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Testing the Hydrological Landscape Unit Classification System and Other Terrain Analysis Measures for Predicting Low-Flow Nitrate and Chloride in Watersheds

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Abstract Elevated nitrate concentrations in streamwater are a major environmental management problem. While land use exerts a large control on stream nitrate, hydrology often plays an equally important role. To date, predictions of low-flow nitrate in ungauged watersheds have been poor because of the difficulty in describing the uniqueness of watershed hydrology over large areas. Clearly, hydrologic response varies depending on the states and stocks of water, flow pathways, and residence times. How to capture the dominant hydrological controls that combine with land use to define streamwater nitrate concentration is a major research challenge. This paper tests the new Hydrologic Landscape Regions (HLRs) watershed classification scheme of Wolock and others (Environmental Management 34:S71-S88, 2004) to address the question: Can HLRs be used as a way to predict low-flow nitrate? We also test a number of other indexes including inverse-distance weighting of land use and the well-known topographic index (TI) to address the question: How do other terrain and land use measures compare to HLR in terms of their ability to predict low-flow nitrate concentration? We test this for 76 watersheds in western Oregon using the U.S. Environmental Protection Agency's Environmental Monitoring and Assessment Program and Regional Environmental Monitoring and Assessment Program data. We found that HLRs did not significantly improve nitrate predictions beyond the standard TI and land-use metrics. Using TI and inverse-distance weighting did not improve nitrate predictions; the best models were the percentage land use—elevation models. We did, however, see an improvement of chloride predictions using HLRs, TI, and inverse-distance weighting; adding HLRs and TI significantly improved model predictions and the best models used inverse-distance weighting and elevation. One interesting result of this study is elevation consistently predicted nitrate better than TI or the hydrologic classification scheme.

Keywords Water quality · Environmental monitoring and assessment program · Nitrate · Chloride · Catchment hydrology · Hydrologic landscape region · Predicting low-flow nitrate concentrations

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The controls on streamwater nitrate are poorly understood. For catchments with mixed land use, including agricultural development, urban, and suburban development, land use has been found to exert a dominant control on streamwater nitrate concentrations (Schilling 2002; Jordan and others 1997; Owens and others 1991; Howarth and others 2002). Many spatial statistical models have been proposed that regress proportions of different land uses in a catchment against stream nitrate concentration (Arheimer and Liden 2000; Wickham and others 2002; Jones and others 2001). While the correlation between land use and stream nitrate is well documented in a variety of climate and geographical settings, model performance (e.g., R^2) reported in such studies is rarely in excess of 0.5 (Norton and Fisher 2000; Herlihy and others 1998; Johnson and others 1997).

Catchment models using land use plus additional measures such as nitrogen inputs and annual flow rate have shown slightly more predictive power than statistical models using land use alone (Hunsaker and Levine 1995; Norton and Fisher 2000; Arheimer and Liden 2000; Jones and others 2001). These empirical models attempt to include variables that account for hydrological factors within watersheds that affect nitrate concentrations. While empirical models are useful tools in many instances to predict concentrations in streams, they are somewhat decoupled from the body of literature that examines processes of catchment-scale biogeochemical cycling. Several studies have examined the processes involved in nitrate transport, transformations, and storage (Hjerdt and others 2004; Petry and others 2002; Creed and Band 1998; Jordan and others 1997; McHale and others 2002; Hornberger and others 1994). One somewhat common finding of this work is that hot spots (patches of the catchment with relatively high reaction rates, often enhanced at the terrestrial-aquatic interfaces) exert a profound control on streamwater nitrate dynamics (McClain and others 2003). The interface between oxic and anoxic zones (i.e., the interface between upland and riparian zones) is typically a hot spot for denitrification (Dahm and others 1998; McClain and others 2003; Peterjohn and Correll 1984; Lowrance and others 1984). Microbial studies have found that hot spots for denitrification occur at sites where groundwater flow paths transport nitrate to supplies of available organic carbon within the riparian zone (Hill and others 2000; Sebilo and others 2003) and at sites with flooded or moist soils (Christensen and others 1990). Pinay and others (1989) and many others have shown that elevational differences can significantly affect soil saturation levels, which in turn affects the denitrification potential. Within wet zones of the catchment (e.g., riparian areas), the seasonality of soil saturation levels (perennially saturated, seasonally inundated, and dry or rarely inundated) has also been shown to affect denitrification potential and thus patterns of nutrient export (Baker and others 2001).

