatial correlation between low efficiency areas (Figure 8b) and current condition hotspots leading to the opportunity hotspots in Figure 8d—primarily in the Great Lakes region, on the Mid-Atlantic Coast, and, to a lesser degree, in the West.

Timber Mortality (MOR)

A less well-studied aspect of ecosystem condition indicators involves the effect of various stressors on disease incidence (Rapport et al. 1985). One group of organisms where there has been a number of studies examining the relationship between stress and disease is trees (Manion 1981). The ultimate stress that predisposes a tree to death may be quite different from the proximate mortality factor. For example, Dahlsten and Rowney (1980) found that air pollution rendered ponderosa pine (*Pinus ponderosa*) more vulnerable to insect infestation. Our interest here is not to attribute cause to increasing tree mortality but to simply use the mortality rate as an indicator of some undefined stress or set of stresses. Because the data for this indicator are limited to timberland, we excluded those counties that had no timberland (light gray areas in Figures 9a-d). Timberland is defined as "forestland that is producing, or is capable of producing, in excess of 20 ft^3/ac per year of industrial roundwood products under natural conditions, is not withdrawn from timber utilization by statute or administrative regulation, and is not associated with urban or rural development" in our data source.

High mortality rates for timberland currently occur diffusely throughout the country (Figure 9a). Notable areas of clustering occur in Maine, thepcoastal plain and Piedmont regions of South Carolina and North Carolina, northern Minnesota, and the interior West. Many small and scattered current condition hotspots occur throughout the South. The areas with low efficiency scores from the DEA results (Figure 9b) are prevalent in the interior West, and also in the Great Lakes region, the Mississippi River Valley, the Gulf Coast, and the East Coast. In contrast, the areas with high efficiency scores (Figure 9c) are concentrated on the West Coast and then scattered throughout the rest of the country except for a large gap in the Southwest. They have minimal coincidence with the current condition hotspots in Figure 9a. The opportunity hotspots in Figure 9d are small and scattered across most of the country with the exceptions of the Northeast and the far West (including Arizona). For this indicator, few cohesive areas of opportunity are indicated.

Timber Growth (GRO)

When under stress, trees alter their normal pattern of carbon allocation by decreasing stem growth (Waring 1987). Consequently, reductions in tree growth will often precede a detectable change in tree mortality. Although timber growth and mortality rates are expected to correlate, reductions in timber growth may actually serve as an early

