Environmental Management of Soil Phosphorus: Modeling Spatial Variability in Small Fields

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ABSTRACT

The mapping of soil P concentration is necessary to assess the risk of P loss in runoff. We modeled the distribution of Mehlich-3 extractable soil P (M3P) in an east-central Pennsylvania 39.5-ha watershed (FD-36) with an average field size of 1.0 ha. Three interpolation models were used: (i) the field classification model—simple field means, (ii) the global model—ordinary kriging across the watershed, and (iii) the within-field model—ordinary kriging within fields with a pooled within-stratum variogram. Soils were sampled on a 30-m grid, resulting in an average of 14 samples per field. Multiple validation runs were used to compare the models. Overall, the mean absolute errors (MAEs) of the models were 76, 71, and 66 mg kg^{-1} M3P for the field classification, global, and within-field models, respectively. The field classification model performed substantially worse than did the kriging models in five fields; these fields exhibited strong spatial autocorrelation. The within-field model performed substantially better than did the global model in three fields where autocorrelation was confined by the field boundary. However, no differences in P index classification were observed between the three prediction surfaces. The field classification model is simpler and less expensive to implement than the kriging models and should be adequate for applications that are not sensitive to small errors in soil P concentration estimates.

Phosphorus is an essential element for plant and animal growth and its input has long been recognized as necessary to eliminate plant nutrient deficiencies and to maintain profitable crop and livestock production. Excess P inputs, however, can increase the biological productivity of fresh waters by accelerating eutrophication (USEPA, 1996). Eutrophication is the natural process of lake and stream aging through nutrient enrichment, but may be unnaturally accelerated by human-induced nutrient loadings. State and Federal authorities are moving towards stricter P management and increased pollution prevention support. Agriculture accounts for the major proportion of total inputs of P to major freshwater systems in the USA (USEPA, 1996).

There is evidence that the great majority of agricultural P export originates from a small portion of the landscape in humid, upland agricultural watersheds (Gburek and Sharpley, 1998). These areas have been termed critical source areas and are characterized by having high potential to release P into surface or subsurface runoff in conjunction with hydrologic connectivity with streams or ditches. Targeting critical source areas would increase the efficiency and reduce the economic costs of control. In response, a site vulnerability assessment tool, the P index, has been developed to target P management (Lemunyon and Gilbert, 1993). The P index accounts for source (soil P and rate, method, and timing of applied P) and transport (surface runoff, erosion, leaching, and landscape position) factors controlling P loss in surface runoff and ranks sites for their potential risk of P loss.

In areas with large fields, the mean or median soil test value is generally used as the best estimate of P concentration in a field, except in cases where precision sampling and fertilizer application are used. In areas with small fields, such as Pennsylvania, a single bulk composite or the mean or median soil test value is traditionally used as the best estimate of P concentration. Under these models, information on farm- and field-scale variability is not used for the estimation of P distribution. More complex interpolation methods, such as those from the disciplines of geostatistics and precision agriculture, incorporate spatial variability into estimates of P distribution. Field-scale variability, which is confined to field boundaries, may be caused by uneven fertilizer distribution or movement within fields. Farm-scale variability, which is not confined to field boundaries, is likely caused by larger scale management factors such as distances to roads or manure storage facilities. Natural factors, such as variations in weathering, soil parent material, erosion, and water movement patterns, may also influence soil P distribution (Larson et al., 1997). The influence of management is probably stronger than natural factors in fields with very high soil P and a history of large P applications. The choice of an interpolation method should be based on an assessment of the scale and strength of autocorrelation present and the costs associated with the sampling design.

The variogram is an important tool to detect the presence of spatial autocorrelation and to estimate the variability structure of soil properties (McBratney and Webster, 1986). A global variogram can be used to assess the variability structure of a soil property across a watershed, but it does not account for smaller-scale factors such as field boundaries. Variograms can also be developed for each field individually (Goovaerts, 1997). Several researchers have used within-field, more generally termed within-stratum, variography to estimate the spatial variability structure of soil properties (Stein et al., 1988; Boucneau et al., 1998). However, data sparsity may prevent the reliable estimation of spatial semivariance functions within each stratum (Webster and Oliver, 1992). At least 50 to 100 data points may be necessary to achieve a stable variogram, depending on lag spacing and the smoothness of the spatial variation (Voltz and Webster, 1990; Burrough and McDonnell, 1998).