How to capture the dominant hydrological controls that combine with land use to define streamwater nitrate concentration is a major research challenge. One of the most vexing issues is that every catchment appears somewhat unique in terms of its hydrology and physiology (Beven 2000) and physiographic variables alone do little to enhance the land use-alone empirical models. Clearly, hydrologic response varies depending on the states and stocks of water, flow pathways, and residence times. To improve predictions, these variables need to be represented in a simple way across different watersheds. There have been recent calls for a watershed classification that groups typologies of hydrological processes from one region to the next (McDonnell and Woods 2004; Wagener and others 2007), providing a typology of dominant hydrological components of catchments. In the context of streamwater nitrate, this could be a first step in linking empirical biogeochemical models with hydrology over broad areas. While attempts have been made at catchment classification (Chapman 1987; Winter 2001; Omernik and Griffith 1991; Preston 2000; Baker and others 2001), the recent hydrologic landscape region (HLR) classification scheme developed by Wolock and others (2004) is the first objective hydrological classification of its kind to cover the entire United States. It groups watersheds into 20 HLRs with similar hydrologic settings. Wolock and others (2004) further characterized four combinations of primary hydrologic flowpaths for the HLRs: (1) shallow groundwater and deep groundwater (SGW-DGW), (2) overland flow and deep groundwater (OF-DGW), (3) shallow groundwater (SGW), and (4) overland flow (OF). HLRs were found to delineate regions of distinct land-surface form and geologic texture better than the ecoregion classification developed by Omernik and Griffith (1991), and regions with similar climate, land cover, and water quality characteristics were equally well defined using HLRs and ecoregions.

We test whether classified HLRs aid in our ability to predict low-flow nitrate concentrations in watersheds, and the idea that the classified hydrological behavior will exert a dominant control on streamwater nitrate concentration across catchment conditions of different land use. We hypothesize that low-flow samples will identify anthropogenic sources of stream nitrate more accurately than samples taken during wet conditions based on previous studies that have shown land use significantly altering stream nitrate concentrations during base-flow conditions (e.g., Heisig 2000). In addition to the HLR, we use a number of other topographic measures to compare their effectiveness to the HLR classes. The topographic index (TI; Beven and Kirkby 1979) and weighted areal percentages of land use within catchments are used along with the inverse-distance and inverse-distance squared method of Kehmeier (2000). We hypothesize that modifying land use areal estimates with the in-stream and out-of-stream inverse-distance metrics may improve nitrate predictions by accentuating near-stream hydrobiogeochemical processes (i.e., uptake by riparian vegetation, denitrification, etc.) and capturing some of the hot-spot importance identified in process studies.

In this study, we explore the use of simple conceptual relationships to improve statistical models. We take advantage of an extensive 97-catchment database of low-flow water quality sampling from the U.S. Environmental

Protection Agency's Environmental Monitoring and Assessment Program (EMAP), the Regional Environmental Monitoring and Assessment Program (REMAP; Stoddard and others 2005), an EPA agricultural-riparian study database (Moser and others 1997), and a prepilot EMAP study (Herlihy and others 1997; Peck and others 2005a, b). We use these data to explore the use of HLRs and other land use and topographic information to predict stream nitrate concentrations. Although the HLR classification scheme is on a national scale and our dataset is on a regional scale, we believe that it is useful to test this general scheme to determine whether it can be used as a practical tool for water quality predictions and watershed management. In addition to low-flow nitrate, we use chloride as a relatively conservative geochemical constituent (largely affected by hydrology and not affected by denitrification, nitrification, plant uptake, etc.). While land use has been shown to affect chloride concentrations (Herlihy and others 1998; Smart and others 1998), chloride is often used in pristine catchments as a conservative tracer of water (Kirchner and others 2001; Neal and Rosier 1990; Nyberg and others 1999). Comparison between the highly reactive nitrate and the quasi-conservative chloride help to separate hydrological vs. biogeochemical controls in our statistical models. We explore the following questions:

1. Can HLR be used as a way to predict low-flow nitrate?
2. How do other terrain and land use measures compare to HLR in terms of their ability to predict low-flow nitrate concentration?

Methods

Study Areas

Catchments in the Willamette River Basin in western Oregon were used for model development. Western Oregon has a Mediterranean climate, with wet winters and dry summers. Average long-term precipitation in western Oregon is 1653 mm. Figure 1 shows the location of sampling sites at the outlet of study catchments. Table 1 shows general characteristics of the study catchments. The dominant geology is calcerous-alakaline volcanics, with mafic volcanics, lake sediment, sandstone, and shale and mudstone also present in significant amounts (Hulse and others 2002). Soil types include various types of clay, weathered alluvium, and volcanic soils.

The dataset includes 97 catchments with chemistry data and land use coverage, and is comprised of data from EMAP, REMAP, an EPA agricultural-riparian study (Moser and others 1997) and a prepilot EMAP study (Herlihy and others 1997; Peck and others 2005a, b). Samples for the agricultural-riparian study and EMAP were collected in 1997. Prepilot samples were collected in 1993–1997, and REMAP samples were collected in 1994 and 1995. All samples were collected during the summer low-flow period (June through September).

Land use/land cover data (30-m resolution) and digital elevation models (DEMs) were used for each of the study watersheds (Oetter and others 2000; Hulse and others 2002; King and Beikman 1974). Satellite images were taken in 1990 for the land use/land cover data, with a classification accuracy varying from 50% to 100% (Hulse and others 2002). Land cover is divided into 65 classifications, including different types of agricultural crops, forested/natural vegetation, and urban/human development. Several sites were removed from the dataset due to errors in the DEMs in low gradient regions that caused inaccurate delineations of the watershed boundary and stream network. Some catchments also had missing water quality data. This resulted in 76 sites (39 in the Willamette Valley and 37 in the upland Cascade and Coast ranges). Due to some catchments having more than one HLR grouping within the catchment boundary, only 71 catchments were ultimately used in models using HLRs.

Model Description

All land use characterizations were grouped into three land use categories: forested, agricultural, and urban. Natural vegetation, riparian vegetation, and forest were placed in the forest category. The agricultural category included orchards, row crops, and any other type of farming activity. Roads, housing developments, and urban areas were included in the urban category. Classifications were grouped into these categories to decrease the number of variables in the resulting model. The TI was calculated for each cell (as defined by the DEM) in a watershed using the following equation:

$$TI = \ln\left(\frac{a}{\tan\beta}\right) \quad (1)$$

where a is the upslope contributing area per unit contour length, and β is the local slope angle (Beven and Kirkby 1979). Cells with zero local slope angle (<10% of the sampled watersheds had cells with zero local slope angle) were considered sinks for water and not expected to contribute to the flow gradient. Thus, they were removed from the analysis.

Using the DEM files for each catchment, a flow direction grid was created that described the direction of flow (north, south, east, west, northeast, northwest, southeast, or southwest) for each cell in the catchment. The steepest gradient between a cell and the eight neighboring cells determined the direction of flow. The flow direction grid

