Coupling Geographic Information Systems and Models for Weed Control and Groundwater Protection[1]

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Abstract. The Chemical Movement through Layered Soils (CMLS) model was modified and combined with the USDA-SCS State Soil Geographic Data Base (STATSGO) and Montana Agricultural Potentials System (MAPS) digital databases to assess the likelihood of groundwater contamination from selected herbicides in Teton County, MT. The STATSGO and MAPS databases were overlaid to produce polygons with unique soil and climate characteristics and attribute tables containing only those data needed by the CMLS model. The Weather Generator (WGEN) computer simulation model was modified and used to generate daily precipitation and evapotranspiration values. A new algorithm was developed to estimate soil carbon as a function of soil depth. The depth of movement of the applied chemicals at the end of the growing season was estimated with CMLS for each of the soil series in the STATSGO soil mapping units and the results were entered into ARC/INFO to produce the final hazard maps showing best, weighted average, and worst case results for every unique combination (polygon) of soil mapping unit and climate. County weed infestation maps for leafy spurge and spotted knapweed were digitized and overlaid in ARC/INFO with the CMLS model results for picloram to illustrate how the results might be used to evaluate the threat to groundwater posed by current herbicide applications. **Nomenclature:** Picloram (4-amino-3,5,6-trichloro-2-pyridinecarboxylic acid); leafy spurge, *Euphorbia esula* L. #[3] EPHES; spotted knapweed, *Centaurea maculosa Lam.* # CENMA.

Additional index words: Groundwater contamination, computer model, *Centaurea maculosa*, *Euphorbia esula*, CENMA, EPHES.

INTRODUCTION

Most Montana county weed districts conduct noxious weed mapping programs. Counties are required to maintain inventories of weed distributions for management and educational purposes. A county-scale weed inventory can help district weed supervisors estimate the kinds and quantities of herbicides that are needed, schedule control activities, and plan control routes. A continually updated weed inventory keeps track of changes in weed distributions. It can be used to show the effectiveness of weed control programs when compared with maps showing areas where controls have been applied. Weed maps are also useful tools for informing the public about noxious weed problems when included in news releases and other public educational activities.

Most Montana county weed control programs continue to emphasize herbicide applications at a time when public concern for the potential contamination of groundwater resources is increasing. Approximately 50% of Montana's population obtains its drinking water from wells that tap groundwater; consequently, the transport of agricultural chemicals, including nitrates and pesticides, through soils into groundwater represents a potential threat to water quality in Montana and elsewhere. The U.S. Environmental Protection Agency reported that 17 pesticides had been detected in the groundwater of 23 states at concentrations ranging from trace amounts to several hundred parts per million (19). Locally, the Environmental Management Division of the Montana Department of Agriculture reported detectable quantities of picloram, 2,4-D [(2,4-dichlorophenoxy)acetic acid], MCPA [(4-chloro-2-methylphenoxy)acetic acid], dicamba (3,6-dichloro-2-methoxybenzoic acid), and aldicarb [2-methyl-2(methylthio) propionaldehyde 0-methylcarbamoyl oxime] in groundwaters around the state (4). Public health risks increase and environmental problems occur when groundwater becomes polluted with these chemicals. County weed control programs may contribute to these problems

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[3]Letters following this symbol are a WSSA-approved computer code from Composite List of Weeds, Revised 1989. Available from WSSA, 309 W. Clark St., Champaign, IL 61820.

because county weed supervisors currently lack the tools and databases required to identify weed-infested areas where herbicide applications are likely to contaminate groundwater.

This paper describes a procedure for identifying potential pesticide contamination problems and some sample results. The methods combine modified versions of the CMLS model (10, 11) and WGEN weather generator (18) with the STATSGO (1, 17) and MAPS (10) databases. CMLS[4] is a one-dimensional solute transport model that utilizes piston flow theory to simulate the vertical movement of selected chemicals in and beyond the agricultural root zone in a layer by layer manner. Although this model was written primarily as a management and educational tool, it has been tested favorably and used in many parts of the country (5, 9). Current studies are underway at two field sites in Montana to compare CMLS output to observed transport of nonsorbing tracers and several herbicides. The WGEN weather generator[5] was designed to estimate daily weather at locations with no weather stations and/or to extend daily records at locations with weather stations. The model provides daily precipitation, maximum and minimum temperatures, and solar radiation values with the same statistical characteristics as the actual weather at specified locations.

The STATSGO[6] database was developed at a scale of 1:250 000 by generalizing more detailed soil survey maps and is used primarily for regional resource planning, management, and monitoring (17). MAPS[7] is a computer-driven database that divides Montana into approximately 18 000 20-km^2 cells and stores more than 200 different land and climate characteristics for each of these geographic units. This new method was used to assess the likelihood of groundwater contamination from selected herbicides in Teton County, MT. County weed infestation maps for leafy spurge and spotted knapweed were digitized and overlaid in ARC/INFO[8] with the CMLS model results for picloram to illustrate the threat to groundwater posed by current applications.