Most research concerning soil nutrient distribution

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Abbreviations: Log M3P, logarithm of M3P; M3P, Mehlich-3 extractable soil P; MAE, mean absolute error.

has focused on individual fields (Pierce et al., 1995; Gupta et al., 1997). For a 16-ha field, a common field size in the Midwest, about three samples per hectare are needed for 50 data points per field (~50-m grid). For a 2-ha field, a field size common in the northeastern USA and other parts of the country, a sampling intensity of about 25 samples per hectare is required to produce the 50 data point minimum (~18-m grid). This sampling intensity is not economically feasible for many agronomic and environmental applications. In such cases, a single pooled within-stratum variogram can be computed, based on the assumption that the spatial variability structure is the same within each stratum. The pooled within-stratum approach has been used to interpolate soil textural fractions across soil mapping units (Voltz and Webster, 1990; Van Meirvenne et al., 1994).

Soil P distribution maps calculated using a field mean are generally used for the P index. However, some researchers have used P distribution maps with subfield scale variability (Eghball and Gilley, 1999; Gburek et al., 2000a). Gburek et al. (2000b) applied the P index at field and 25-m^2 cell scales across the same watershed that we are investigating in this study. Results were generally similar, yet there were some differences resulting from the different soil P map and finer resolution of runoff and erosion characteristics based on locally steeper slopes within fields. The authors raised the question whether a subfield resolution will be necessary for P index application or whether other proposed P index modifications will be sufficient to account for fine-resolution factors.

The studied watershed, FD-36, is the site of ongoing USDA–ARS research on chemical and hydrologic factors controlling P transport. A primary objective of the project is to delineate critical source areas of P, areas both high in soil P and within runoff producing zones (Gburek and Sharpley, 1998). The objectives of the study reported in this paper were to detect and analyze the spatial autocorrelation of soil P in the watershed, and to compare and validate three interpolation models (one classical and two geostatistical) for the estimation of soil P distribution in the watershed.

MATERIALS AND METHODS

Field Site and Soils Analysis

The study was conducted on a 39.5-ha watershed (FD-36) in south-central Pennsylania which is typical of upland agricultural watersheds within the nonglaciated, folded and faulted, Ridge and Valley Physiographic Province of this region. Soils were mapped as Alvira (Fine-loamy, mixed, mesic Aeric Fragiaquults), Berks (Loamy-skeletal, mixed, active, mesic Typic Dystrudepts), Calvin (Loamy-skeletal, mixed, mesic Typic Dystrudepts), Hartleton (Loamy-skeletal, mixed, mesic Typic Hapludults), and Watson (Fine-loamy, mixed, mesic Typic Fragiudults) channery silt loams (Soil Survey Staff, 1975). Detailed land use and agronomic management data are collected through an annual farmer survey. Further details about the FD-36 watershed can be found in Gburek and Sharpley (1998).

FD-36 has mixed land use (about 50% soybean [*Glycine max* (L.) Merr.], wheat [*Triticum aestivum* L.], or corn [*Zea mays* L.], 30% woodland, and 20% pasture, meadow, or turfgrass). The watershed has 22 cropped fields with an average field size of 1.0 ha. In many cases, these fields are laid out in strips. However, we decided to analyze each of these strips as individual fields because they are not managed in a coherent rotation. Rather, each field (or strip) is essentially managed as a separate unit. In the 5 yr prior to sampling, selected fields north of the stream received about 60 m^3 ha^{-1} yr^{-1} swine (*Sus scrofa*) slurry in spring and no fertilizer P. This amounts to about 100 kg P ha^{-1} yr^{-1} assuming a slurry P concentration of 1.6 g L^{-1} (Eck and Stewart, 1995; Sharpley et al., 1998). South of the stream, ~5 Mg ha^{-1} yr^{-1} of poultry manure was applied to cropland in the spring. This amounts to ~85 kg P ha^{-1} yr^{-1} assuming a manure P concentration of 16.9 g kg^{-1} (Eck and Stewart, 1995; Sharpley et al., 1998).