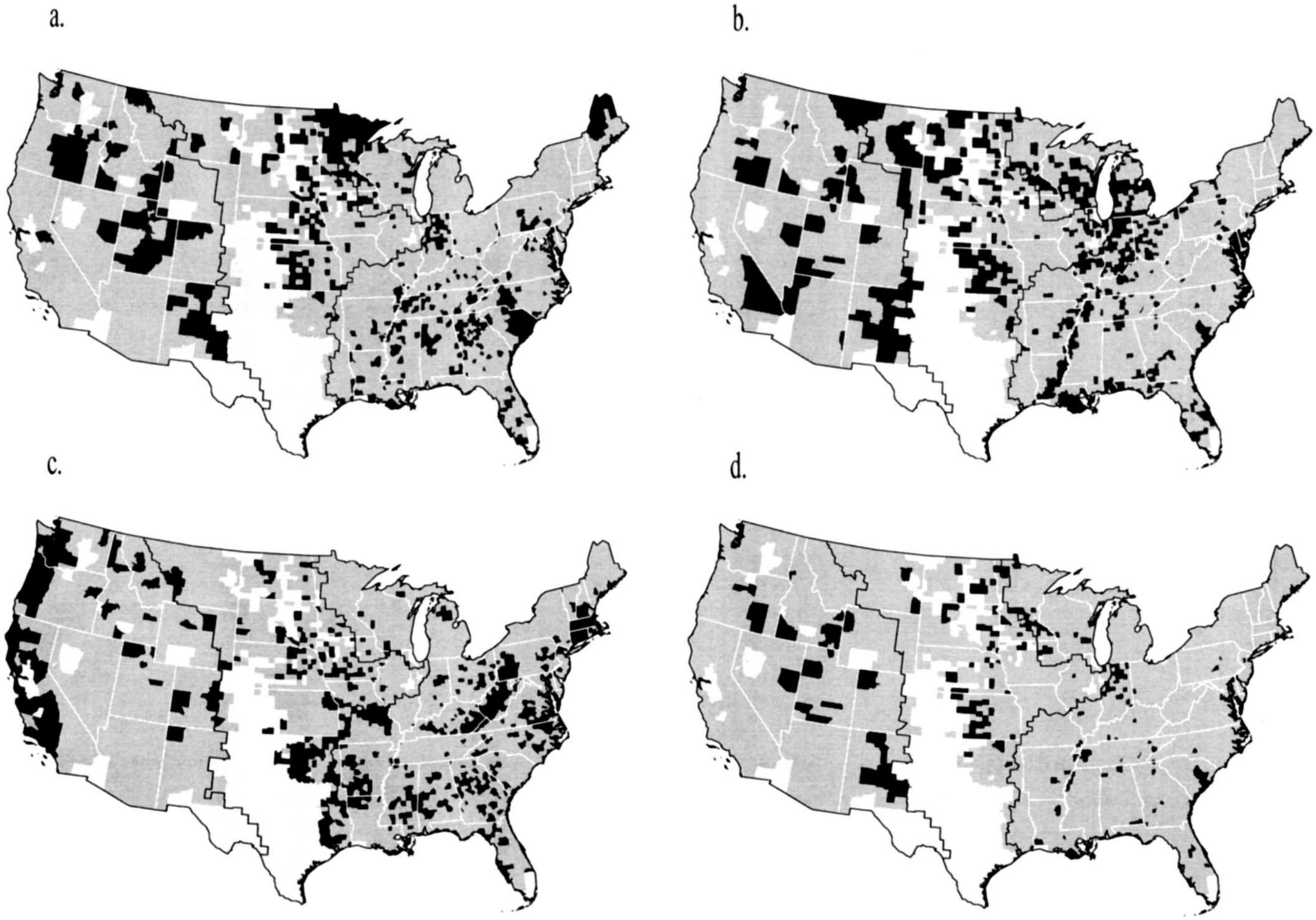

Figure 9. Maps of (a) current condition hotspots, (b) areas with relatively low efficiency scores, (c) areas with relatively high efficiency scores, and (d) coincidence of current condition hotspots with areas of relatively low efficiency for MOR.

warning sign, relative to timber mortality, of ecosystem stress. Again, because the data for this indicator are limited to timberland, we excluded those counties that had no timberland (light gray areas in Figures 10a–d).

The results for GRO (in Figures 10a–d) are quite similar to those just discussed for MOR (note that GRO is defined as 1 minus the ratio of actual growth to potential growth). The current condition hotspots (Figure 10a) are, if anything, slightly more diffuse. And the areas with relatively low efficiency scores (Figure 10b) are not highly coincident with the current condition hotspots, resulting in the small and scattered opportunity hotspots in Figure 10d. Overall, our analysis does not suggest any particular, cohesive areas of opportunity for improving timber productivity or condition. In the South, where timber is managed intensively, mortality and foregone growth appear to be minimal. In other areas of timberland, whatever problems we may currently have in timber condition are scattered in terms of their co-occurrence with low relative efficiency.

Deviation from Mean Streamflows (STR)

Human alteration of land cover has obvious direct effects on terrestrial systems. Those alterations coupled with increasing human populations also affect aquatic systems through their influence on the hydrologic cycle. Clearing of land for agriculture or urban development can increase the amount of water reaching water courses by reducing transpiration, interception, and infiltration (Arnold and Gibbons 1996, Goudie 2000, Weng 2001). However, agricultural development and human population growth can reduce in-stream flows through increased water withdrawals (Brown 2000). Because ecosystem stress may manifest as increased or decreased streamflow, this indicator is measured as the absolute value of the deviation in the mean annual flows observed during the 1990s from the long-term (1960–1989) mean.

The current condition hotspots for STR (Figure 11a) are clustered in the Midwest and in the far West. However, streamflow hotspots are also scattered through the rest of the country with a less spatially contiguous pattern. This would indicate that streamflow deviations are rather ubiquitous. The low efficiency scores from the DEA results for STR do not show a very strong spatial pattern (Figure 11b) but do coincide somewhat with the current condition hotspots in Figure 11a, suggesting opportunity hotspots in the Midwest and the far West and also in a number of smaller areas in the rest of the country (Figure 11d). The areas with high efficiency scores from the DEA analysis (Figure 11c) are relatively scattered and do not exhibit a strong correlation with the current hotspots in Figure 11a.