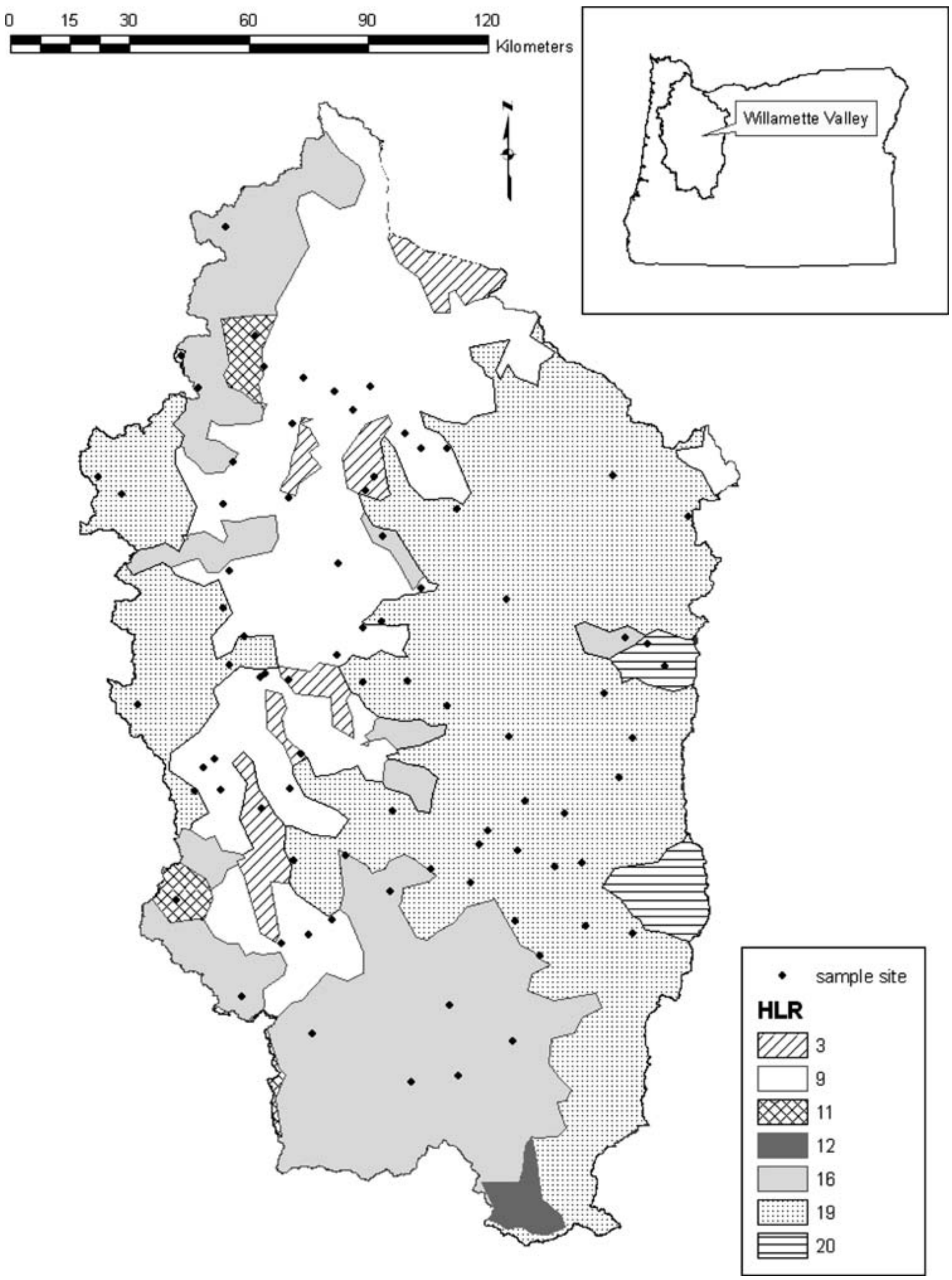

Fig. 1 Sampling sites at the outlet of study catchments and hydrologic landscape regions in western Oregon