In July 1996, a total of 301 soil samples (0–5-cm depth) were collected in the cropped areas of the watershed on a roughly 30-m grid (Fig. 1). Sampling locations were altered on several parts of the watershed to provide better coverage within variable field boundaries. Six cores (0–5-cm depth) were taken using a 2-cm auger within a 1-m radius of the sampling location and composited. This depth of soil sampling is environmentally based and represents the depth of soil interacting with rainfall and surface runoff that controls P release and transport in runoff (Sharpley et al., 1996). The samples were air dried and sieved (2 mm). Mehlich-3 soil P concentration was determined by extraction of 1 g soil with 10 mL of 0.2 M CH_3COOH, 0.25 M NH_4NO_3, 0.015 M NH_4F, 0.013 M HNO_3, and 0.001 M EDTA for 5 min (Mehlich, 1984). Phosphorus in filtered and neutralized extracts was determined by the method of Murphy and Riley (1962).

Statistical Analysis

Three interpolation models (field classification, global, and within-field) were used to estimate the distribution of M3P in the watershed. In the field classification model, the simple mean is used to estimate the M3P concentration within each field. This model corresponds to the taking of a single bulk soil sample to represent a field, the soil sampling procedure currently recommended by the Pennsylvania State College of Agricultural Sciences (Serotkin and Tibbetts, 1998). The autocorrelation between points depends only on whether the points are within the same field.

In the global model, the spatial autocorrelation between points is a function of the distance between points and is not affected by field boundaries. A global omnidirectional variogram was generated based on all the points in the watershed, with semivariance, $\gamma(h)$, estimated as:

$$\gamma(h) = \frac{1}{2|N(h)|}\sum_{N(h)}(z_i - z_j)^2 \qquad [1]$$

where $N(h)$ is the number of pairs of data locations at a lag distance (h) apart, and z_i and z_j are point locations. Variograms were fitted using weighted nonlinear least squares regression (Cressie, 1985). Ordinary kriging was then used for interpolation.

In the within-field model, the autocorrelation between points is modeled only for point pairs within the same field. Individual variograms for each field were lumped to create a single pooled within-stratum variogram (Goovaerts, 1997, p. 187). This can also be viewed as a global variogram restricted to point pairs within the same field. The pooled within-stratum variogram, $\gamma_{ws}(h)$, was estimated using the following equation:

$$\gamma_{ws}(h) = \frac{\sum_{k=1}^{K} N(h; s_k)\hat{\gamma}(h; s_k)}{\sum_{k=1}^{K} N(h; s_k)} \qquad [2]$$

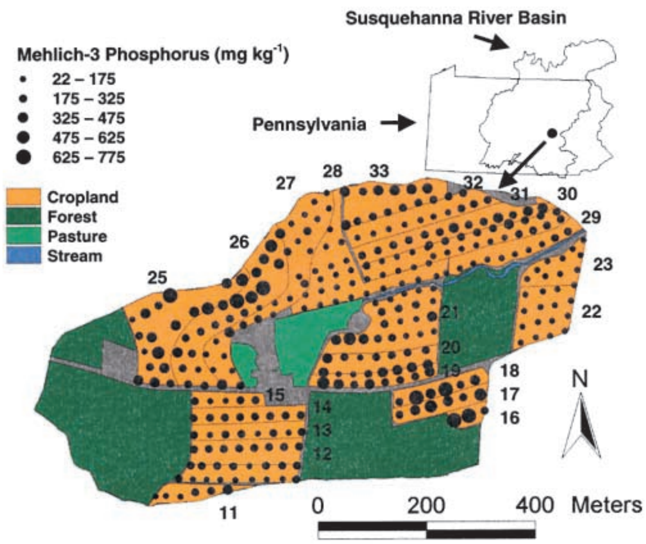

Fig. 1. Location of FD-36 watershed with land uses and soil sampling locations. Symbol size is proportional to Mehlich-3 phosphorus (M3P) concentration. Numbers near and within fields are field identification numbers.

where $\gamma h; s_k)$ is the variogram value for the kth stratum, and $N(h; s_k)$ is the number of pairs of data locations a distance h apart that jointly belong to the kth stratum. Ordinary kriging was applied within each field individually using the parameters for the pooled within-stratum variogram.

Validation was performed by randomly removing one-third of the data points from each field for use as a validation data set. The three interpolation models were used to estimate M3P concentration at the validation data points and residuals were recorded. Predictions were calculated solely on the non-validation data set. Note that this also included a reestimation of the variogram. This estimation was performed with weighted least squares regression and was checked visually. This process was repeated 25 times so that at least two residual estimates were obtained for each data point. Residuals were averaged for a generalized residual estimate. Interpolation methods were compared based on residuals and MAE. Statistical analyses were conducted with S-Plus 2000 and S+SpatialStats v.1.1 (Mathsoft, Inc., 1996, 1997) and the SAS System (SAS Institute, 1990).