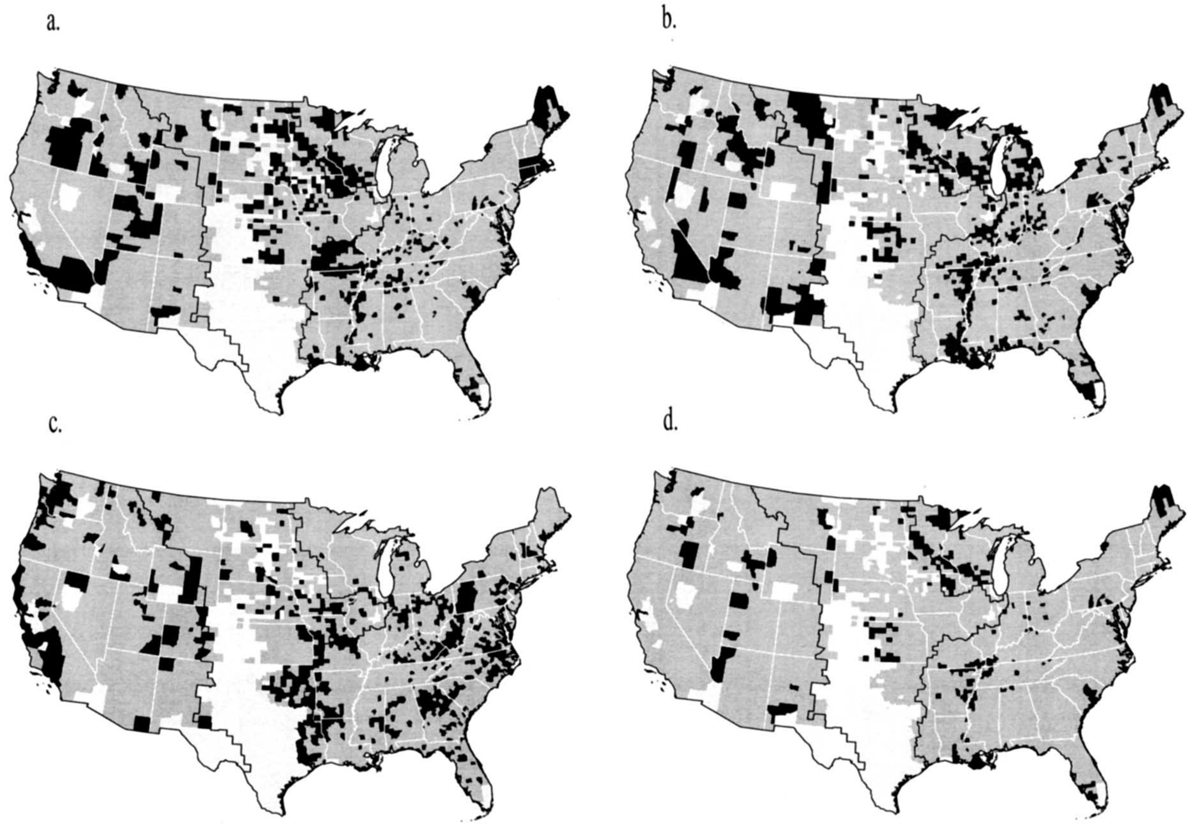

Figure 10. Maps of (a) current condition hotspots, (b) areas with relatively low efficiency scores, (c) areas with relatively high efficiency scores, and (d) coincidence of current condition hotspots with areas of relatively low efficiency for GRO.

Figure 11. Maps of (a) current condition hotspots, (b) areas with relatively low efficiency scores, (c) areas with relatively high efficiency scores, and (d) coincidence of current condition hotspots with areas of relatively low efficiency for STR.

Total Nitrogen in Surface Waters (NTG)

In disturbed systems there is often a loss of nutrients through leaching and soil erosion (Likens et al. 1978). Chemical cycles become leaky, causing elevated nutrient delivery and accumulation in aquatic systems (Rapport et al. 1985, Magdoff et al. 1997, NRC 2000). Furthermore, nutrient loads in aquatic systems can become elevated due to direct input from sewage, animal waste, and synthetic fertilizer application (Goudie 2000). Nitrogen is an important element in plant and animal nutrition, but elevated levels can have detrimental effects on ecosystem function and human health (NRC 2000). We use a measure of total nitrogen in surface waters (also called total Kjeldahl nitrogen) as described in Mueller et al. (1995).

Current areas of high total nitrogen levels (Figure 12a) appear diffusely across the country with some spatial clustering in the upper Midwest, the arid Southwest, and peninsular Florida. The areas with low efficiency DEA scores (Figure 12b) include the upper Midwest, particularly around the Great Lakes region, the lower Mississippi River Valley, and throughout the interior West. Secondary areas of clustering appear along the Atlantic and Gulf Coasts. High efficiency scores from the DEA analysis are found in counties scattered throughout the country (Figure 12c) and appear to be spatially uncorrelated with counties identified as current condition hotspots (Figure 12a). The opportunity hotspots (Figure 12d) are indicated in the arid Southwest, the upper Midwest, and along the Mississippi River Valley. Less prominent areas where current conditions are stressed and efficiency is relatively low also occur along the Gulf Coast and peninsular Florida.