MODELS AND DATA SOURCES

CMLS model. The CMLS model was developed by Nofziger and Hornsby (11, 12) to interactively simulate chemical movement through soil with easily obtained soil, chemical, and weather inputs. CMLS divides the soil into as many as 20 layers and estimates the position of the chemical in the soil at different times using an algorithm first proposed by Rao et al. (15). The soil properties affecting chemical movement (soil texture, bulk density, field capacity and permanent wilting point volumetric water contents, and soil organic-carbon content) may vary among the layers, but are assumed to be uniform within each layer. Two chemical properties (the partition coefficient (K_{oc}) normalized to soil organic carbon and degradation half-life) and the climatic and cultural factors known to affect chemical movement (plant root depth, daily rainfall/irrigation and daily evapotranspiration amounts) are also required by the model.

These input data are used in conjunction with the following six model assumptions: (a) all soil water residing in pore spaces participates in the transport process, (b) water entering the soil redistributes instantaneously to field capacity, (c) water is removed by evapotranspiration from each layer in the root zone in proportion to the relative amount of water available in that layer, (d) upward movement of water does not occur anywhere in the soil profile, (e) the adsorption process can be described by a linear, reversible, equilibrium model, and (f) the half-life for biological degradation of the chemical is constant with time. Nofziger and Hornsby (11) explain why these assumptions are valid for many soils and when they are likely to be violated.

The CMLS model calculates the fraction of the applied chemical remaining in the entire soil profile and the position of the solute front at time intervals specified by the user. The PC[9] version of the CMLS model is menu-driven and requires the user to specify the chemical and soil of interest, the names of the data files

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[4]For more information about CMLS and a copy of the software, contact Dr. David L. Nofziger, Dep. Agron., Oklahoma State Univ., Stillwater, OK 74078.

[5]The WGEN manual includes the FORTRAN code for the model and some sample input data.

[6]The STATSGO and soil interpretative attribute databases can be obtained from the USDA-SCS National Cartographic Center, P.O. Box 6567, Fort Worth, TX 76115.

[7]For more information about MAPS or how to build a MAPS-style raster database for your state, contact Dr. Gerald A. Nielsen, Dep. Plant Soil Sci., Montana State Univ., Bozeman, MT 59717.

[8]Geographic information system produced and sold by Environmental Systems Research Institute, Inc., 380 New York St., Redlands, CA 92373.

[9]Abbreviations: PC, personal computer; BD, bulk density; OC, soil organic carbon content; OM, soil organic matter content; AWC, available water holding capacity; ET, evapotranspiration; PET, potential evapotranspiration.

containing chemical and soils data, the depth to the bottom of the root zone for the crop being grown, the names of the data files containing weather data for the location of interest, and the date and depth of application of the chemical. The mainframe version was used for this study because of the large variety of soil and weather conditions experienced in a county-sized area. This version requires the same data files for each and every location (i.e., unique climate and soil polygon) to which the model is applied.

The soils data files were prepared from the STATSGO database and the weather data files were compiled from U.S. Weather Service climate records for the Town of Choteau and the MAPS data base. The weather files were then matched with the soils records with ARC/INFO and a series of FORTRAN programs written by the authors. The chemical data file was compiled from published literature (7, 12). Digital copies of the county weed infestation maps and the final overlays and maps were prepared with ARC/INFO. The overall approach is summarized with the schematic diagram in Figure 1 and the individual steps are described in more detail in the four subsections which follow.

Soil attributes. The STATSGO database divides the landscape into map units (i.e., polygons) and the percentage compositions of the soil series that occur in these general map units are recorded. A series of geocodes is provided for linkage with the national Soil Interpretations Record database that provides detailed information on the properties for each soil, usually as ranges of high and low values by soil layer (1). The soils which compose each map unit will have generally formed in similar kinds of parent material and have a similar repeating pattern of landforms, but will vary in one or more characteristics (texture, available water holding capacity, etc.). This arrangement means that simple maps cannot be used to present information on a specific soil series attribute because there is no map delineation for the locations of individual soil series which make up each STATSGO mapping unit. Bliss and Reybold (1) have described the general process that should be used for linking soil attributes to soil maps and also provide a series of examples to illustrate the wealth of attribute data that can be accessed through the STATSGO products. Our approach, summarized in Figure 1, generally follows their schematic diagram linking geographic information systems and the two STATSGO database components.

Our work with the STATSGO database started with the four STATSGO coverages (i.e., ARC/INFO versions of the 1:250 000-scale soil maps) containing parts of Teton County. These coverages were combined and "clipped" to match the Teton County boundary with ARC/INFO to form a new coverage containing 145 polygons (i.e., STATSGO mapping units). A series of FORTRAN programs was written and used to: (a) read the STATSGO Component data file and write the STATSGO soil mapping unit code and soil series sequence (component) numbers, codes and names to an indexed file, (b) combine this indexed file with the STATSGO Layer file based on soil mapping unit and soil series codes, and (c) extract and write the soil layer attributes required to calculate CMLS soil inputs to a new file. Another FORTRAN program was then written and used to calculate the actual CMLS model inputs. This program checked the layer records for missing data and computed the CMLS inputs for each layer and soil series with complete information in each of the STATSGO mapping units. Eight soil inputs (percent clay, silt, and sand; bulk density; organic matter content; and −0.01 MPa, −1.5 MPa, and saturation volumetric water contents) were computed for our version of the CMLS model as follows.