RESULTS AND DISCUSSION

Mehlich-3 P values ranged from 22 to 775 mg kg^{-1} across the watershed with a mean of 225 mg kg^{-1} and a coefficient of variation of 65. Fields had mean M3P from 40 to 553 mg kg^{-1} with within-field ranges (maximum minus minimum value) from 28 to 702 mg kg^{-1}. Within-field M3P coefficients of variation ranged from 13 to 70 with an average of 38.

Values were based on exploratory data analysis and the Shapiro–Wilk statistic, it was determined that the M3P was not normally distributed either globally or within fields. The logarithm of M3P (LogM3P) was determined to be normally distributed within fields, although it was negatively skewed globally (skewness = 2.4). The field means of LogM3P (rather than individual values) were also determined to be normally distributed. The mean and variance of LogM3P were 5.18 and 0.55, respectively, and when averaged by field were 5.27 and

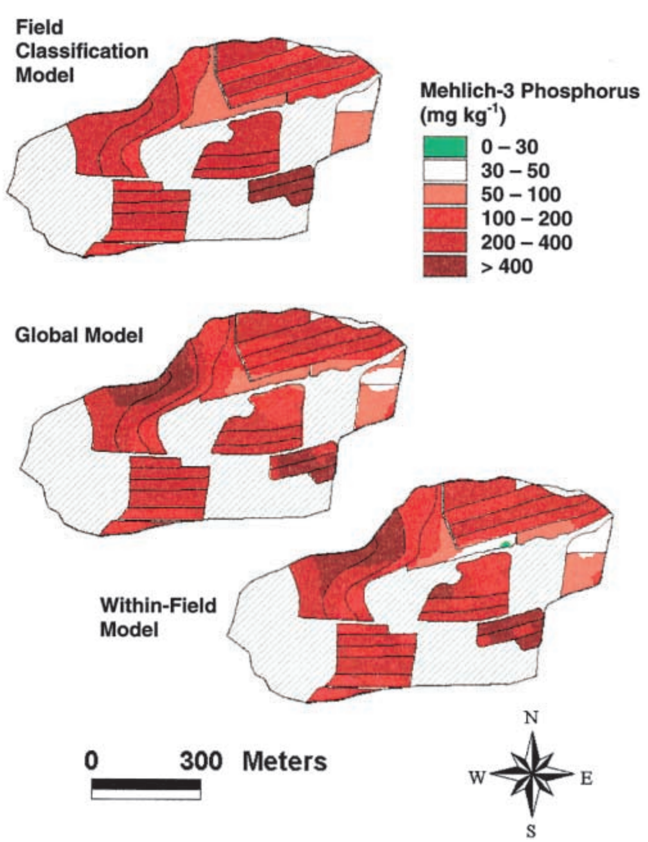

Fig. 3. Prediction surfaces of Mehlich-3 phosphorus (M3P) concentration in watershed FD-36. Classifications are based on agronomic and environmental critical levels.

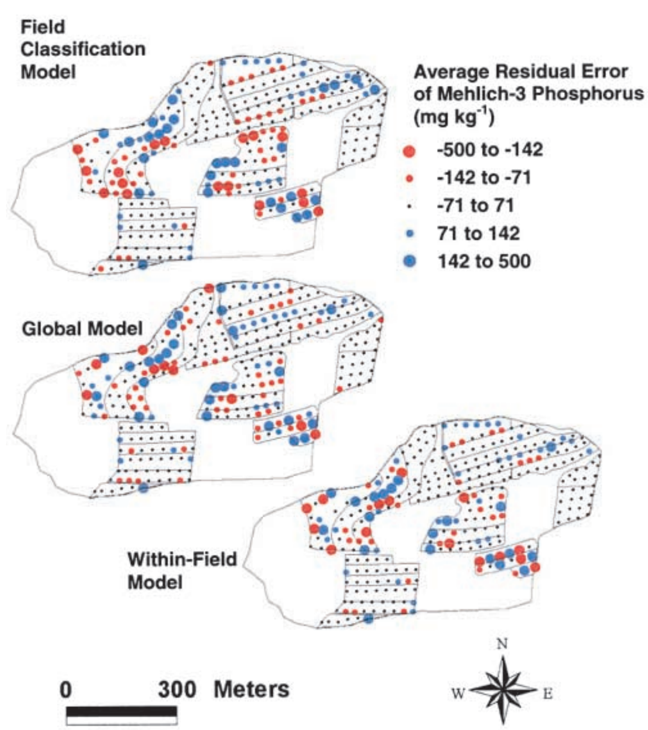

Fig. 4. Residuals from validation of prediction of Mehlich-3 phosphorus (M3P) concentration in watershed FD-36. Classifications are based on multiples of 71 mg kg^{-1}, which was the average residual across all three models.