Total Phosphorous in Surface Waters (PHO)

Phosphorous concentrations are another common indicator of water quality (O'Neill et al. 1997) that can alter ecosystem condition through their accelerating effect on eutrophication (Goudie 2000). Elevated phosphorous levels are caused by many of the same agents as nitrogen, namely sewage, animal waste, fertilizers, and detergents. Because of the shared origins, phosphorous levels are expected to correlate with nitrogen levels. However, there are reasons why these two nutrients are not necessarily redundant indictors of water quality. Phosphorous is less mobile than nitrogen, adhering strongly to soil constituents. Consequently, phosphorous levels in surface waters are affected by the type, texture, and level of organic matter in the soil (NRC 2000). We use a measure of total phosphorous (mg of P/L) as described in Mueller et al. (1995).

Areas of high total phosphorous currently appear diffusely across the country (Figure 13a). There is some geographic similarity with nitrogen, namely a concentration of counties supporting high levels of phosphorous in the upper Midwest, the Southwest, the southern Mississippi River Valley, and the Gulf Coast. However, the pattern also deviates from nitrogen in notable ways: areas of stress are indicated diffusely throughout the Southeast,

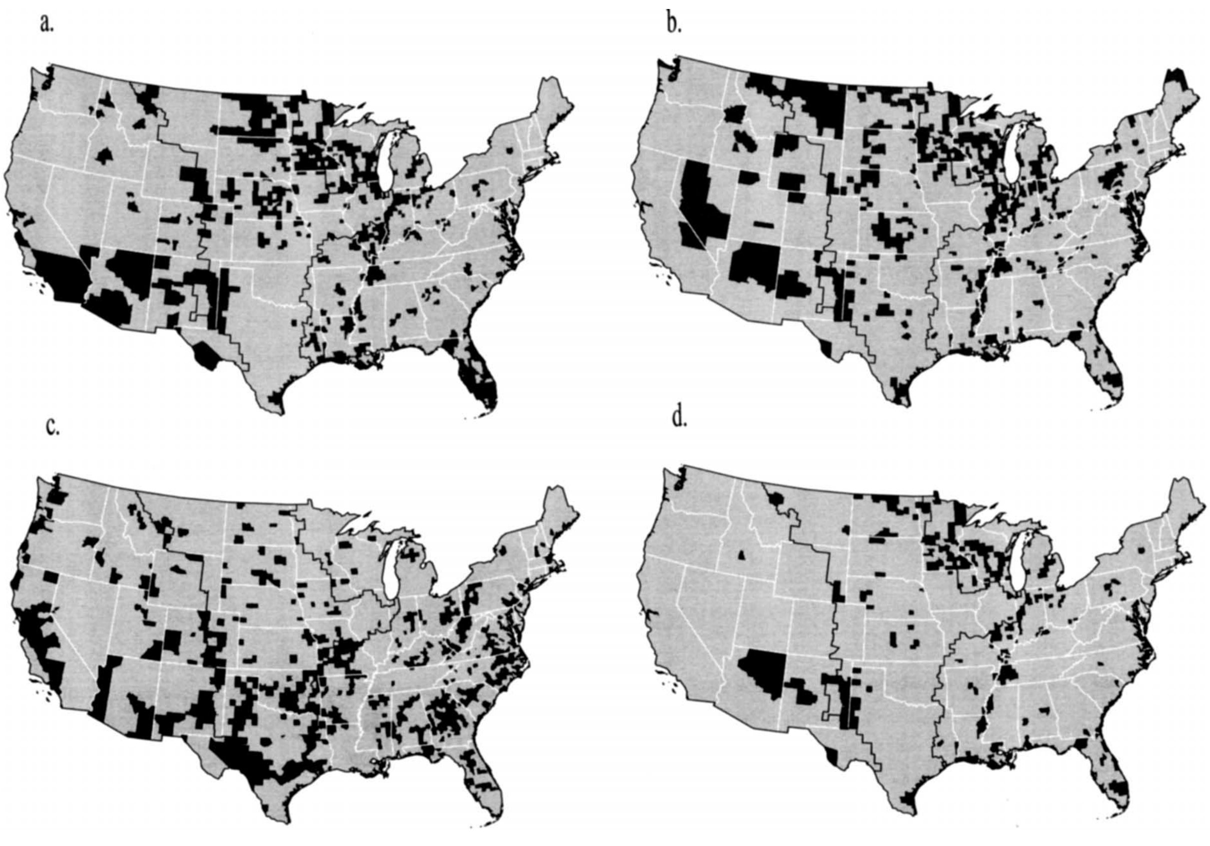

Figure 12. Maps of (a) current condition hotspots, (b) areas with relatively low efficiency scores, (c) areas with relatively high efficiency scores, and (d) coincidence of current condition hotspots with areas of relatively low efficiency for NTG.