Bulk density (BD)[9] and percent clay were obtained by computing the midpoints of the ranges specified for each soil layer in the STATSGO database. Percent sand was computed as:

$$\%\ \text{sand} = 100\ [(n_{10} - n_{200})/n_{10}] \quad (1)$$

where n_{10} and n_{200} are the average percentages of soil passing through the no. 10 and 200 soil sieves, respectively. The percent clay and percent sand were then subtracted from 100 to estimate percent silt.

Surface and subsurface soil layer organic-carbon contents (OC)[9] were computed by different methods. The average organic matter content (OM)[9] was multiplied by 0.5 to obtain OC values for surface layers. Because STATSGO reports only OM contents for surface layers, subsurface OC values were estimated by the following methods.

The Montana Soil Pedon Database (6) was used to access laboratory determined soil OC values by profile depth for over 60 agricultural soils in Montana (Figure 2). Linear regression analysis of soil OC values with profile depth produced equation 2 ($r^2 = 0.71$), which was used to compute subsurface OC values for soil with surface OC values exceeding 0.8%.

$$OC_i = 1.71 + 0.117\ (OC_s) - 0.367\ [\ln(D_i)] \qquad (2)$$

where OC_i is the organic carbon content of the ith layer in percent, OC_s is the average organic carbon content of the surface layer in percent, and D_i is the average depth of the ith layer in meters divided by profile depth in meters times 100.

For soils with surface OC values below 0.8%, equations developed by Jury et al. (7) were found to best estimate subsurface OC values (based on comparisons with the Montana Soil Pedon data). These equations, originally developed to estimate subsurface microbial populations, are as follows:

$$OC_2 = OC_s\ e^{-\gamma\,(Z-L)} \qquad (3)$$

$$OC_i = OC_s\ e^{-\gamma\,(H-L)} \qquad (4)$$

where OC_2 is the organic carbon content of the second layer, γ is a depth constant of 3 m^{-1}, Z is the average depth of the second layer in meters, L is the depth of the surface layer in meters, OC_i is the organic carbon content in horizons below the second layer, and H is the depth from the surface to the top of the ith layer in meters.

Standard equations reported in the literature (16) were used to compute the three volumetric water contents needed by the CMLS model as follows:

$$\Theta_{v.1} = (n_{10}/100) * [0.4118 - 0.0030(\%\ sand) + 0.0023(\%\ clay) + 0.0317(\%\ OM)] \qquad (5)$$

$$\Theta_{v.15} = (n_{10}/100) * [0.25 + 0.005(\%\ clay) + 0.0158(\%\ OM)] \qquad (6)$$

$$\Theta_{vSAT} = (n_{10}/100) * [0.7899 - 0.0037(\%\ sand) + 0.01(\%\ OM) - 0.1315(BD)] \qquad (7)$$

where $\Theta_{v.1}$, Θ_{v15} and Θ_{vSAT} are the –0.01 MPa, –1.5 MPa and saturation volumetric water contents, respectively, n_{10} is the average percentage of soil particles passing through a no. 10 soil sieve, % OM is average organic matter content expressed as a percentage, and BD is the average bulk density in g cm^{-3}.

These eight soil parameters were computed for each soil layer and printed to a file for input to our workstation version of CMLS. The same FORTRAN program was also used to compute the available water holding capacity (AWC)[9] of the entire soil profile for each soil series (in cm) as this information was needed to compute the daily evapotranspiration (ET)[9] values in cm required by CMLS. The profile AWC values were estimated by multiplying the widths of the individual soil layers (cm) by their AWCs (cm of water per cm of soil) and summing these subtotals. Profile AWCs of less than 2.54 cm (1 inch) were arbitrarily assigned a value of 2.54 cm for the ET computations described in the next subsection.

Weather attributes. Our application of the CMLS model required daily precipitation and evapotranspiration (ET) totals for 324 MAPS cells located in Teton County. The MAPS cell boundaries were converted to a polygon coverage with the PC ARC/INFO "gridpoly" command and "clipped" to include only those cells within Teton County. Attribute tables consisting of mean monthly precipitation totals and temperatures were transferred from the MAPS database (10) to ARC/INFO attribute tables as well. The Teton STATSGO and MAPS coverages were overlaid by using the "intersect" command in the ARC/INFO Overlay module to produce a new countywide coverage consisting of 1215 unique soil mapping unit and climate polygons.

The WGEN weather simulator (18) was then modified and expanded to generate the weather parameters required by CMLS. WGEN generates daily values of precipitation, minimum and maximum temperatures, and solar radiation for an n-year period at a given location. The WGEN PAR option was used to generate parameters from the long-term daily records available for the Choteau (in Teton County) and Great Falls (the nearest station with daily total solar radiation data) climate stations maintained by the U.S. Weather Service. WGEN PAR reads daily precipitation, minimum and maximum temperatures, and total solar radiation values and writes the generation parameters (probabilities, long-term averages, etc.) required by WGEN to another data file. This approach was used in conjunction with WGEN to compute daily weather values for the MAPS cell containing the Town of Choteau. Another WGEN option was used to generate daily weather values for the other 323 MAPS cells. Mean monthly minimum and maximum temperatures and precipitation totals for these cells were transferred to an ASCII file with the "dump" command in the PC ARC/INFO Tables module so they could be used as correction factors within WGEN to prepare daily weather variables for these locations.