0.17, respectively. Analyses were run using both the M3P and LogM3P variables. Results and conclusions were not substantially different between the two variables, therefore only M3P results are presented.

FD-36 Data Analyses

Both the global and the pooled, within-field omnidirectional variograms are presented in Fig. 2. The nonwithin-field semivariance values, based on point pairs that are not in the same field, are also presented. Numbers near points indicate the number of data pairs within the lag increment (only labeled when <100 data pairs). A spherical semivariance function provided a better fit than did exponential, gaussian, or linear functions for both variograms based on the Akaike's information criteria (Akaike, 1973).

Both variograms exhibit autocorrelation. The fitted spherical semivariance function for the global variogram has a range of 267 m, a sill of 24 700, and nugget of 5270, while the within-stratum variogram has a range of 270 m, a sill of 16 700, and a nugget of 5290. Note that because of the sampling design there are no point pairs with lag distances near the origin; therefore, the nugget estimate is not supported. These ranges are slightly greater than those found by Pierce et al. (1995) for soil P concentration with a 30.5-m sampling grid. The sill for the within-field variogram is smaller than the sill for the global variogram, an indication that within-field point pairs had a smaller variance than did global point pairs. The pooled within-stratum variogram exhibits a similar range and nugget than does the global variogram. At lag increments of about 200 m, the pooled within-stratum variogram has substantially smaller semivariance values than does the global variogram. The nonwithin-field semivariance values provide evidence of spatial autocorrelation beyond field boundaries.

Interpolation Results

Prediction surfaces based on the three interpolation models are presented in Fig. 3. Mehlich-3 P divisions are based on agronomic limits and proposed environmental limits. The 30 mg kg^{-1} level is the minimum optimal M3P test recommended by the Pennsylvania State College of Agricultural Sciences (Serotkin and Tibbetts, 1998). Between 30 and 100 mg kg^{-1} M3P, there will generally be little crop response to P fertilizer, but little enrichment of P in surface runoff is expected (Sharpley et al., 1996; Weld et al., 2000). Between 100 and 200 mg kg^{-1} M3P, no crop response is expected and some enrichment of P in surface runoff is expected to occur, while between 200 and 400 mg kg^{-1} M3P, considerable enrichment is expected. A > 400 mg kg^{-1} M3P level was also included to represent the areas of very high P concentration observed in the watershed.

The field classification model prediction surface is substantially different than the surfaces predicted by the kriging models, while the kriging models predict similar surfaces with only a few areas of substantial difference. Both the kriging models predict an area in the northwest area of the watershed with M3P values >400 mg kg^{-1} M3P. This area is not identified by the field classification model. Near the center of the watershed, there is a relatively low P area (<50 mg kg^{-1}) predicted by the within-field model that is not identified by the other models. The only M3P estimates below 30 mg kg^{-1} (the agronomic critical level) are found in this area.

The distribution of generally high P concentrations in the watershed are likely influenced only by management practices. There does not seem to be an impact of landscape position, surface soil texture, and other natural factors (data not presented).

Validation

The above analyses demonstrated that there is spatial variability in the watershed at farm- and field-scales. Validation was used to assess the importance of this spatial variability. In Table 1, validation results are presented by field and as an overall average. In Fig. 4, the average residuals are presented for each model.