peninsular Florida is less prominent, and areas of stress in the upper Midwest occur farther south. Areas with lower efficiency scores (Figure 13b) are prominent throughout the interior West, in the mixed deciduous-coniferous forests of the Great Lakes and northern New England region, and along both the Gulf (see the Mississippi delta region in particular) and southern Atlantic Coasts. In contrast, the areas with higher efficiency scores (Figure 13c) are scattered across the country with little contiguity and exhibit little correlation with the current condition hotspots (Figure 13a). Areas of overlap between the current condition hotspots (Figure 13a) and the low efficiency areas (Figure 13b) indicate opportunity hotspots primarily in the Southwest and secondarily along the Gulf Coast (Figure 13d).

Ph in Precipitation (PHL)

Chemical compounds can also impact ecosystem condition through the process of atmospheric deposition. Increased acidification of precipitation (higher loads of H^+) is prominent among these concerns (Likens and Bormann 1974). Sulfur oxides and nitrogen oxides from fossil-fuel combustion are the primary compounds causing increased acidity in precipitation, and its effects on the structure and function of ecosystems are potentially widespread causing, among other things, accelerated leaching of soil nutrients, increased solubility of toxic heavy metals, reductions in fish and algae diversity, slower growth in forests, and reduced seed germination (Goudie 2000).

The current condition hotspots for PHL (Figure 14a) are extremely clustered, with four large areas identified. The areas with low efficiency scores in the DEA results (Figure 14b) include the Northeast, the East Coast, the Gulf Coast, the southern Mississippi River Valley, the Great Lakes region and surrounding areas, and the interior West. The areas with high efficiency scores (Figure 14c), on the other hand, are scattered throughout most of the country (with gaps in the Northeast and Southwest). They have minimal coincidence with the current condition hotspots in Figure 14a. The opportunity hotspots (Figure 14d) are not terribly large, but there are distinct areas in the Northeast, the East Coast, and the Southwest.

Total Toxic Chemical Releases to the Environment (TRI)

Chemical pollutants can take many forms. Previous indicators have been targeted to a restricted set of compounds. This indicator attempts to capture changes in ecosystem condition caused by a much broader suite of contaminants. The TRI contains information on the releases of nearly 650 chemical categories to the air, water, and land. Because of the diversity of contaminants and their widely varying toxicities, it is difficult to outline generally the ecosystem effects stemming from these pollutants.

The current condition hotspots for TRI (Figure 15a) are very dispersed, showing little discernible spatial cohesion. The areas with low efficiency scores in the DEA results