The original WGEN model produced the daily precipitation but not the daily ET values needed by

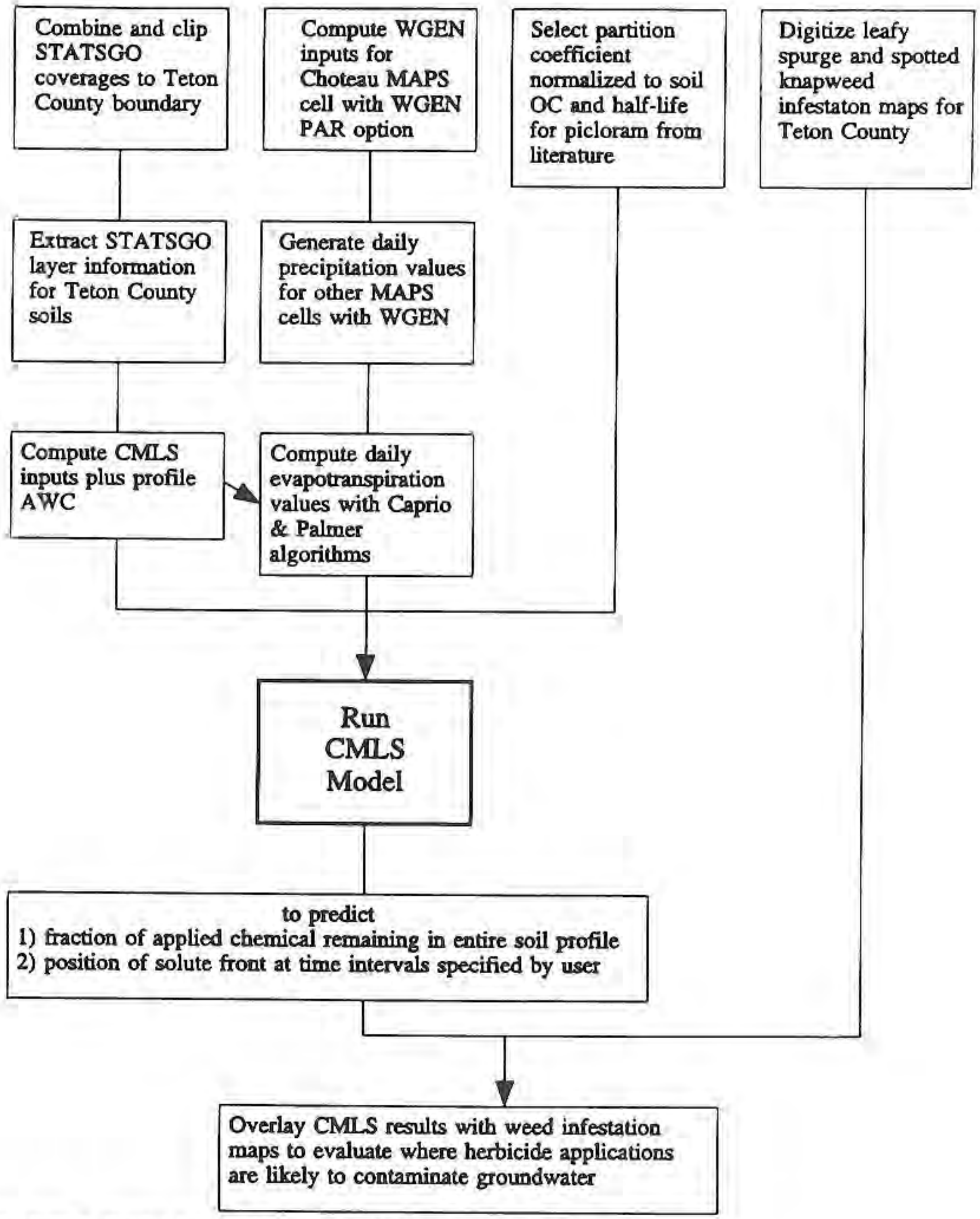

Figure 1. Schematic diagram showing linkages between individual models and data bases.