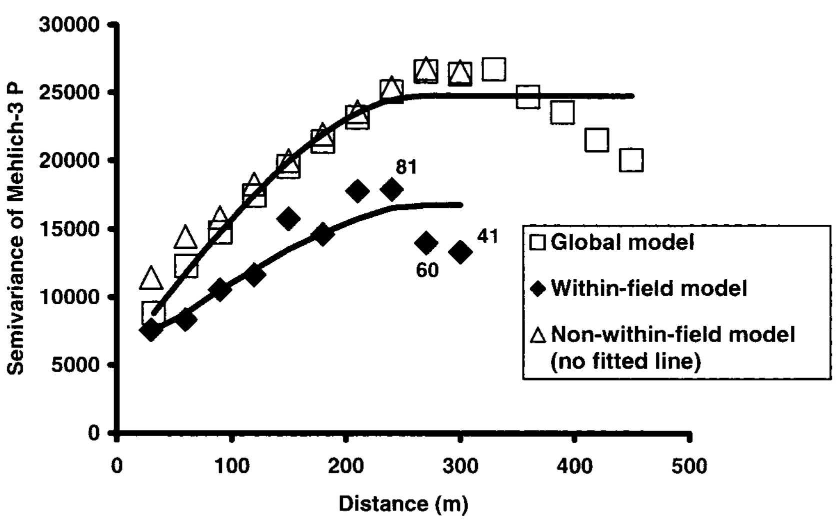

Fig. 2. Global and pooled within-stratum variogram for Mehlich-3 phosphorus (M3P) with spherical semivariance function fitted by weighted least squares. Nonwithin-field semivariance values are also presented. Numbers near points indicate the number of data pairs within the lag increment. Points without number labels are based on >100 data pairs.

Table 1. Mean and standard deviation Mehlich-3 phosphorus (M3P) in fields and overall average. Validation results with average fit by field and overall and mean absolute error (MAE) by field and overall.

Field Id	Number of Samples	Average M3P–field classification model	Standard Deviation M3P	Average fitted global model M3P	Average fitted within-field model M3P	MAE field classification model	MAE global model	MAE within field model
		mg kg^{-1}						
11	23	191.9	72.8	201.7	192.4	54.9	57.4	58.0
12	8	257.6	37.8	222.1	257.0	37.2	40.7	39.3
13	8	206.5	62.1	229.7	207.8	58.2	57.7	65.6
14	8	233.7	39.2	221.8	229.7	31.1	38.0	26.8
15	5	192.0	36.4	219.6	186.8	36.4	41.5	30.6
16	3	552.9	228.2	476.9	652.0	263.0†	223.9‡	242.4
17	6	405.2	123.3	455.6	404.1	122.1	128.9	135.2
18	6	454.6	172.4	416.5	470.0	180.8	165.1‡	200.4†
19	15	325.3	98.4	314.3	317.0	81.5	82.6	75.5
20	8	241.6	91.0	281.3	234.0	79.5	83.4	63.8‡
21	21	201.5	141.8	175.2	202.1	114.8†	89.8	88.7
22	15	74.1	30.3	77.3	74.4	23.9	25.3	21.7
23	11	40.8	10.4	67.3	40.8	10.0	27.8	10.7
25	18	368.8	139.1	348.7	362.5	111.7	108.1	108.1
26	22	367.1	190.5	333.5	363.0	157.3†	116.2	122.9
27	25	169.3	97.0	202.2	161.6	70.0	85.2	70.6
28	23	81.5	43.4	117.4	81.8	39.6	45.1	24.1‡
29	9	112.4	77.5	111.6	108.6	66.8†	39.1	38.6
30	29	179.0	95.8	182.5	175.6	79.9†	48.9	62.1
31	13	312.8	41.0	233.2	315.2	35.3	81.7†	28.9
32	12	190.8	59.1	252.3	194.1	54.0	72.2†	32.8‡
33	13	311.0	92.6	272.2	311.3	89.1	79.5	88.0
Overall average	301	225.3	146.5	224.6	224.3	76.0	71.6	65.9

† Indicates that model performed worse than the other two models (>15 mg kg^{-1} difference).
‡ Indicates that model performed better than the other two models (>15 mg kg^{-1} difference).

Classification breaks at 71 and 142 correspond to 1 and 2 times the average MAE across all models. The average MAE of the within-field model is 6.7 and 11.1 mg kg^{-1} M3P better than the global and field classification models, respectively. These differences are small and indicate that, overall, the three models performed similarly. From the complete data set, the average deviance from the mean within fields was 71 mg kg^{-1}. Although this is a biased estimator, this value roughly compares with the average MAE values observed in the validation data sets, an indication that the removal of one-third of the data did not severely degrade prediction precision.

The average MAE was highly correlated to within-field standard deviation ($R^2 = 0.86$), soil P concentration ($R^2 = 0.73$), and the positive interaction between within-field standard deviation and P concentration ($R^2 = 0.93$). All three models were unbiased estimators overall (overall mean within 1.0 mg kg^{-1} M3P).