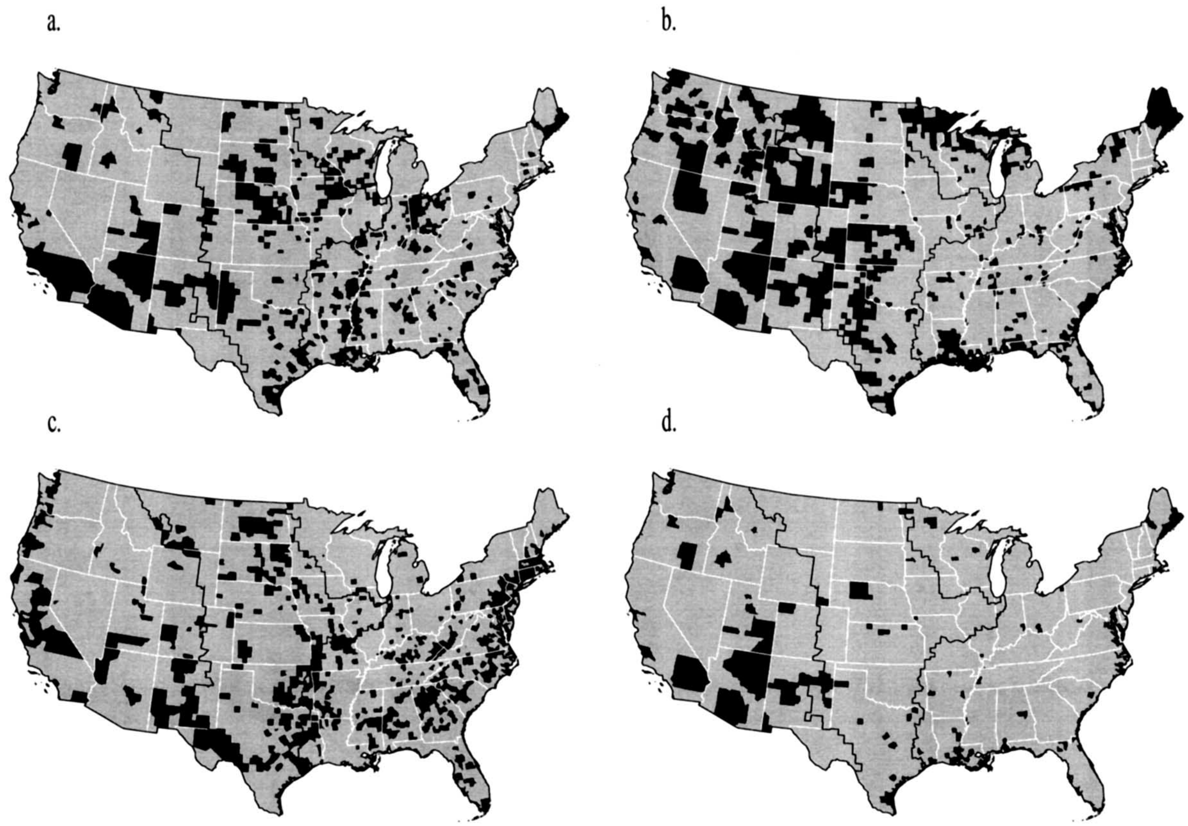

Figure 13. Maps of (a) current condition hotspots, (b) areas with relatively low efficiency scores, (c) areas with relatively high efficiency scores, and (d) coincidence of current condition hotspots with areas of relatively low efficiency for PHO.

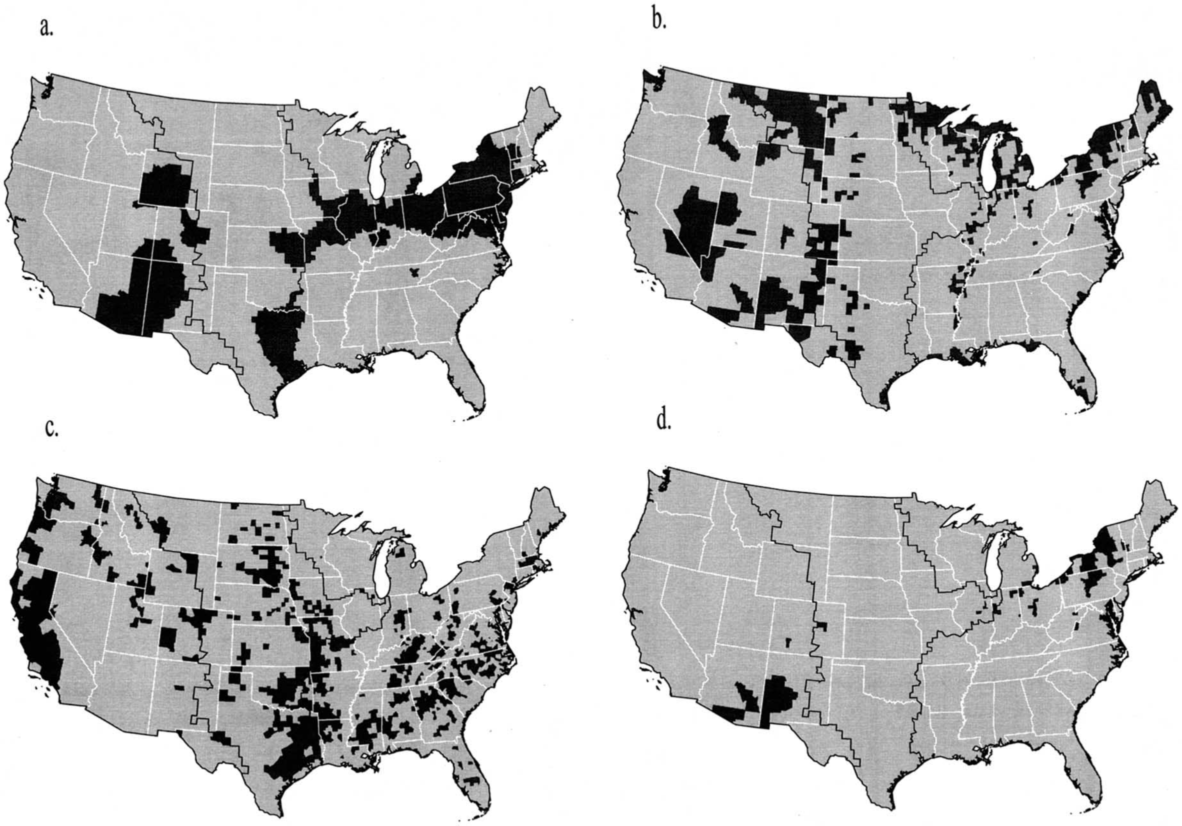

Figure 14. Maps of (a) current condition hotspots, (b) areas with relatively low efficiency scores, (c) areas with relatively high efficiency scores, and (d) coincidence of current condition hotspots with areas of relatively low efficiency for PHL.