CMLS. Two additional steps were required to generate spatially-variable daily ET data: (a) the original WGEN model was used to compute daily potential evapotranspiration (PET)[9] values by adding a solar thermal unit model developed by Caprio (3) which used the daily mean temperature and total solar radiation values that were produced by the original version of WGEN as inputs, and (b) we estimated daily ET values from these PET values and the profile AWC for every unique combination of MAPS cell and STATSGO soil series. A separate FORTRAN program was written for this last step because the ARC/INFO "joinitem" command could not achieve the desired geographic linkage because the common (relate) attribute was not unique in at least one

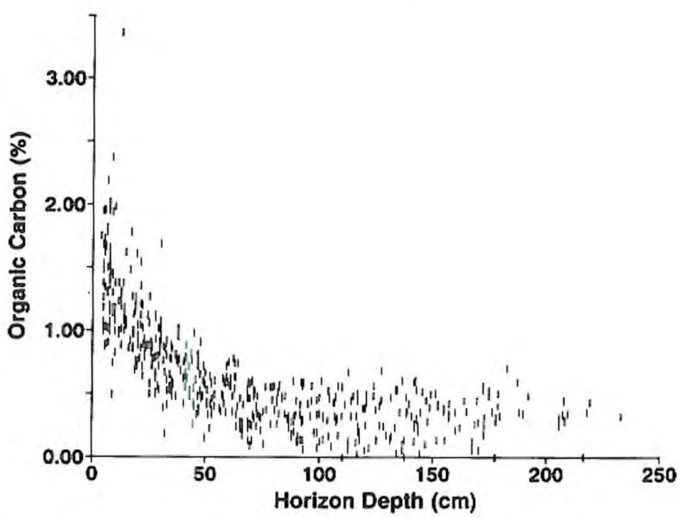

Figure 2. Soil organic-carbon content by profile depth for Montana agricultural soils (6).

of two files. Our FORTRAN program combined soils and climate records for all 5698 unique combinations of MAPS cells and soil series occurring in the STATSGO soil mapping unit(s). The PET output produced with the expanded WGEN model for all 324 MAPS cells was read one cell at a time and the appropriate soil parameters for that cell were accessed sequentially and used with the ET algorithm from the Palmer drought index model (13) to generate 15 yr of daily ET data for each accessed record. The ET data were written to a file which also contained the daily precipitation data generated by WGEN. This data file served as the climate input for the CMLS model.

Chemical attributes. The chemical attributes required for CMLS input include the partition coefficient normalized to soil organic carbon (K_{oc}, L kg^{-1}) and the half-life ($t_{1/2}$, days). For picloram, we used a K_{oc} of 48 L kg^{-1} and a surface half-life value ($t_{1/2}$, 0) of 100 d (7, 12). For soil horizons below the surface layer we used a biodegradation depth function developed by Jury et al. (7):

$$t_{1/2}(i) = t_{1/2}(0)\ e^{\gamma(Z-L)} \qquad (8)$$

where $t_{1/2}(i)$ is the half-life for the ith layer, γ is a depth constant equal to 1.5 m^{-1}, Z is the average depth of the ith layer in meters, and L is the depth of the surface layer in meters. Using a γ value of 1.5 m^{-1} resulted in maximum $t_{1/2}$ values 10 times the surface horizon values. This relationship is generally consistent with the effects of soil depth on herbicide degradation rates ($t_{1/2}$) observed in other studies (2, 8, 14).

Weed infestation maps. Maps supplied by the Teton County Weed Supervisor showing specific locations and areas infested with leafy spurge and spotted knapweed were digitized in ARC/INFO as point and polygon coverages, respectively. These maps were overlaid with the CMLS model results with the "union" command in the ARC/INFO Overlay module. The final tabular output was prepared from the resulting overlays and attribute tables with several commands available in the ARC/INFO Tables module.

RESULTS AND DISCUSSION

The three maps reproduced in Figure 3 show the 324 MAPS cells, 145 STATSGO soil mapping units, and the leafy spurge and spotted knapweed infestations in Teton County. The reference made earlier to 5698 unique combinations of MAPS cells and soil series occurring in the STATSGO soil mapping units meant that an average of 4.7 soil series with complete layer files occurred in each mapping unit. This arrangement (i.e., the way in which the STATSGO records are organized and linked) and the large number of unique polygons limited the types of spatial and tabular output that could be effectively reproduced here.

The scatterplots reproduced in Figures 4a and 4b show the depth of movement of picloram estimated by the CMLS model for each of the unique combinations of MAPS cells and soil series occurring in the STATSGO soil mapping units and 15 yr of weather data (i.e., there are 15 different annual estimates for each MAPS cell/soil series combination). The first graph shows the movement of picloram in response to precipitation events and the second graph shows the combined effects of precipitation and irrigation water inputs. There is no carry-over from one growing season to the next because we started and ended our CMLS runs on 15 April and 15 October each year. The field capacity soil moisture content was used to start each year's simulation. Figure 4a indicates that the model did not predict movement of picloram beyond the root zone for the vast majority (99.5%) of MAPS cell/soil series combinations (polygons) in most of the simulated water years. The application of 10.2 cm (4 inches) of irrigation water on three occasions during the growing season in each simulated weather year moved picloram