For discussion purposes, two models we considered to have performed differently within a field when the difference between the average MAE between the models was >15 mg kg^{-1}. Field identification numbers are georeferenced in Fig. 1, and match those used by Gburek et al. (2000a). The field classification model performed worse in five fields relative to the kriging models (Fields 16, 21, 26, 29, and 30). All three models poorly characterized one of these fields, Field 16, which contains only three sample points and has the greatest within-field variability in the watershed. The other four fields that were poorly described by the field classification exhibit substantial within field spatial autocorrelation (compare Table 1 and Fig. 1). All five of these fields are within 50 m of the stream, and therefore may be among the most hydrologically-active in the watershed.

The global model performed worse than did the within-field model in Fields 28, 31, and 32. The spatial variability in these fields is confined to field boundaries (Fig. 1). The inclusion of farm-scale effects in the modeling of these fields caused a poorer characterization by the global model. The global model also performed worse than the field classification model in fields 31 and 32; in these fields the incorporation of farm-scale variability into the modeling is worse than assuming no spatial autocorrelation. The global model provided the best fit for two fields with very small sample sizes, Fields 16 and 18. In this region of the watershed, the field classification and within-field models failed to incorporate the farm-scale effect of high M3P concentration. The within-field model performed worse than did the other models in Field 18, but was better than both models in Fields 20, 28, and 32. Field 18 is one of the fields with a low sample size (6 samples). Fields 28 and 32 have high within-field spatial autocorrelation that does not extend beyond field boundaries.

Of the 11 fields located within 150 m of the stream, eight were fields that were mapped substantially different by the three models based on the 15 mg kg^{-1} MAE criterion. These fields are particularly important to the characterization of the watershed because the near-stream areas are the most hydrologically active in this region (Gburek and Sharpley, 1998). Points in the landscape must be hydrologically active for the transport of P. Generally, soils in the near stream area had lower M3P concentrations (Fig. 1 and 3). We suggest that management in these fields may have been affected by poor soil drainage, limiting productivity and accessibility to farm equipment. As a result, these near-stream fields received less P and have lower M3P concentrations than adjecent fields.

An additional analysis was conducted to analyze the influence of sampling intensity on validation results. The validation procedure was repeated except the removal rate for the validation data set was increased from 33 to 67%. In many cases, there was too much scatter in the pooled-within stratum variogram generated from the remaining sample points (100 points) to adequately fit the spherical semivariance function. Based on results from those cases where an adequate fit was possible, the average MAEs increased from 76 to 154 mg kg^{-1} for the field classification model, 71 to 153 mg kg^{-1} for the global model and 66 to 150 mg kg^{-1} for the within-field model. The average deviance from the field mean for the full data set was 71 mg kg^{-1}. The precision decrease was substantially greater as sampling intensity decreased from 200 to 100 sampling points in comparison to a decrease from 301 to 200 sampling points.

The P index, as described by Sharpley (2000), was applied to the FD-36 watershed on a 5-m grid using the three prediction surfaces (Fig. 3) generated from the interpolation models. Though slight differences in P index values were observed, no differences in P index classifications were observed in any field in the watershed between the three prediction surfaces. Therefore, for applications that are not sensitive to small errors in soil P concentration estimates, such as the P index, the field classification method should provide adequate results.

Researchers have found that soil P and runoff P are closely related. This relationship has been shown to vary with soil type and management and P application as manure or fertilizer (Sharpley et al., 1996; Sharpley and Tunney, 2000). This variability should be quantified and integrated with error arising from interpolation to characterize the uncertainty inherent in environmental soil P limits.

CONCLUSIONS

Soil P was found to be spatially autocorrelated in the watershed. The autocorrelation was found to have both field- and farm-scale components. The slightly better overall performance of the within-field model versus the global model indicates that field-scale autocorrelation is stronger and more consistent in this watershed.

The importance of the spatial autocorrelation observed in the watershed is small. Overall, the kriging models performed only slightly better than the field classification model in terms of estimating M3P concentrations at unknown locations. There were several fields, particularly those in the near-stream zone, that were modeled substantially better by the kriging models because of strong spatial autocorrelation in these fields. If strong autocorrelation is found to be common in hydrologically-active watershed areas, perhaps because of soil wetness or stewardship practices, then the increased cost and complexity of the kriging models may be warranted for some environmental P management applications. Nonetheless, the strength of the spatial autocorrelation observed in this watershed was not sufficient to affect P index classifications.