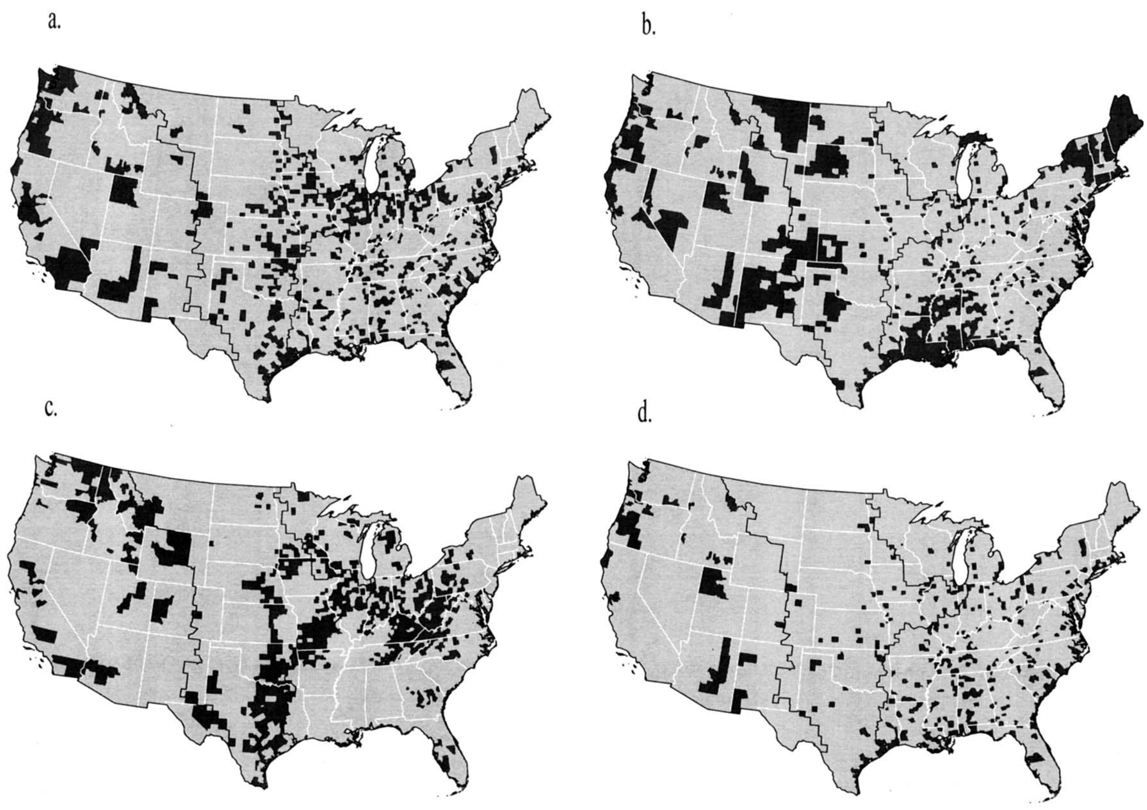

Figure 15. Maps of (a) current condition hotspots, (b) areas with relatively low efficiency scores, (c) areas with relatively high efficiency scores, and (d) coincidence of current condition hotspots with areas of relatively low efficiency for TRI.