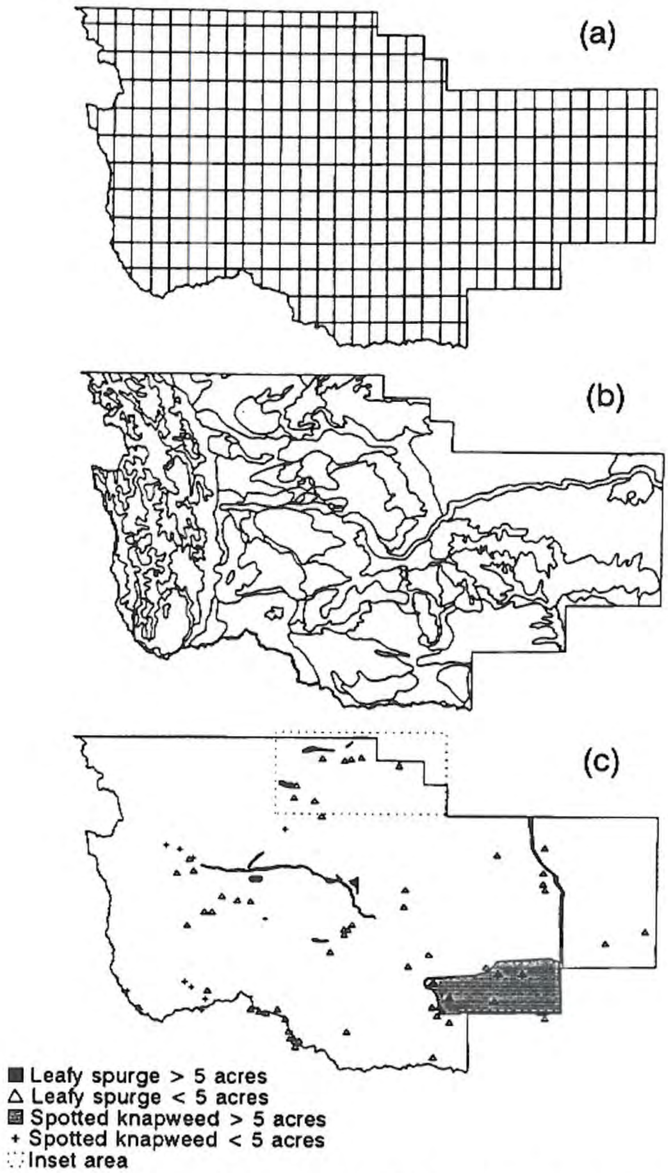

Figure 3. Maps of: (a) 324 MAPS cells, (b) 145 STATSGO soil mapping units, (c) leafy spurge and spotted knapweed infestations in Teton County.

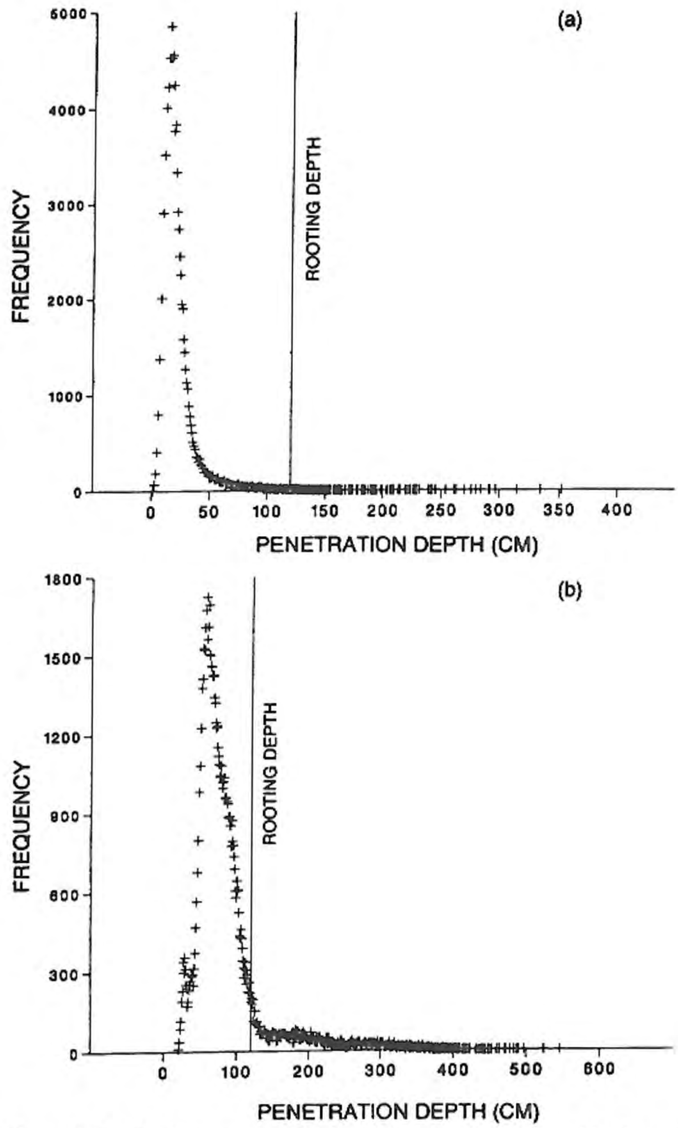

Figure 4. Depth of movement of picloram for every unique combination of MAPS cell and soil series occurring in the STATSGO soil mapping units: (a) without irrigation, and (b) with 30.5 cm of irrigation water applied to entire county.

to greater depths. Approximately 10.6% of the MAPS cell/soil series polygons had predicted picloram movement below the root zone.