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Field Studies of Crop Response to Water and Salt Stress

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ABSTRACT

Studies of crop response to water and salt stress vary either salinity with a high leaching fraction or irrigation in the absence of salinity to isolate and quantify the effects of the two types of stress. Under deficit irrigation with saline water, a water conserving practice, the crop experiences simultaneous matric and osmotic stress, and it is not known if experiments designed to isolate stress effects may be used to predict crop response to simultaneous stresses. Thus, a study was conducted wherein yields were determined under varying levels of salinity and irrigation. Corn (*Zea mays* L.) and melon (*Cucumis melo* L.) were grown at the Arava Research and Development Farm in Yotvata, Israel, and alfalfa (*Medicago sativa* L.) at the Utah Power & Light Research Farm in Huntington, UT. Corn and melon plots were drip irrigated at six ratios of potential evapotranspiration ranging from 0.2 to1.7 in combination with four salinity levels. Alfalfa was irrigated with water of 0.2 and 4.0 dS m^{-1} from a line-source sprinkler. For all three crops, the salinity treatments consisted of a control treatment with a salinity level less than published salt-tolerance thresholds. Interactive effects of salinity and water stress were not observed in these field experiments. At low irrigation levels (≈70% of potential evaporation), yields were unaffected by the salinity level. At the higher irrigation levels, the salinity level caused significant differences in yield. Yield data were fit to piecewise linear models that emphasized the limiting nature of the effects of salt and water stress.

Deficit irrigation is practiced in many arid areas of the world, and increased demand on water supplies worldwide suggests the practice must increase. Moreover, as competition for limited water resources increases, it is reasonable to assume that agriculture will have to make do with waters of poor quality. One challenge of the future will be to maintain or even increase crop production with less water that often may be of poor quality.

Quantitative understanding of crop production under deficit irrigation with saline water is generally based on three assumptions. First, an increase in salinity, above the crop tolerance level, will decrease yield (Maas and Hoffman, 1977; Letey et al., 1985; Letey and Dinar, 1986; Bresler, 1987; Maas, 1990); second, biomass production is linearly related to transpiration (deWit, 1958; Childs and Hanks, 1975; Letey and Dinar, 1986; Bresler, 1987; Shani et al., 2001); and third, the effects of salt and water stress on yields are additive (Nimah and Hanks, 1973; Letey et al., 1985; Letey and Dinar, 1986; Bresler, 1987; Cardon and Letey, 1994; Pang and Letey, 1998). The validity of the first two assumptions is well established. The linear dependence of relative dry matter production ($Y_{actual}/Y_{potential}$) on relative transpiration ($T_{actual}/T_{potential}$) under conditions of water deficit has been validated for variety of climates and crops (deWit, 1958; Childs and Hanks, 1975; Letey and Dinar, 1986; Shani et al., 2001). Under conditions of salt stress (Bresler and Hoffman, 1986; Bresler, 1987) and Na stress (Shani et al., 2001), relative yield and relative transpiration are linearly related.

The validity of the third assumption is less certain. Plants respond to drought by attempting to both decrease transpiration and increase water uptake. Deleterious effects of salinity on crop growth have been attributed to an osmotic effect or a specific-ion effect. Osmotic stress inhibits water uptake from the soil and requires the plant to use energy and carbohydrate in synthesizing organic solutes to adjust its internal osmotic potential (Läuchli and Epstein, 1990; Jacoby, 1994). To a lesser degree, plants may adjust their internal osmotic potential by accumulating some salt from the surrounding solution (Läuchli and Epstein, 1990). Yield loss results from reduced photosynthesis associated with closing stomata (Grill and Ziegler, 1998), from energy and carbohydrate use in osmoregulation, and from sequestered salt interfering with cell function (see e.g., Läuchli and Epstein, 1990). The specific-ion effect results from ion interference with a physiological process in the plant (see e.g., Läuchli and Epstein, 1990; Munns, 1993; Marschner, 1995). Because plants respond to drought induced by limited water or elevated salinity by a similar mechanism, the sum of the matric and osmotic components of the water potential has been used to estimate yield

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Abbreviations: DAP, days after planting; EC, electrical conductivity.