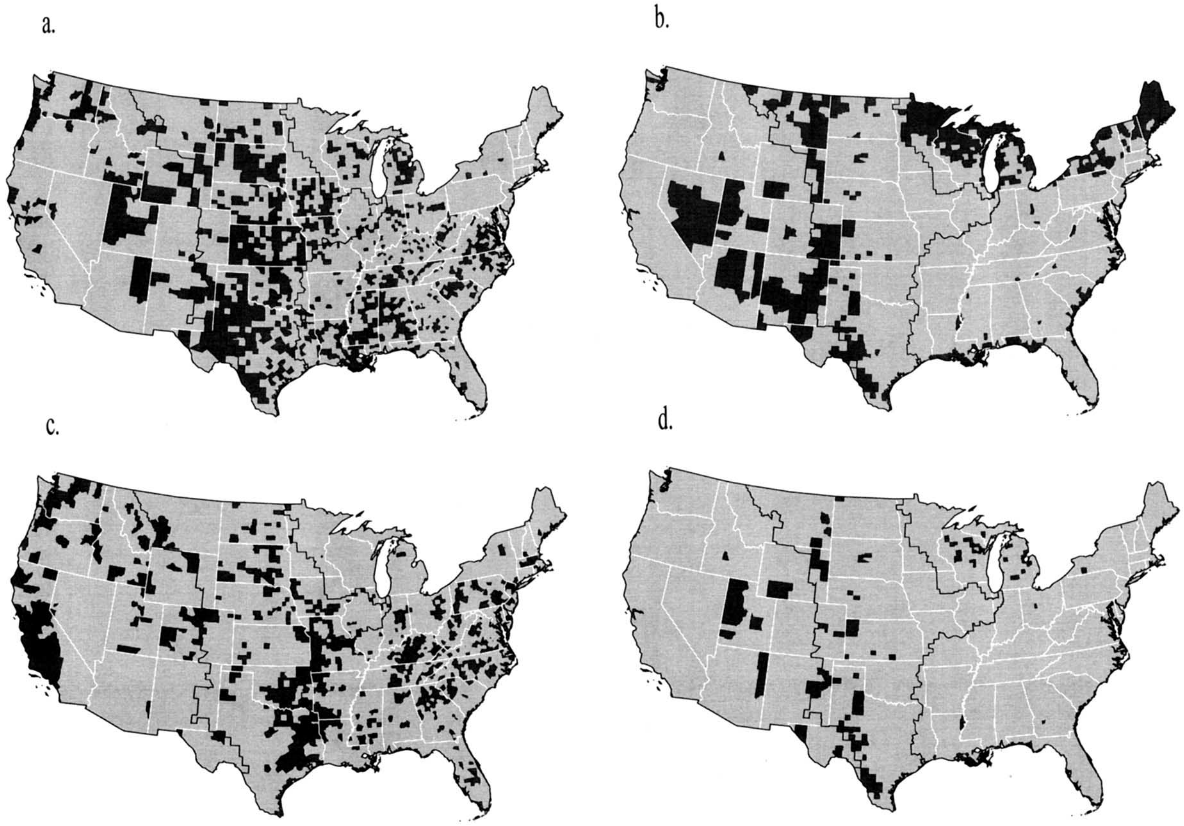

Figure 16. Maps of (a) current condition hotspots, (b) areas with relatively low efficiency scores, (c) areas with relatively high efficiency scores, and (d) coincidence of current condition hotspots with areas of relatively low efficiency for PAD.

(Figure 15b) are scattered across the country but with some concentration in the Northeast, the Gulf Coast and surrounding areas, the interior West, and the West Coast. This is one of the few indicators where the areas with high efficiency scores (Figure 15c) show some spatial cohesion, but these areas still do not correlate significantly with the current condition hotspots (Figure 15a). The opportunity hotspots (Figure 15d) indicated are quite small and scattered, which reflects the result that both the current condition hotspots (Figure 15a) and the low efficiency areas (Figure 15b) are generally scattered across the country. This result is not terribly surprising because of the wide variety of toxic releases included, which are widely dispersed and difficult to manage efficiently anywhere they occur.

Protected Areas (PAD)

Protection of ecological systems has often been accomplished through the establishment of national parks, wilderness areas, wildlife refuges, conservation preserves, or other reserves that are designed to protect their natural condition. Although the establishment of reserve lands is a relatively common conservation strategy, the total area within the United States designated as protected is rare (about 5.1% of the land base in the coterminous United States), and the proportion of land protected varies regionally (DellaSala et al. 2001). We use the proportion of the land base in protected status as a measure of ecosystem condition under the assumption that ecosystems occurring in regions receiving relatively low levels of protection are more likely to have had their characteristic structure and function altered than in regions receiving higher levels of protection.

Currently, areas of the country with low amounts of protected land are scattered throughout the central and southeastern portions of the coterminous United States (Figure 16a). Areas with low efficiency scores in the DEA results show a much more coalesced pattern of occurrence, being clustered in northern New England, the northern Great Lakes region, the western boundary of the Great Plains, and the arid Southwest (Figure 16b). This pattern is similar to that observed for HAB, which seems reasonable because both are general measures of protected/disturbed area. The areas with high efficiency scores (Figure 16c) are predictably orthogonal to the areas with low efficiency scores and are otherwise scattered across the country. They have minimal coincidence with the current hotspots in Figure 16a. The opportunity hotspots indicated in Figure 16d are limited to the Great Lakes region, the western Great Plains, and small, scattered areas in the intermountain West and near the Gulf Coast. These opportunity hotspots are more cohesive than with HAB but are still limited in size and contiguity.