Figure 5 shows the leafy spurge infestations occurring within the inset box (shown with a dashed line in Figure 3c). This map indicates that parts of the four STATSGO soil mapping unit and MAPS cell combinations labelled MT162/4155, MT162/4156, MT502/4155 and MT502/4156 are infested with leafy spurge. The results reported in Tables 1 through 3 indicate that each of these STATSGO soil mapping unit and MAPS cell combinations consisted of several components (i.e., phases of soil series) and some further explanation will be required to show how the "best" (least movement), "weighted average", and "worst" (most movement) predictions were derived.

Table 1 shows: (a) the MAPS cell and STATSGO soil mapping unit identifiers (i.e., geocodes) that are required to reference the different map polygons, and (b) the sizes of the polygons and the percentages covered with leafy spurge. The second entry in this table, for example, records that 17.7% of the polygon com-

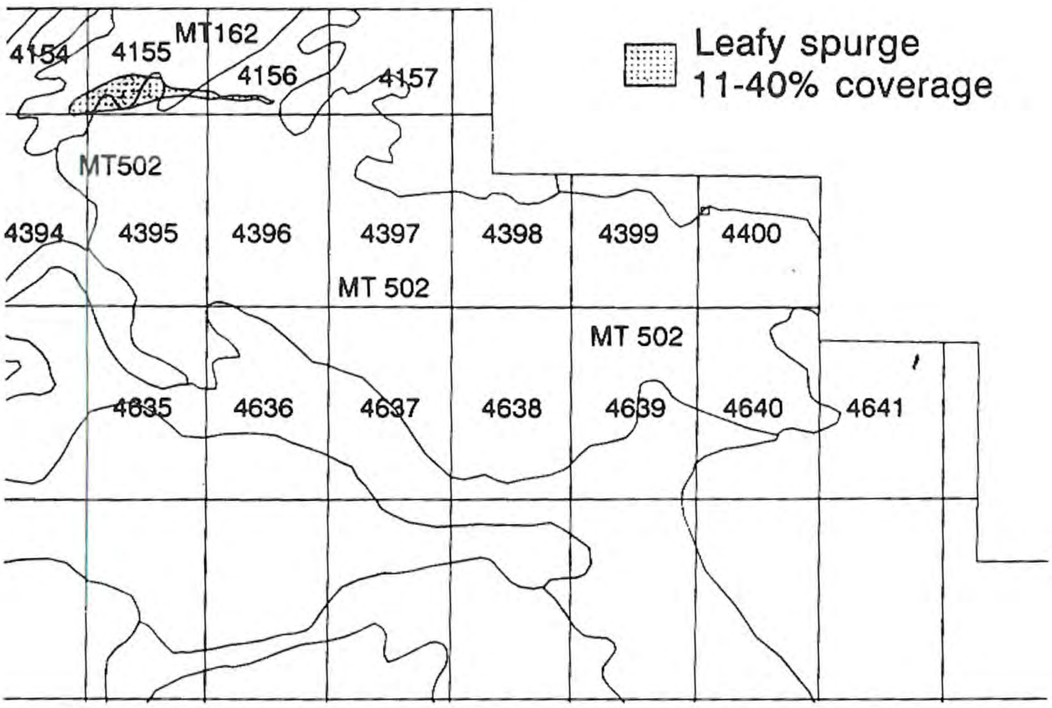

Figure 5. Overlay of MAPS, STATSGO, and weed infestation maps for portion of Teton County shown in Figure 3(c) inset.

bining MAPS cell 4155 and STATSGO soil mapping unit MT162 in Figure 5 is covered with leafy spurge.

The data in Table 2 show the STATSGO soil mapping unit components and the CMLS model predictions for each unique combination of MAPS cell and soil series for which there was a complete record in the STATSGO Layer data file. Several of the individual records in the STATSGO Layer data file lacked measured or estimated bulk densities; consequently, the soil components listed in Table 2 represent only partial lists of the components (i.e., 16 and 68% of the individual soil series by area, respectively) that compose the MT162 and MT502 STATSGO mapping units. Three sets of predictions are provided: the "best" or least movement year, the average depth of movement over 15 weather years, and the "worst" or maximum movement year assuming no irrigation water was applied. However, these predictions provide only a partial view of the potential for groundwater contamination in that the leafy spurge may not cover the same proportion of all of the soil series that compose a particular STATSGO mapping unit. This uncertainty cannot be eliminated because the STATSGO database does not delineate the locations of the individual soil series within each mapping unit (as noted earlier)

Table 3 summarizes the final CMLS predictions by MAPS cell and STATSGO soil mapping unit, such that the "best" and "worst" cases here represent the best soil components and weather years and the worst soil components and weather years, respectively. We adjusted the percentage compositions of the soil components listed in Table 2 upwards so that they "accounted" for 100 percent of the areas of the STATSGO soil mapping units used for these computations; however, we will in the future be able to use the Grossman/Baumer soil texture/bulk density ternary diagram reproduced by Wilson et al. (20) to estimate the missing bulk densities and ensure that all of the appropriate soil series are considered in these assessments.

For the current assessment, the "best" case prediction reported in Table 3 for the MAPS cell and STATSGO soil mapping units labelled 4155 and MT162, respectively was derived from the predictions for the soil components labelled 11 (12.5% of total) and 5 in Table 2 (50% of total; 6.2% used here to make up remainder of infested area) in the "best" weather years (i.e., the year that produced the smallest depth of movement). This example assumed that the 17.7 percent of the STATSGO soil mapping unit covered with leafy spurge

Table 1. Geocodes, areas, and leafy spurge infestations for the MAPS cell and STATSGO soil mapping unit combinations shown in Figure 5.

MAPS cell identifier	STATSGO soil mapping unit	Polygon area	% of polygon covered with leafy spurge
		km^2	
4154	MT162	1.12	0
4155	MT162	8.30	17.7
4156	MT162	4.47	0.9
4394	MT162	0.56	0
4395	MT162	0.17	0
4155	MT502	2.66	28.3
4156	MT502	7.04	5.5
4157	MT502	2.89	0
4395	MT502	14.68	0
4396	MT502	20.17	0
4397	MT502	17.86	0
4398	MT502	13.57	0
4399	MT502	13.44	0
4400	MT502	11.48	0
4635	MT502	1.75	0
4636	MT502	2.94	0
4637	MT502	8.08	0
4638	MT502	17.34	0
4639	MT502	12.00	0
4640	MT502	10.36	0
4641	MT502	0.78	0

was composed entirely of the two "best" soil series (i.e., those soil series that produced the smallest depth of movement). The "worst" case predictions favored the "worst" soil components in the appropriate STATSGO soil mapping units and the "worst" weather years; whereas, the weighted average case assumed that the soil components were represented within the weed infestation area according to their average percentage composition (adjusted from those reported in Table 2 to compensate for those components (i.e., soil series) with missing data that were omitted from the analysis performed for this study) within the entire STATSGO soil mapping unit. The weighted average case also averaged the predicted picloram movement over all 15 weather years. The composite results reported in Table 3 not only describe the threat to groundwater posed by the current herbicide applications at this site, but also indicate the variability that could be expected due to variations in soil and weather conditions. Hence, these results indicate the "best" and "worst" results that could be expected notwithstanding the uncertainty noted earlier.

Our choice of the MAPS and STATSGO databases for input data was important because the information content and level of precision captured in maps are to a large extent scale-dependent. The models, input data, and results that we have described are suited to regional (i.e., county-scale and larger area) assessments of the threat to groundwater posed by current herbicide applications. Approximately two person-months might be required for each application, assuming that: (a) the CMLS model has been validated for local conditions, (b) the appropriate software are accessible and known to the user, and (c) digital copies of the databases

Table 2. Predicted depths of picloram movement for every unique combination of MAPS cell and STATSGO soil mapping unit component (i.e., soil series without missing data).

MAPS cell identifier	STATSGO mapping unit	STATSGO component number	Soil series identifier	Percentage composition	CMLS predictions "Best" case	"Avg." case	"Worst" case
					cm		
4155	MT162	5	MT0069	8	9.5	17.2	23.9
4155	MT162	8	MT0138	4	11.2	20.5	28.2
4155	MT162	10	MT0745	2	11.2	21.5	31.7
4155	MT162	11	MT0122	2	6.9	12.5	17.7
4155	MT502	1	MT0122	40	6.8	12.2	17.4
4155	MT502	3	MT0088	13	11.3	21.7	30.2
4155	MT502	4	MT0374	8	7.3	13.6	19.8
4155	MT502	5	MT0122	5	6.8	12.2	17.4
4155	MT502	8	MT0088	2	11.3	21.7	30.2
4156	MT162	5	MT0069	8	8.5	18.4	31.4
4156	MT162	8	MT0138	4	10.0	22.2	38.4
4156	MT162	10	MT0745	2	10.0	23.5	47.2
4156	MT162	11	MT0122	2	5.4	13.5	25.7
4156	MT502	1	MT0122	40	5.4	13.2	25.2
4156	MT502	3	MT0088	13	10.4	23.8	39.5
4156	MT502	4	MT0374	8	6.6	14.7	27.0
4156	MT502	5	MT0122	5	5.4	13.2	25.2
4156	MT502	8	MT0088	2	10.4	23.8	39.5

Table 3. Predicted depths of picloram movement for selected soil series and weather years as a function of MAPS cell and STATSGO soil mapping unit.

MAPS cell identifier	STATSGO mapping unit	CMLS Model Predictions "Best" case	"Weighted avg." case	"Worst" case
			cm	
4155	MT162	7.7	18.0	30.7
4156	MT162	6.8	14.5	30.2
4155	MT502	7.1	19.4	42.3
4156	MT502	5.4	15.7	39.5

required to run CMLS are available. Our methods are capable of identifying areas that deserve further study and we are now exploring: (a) the possibility of adding roadways to the regional-scale assessments (because most county weed board spraying occurs along roadsides and overlapping coverages may provide information on potential areas of surface and subsurface water contamination), and (b) the viability of using 1: 24 000-scale input data with the same procedures to produce maps and tabular output consistent with USDA-SCS management units.

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