was then used to create a stream network with a minimum upstream drainage area of 500 cells (according to the DEM coverage). Drainage areas with <500 cells did not create a definable stream network. Out-of-stream distances were calculated according to flow paths from the flow direction grid and were defined as the flow-path distance from a location (cell) in the catchment to the point of entry to the stream. In-stream distances were calculated according to stream networks, and were defined as the distance in the stream from the point of entry (determined from the end point of the out-of-stream flow path) to the outlet of the catchment. Figure 2 shows the out-of-stream and in-stream distances (d) for one of the sampled watersheds. To calculate area, inverse-distance (1/d) and inverse-distance squared ($1/d^2$), algorithms were used (Kehmeier 2000). The algorithm calculated in-stream and out-of-stream inverse-distance (1/d) and inverse-distance squared ($1/d^2$) for each cell in the catchment, then summed up the distance values [in-stream, out-of-stream, and total (in-stream + out-of-stream) 1/d and $1/d^2$] for each category of land use and numerical value of TI. To minimize the effects of watershed size, land use variables were normalized by the total sum of all cells in the watershed [i.e., forested area was divided by total area, forested (in-stream distance)$^{-1}$ was

Table 1 General catchment characteristics for western Oregon

	Mean	Minimum	Maximum
Watershed area (ha)	3,848	59	45,867
Site elevation (m)	339	24	1,213
Mean elevation (m)	544	49	1,872
Slope at site (%)	3.63	0.00	15.00
Mean slope (%)	20.24	0.30	55.05
Road density (m/m^2)	0.00264	0.00020	0.01100
Average precipitation (mm)	1,653	1,029	3,319
% forest	73.32	0.70	100.00
% agriculture	21.17	0.00	96.90
% urban	5.52	0.00	82.81
Nitrate (mg/L)	2.11	0.00	34.03
Chloride (mg/L)	9.93	0.33	143.37

divided by total (in-stream distance)$^{-1}$, etc.], and a weighted average was calculated for TI:

$$\sum_{i=1}^{n}\left[TI_i * (out\text{-}of\text{-}stream\ distance)_i^{-2}\right] \Big/ \sum_{i=1}^{n}\left[(out\text{-}of\text{-}stream\ distance)_i^{-2}\right] \qquad (2)$$

where i is the individual cell number and n is the total number of cells in the catchment. As a result of normalizing the variables, the three land use measures summed to 1 and the resulting solution was not unique. One of the land use measures had to be removed, and we chose the urban land use since it comprises a smaller percentage (5.52%) of land use in the catchments.

Maps of HLRs were provided by the U.S. Geological Service (USGS) and were grouped according to Wolock and others (2004). The HLR classification was developed on a 200-km^2 watershed scale. This larger-scale classification scheme enables us to encompass most of the sampled watersheds, which have a large range in area. Hydrologic landscape regions for western Oregon are shown in Fig. 1. Not all of the HLRs are represented, since western Oregon does not have the complete range of geologic, soil, and precipitation types found in the United States. Groups 3, 9, 11, 12, 16 19, and 20 were represented (see definitions below). All of these groups were present in the modeled catchments except for group 12. These groups reflected characteristics of subhumid plains with overland flow and deep groundwater (group 3), humid plateaus with overland flow and deep groundwater (group 9), humid plateaus with overland flow (group 11), semiarid plateaus with shallow groundwater (group 12), humid mountains with shallow groundwater (groups 16 and 20), and very humid mountains with shallow groundwater (group 19). All of these groups had a positive precipitation minus potential evapotranspiration (PET) value, except for group 12 (Wolock and others 2004). Group 12 is on the southern tip of the Willamette Valley in western Oregon, which is typically drier than the rest of the valley and is not present in any of the modeled catchments. The six groups (Groups 3, 9, 11, 16 19, and 20) were added to the linear model equations. The resulting variables were qualitative; catchments were assigned a value of 1 (the catchment is classified in this group) or 0 (the catchment is not classified in this group). One of the groups (Group 11) was removed from the linear models to minimize the effects of collinearity. Because a catchment will have one of these variables when it does not have the other five, the groups are all somewhat collinear. The removal of Group 11 resulted in only Groups 3, 9, 16 19, and 20 being represented in the equations.

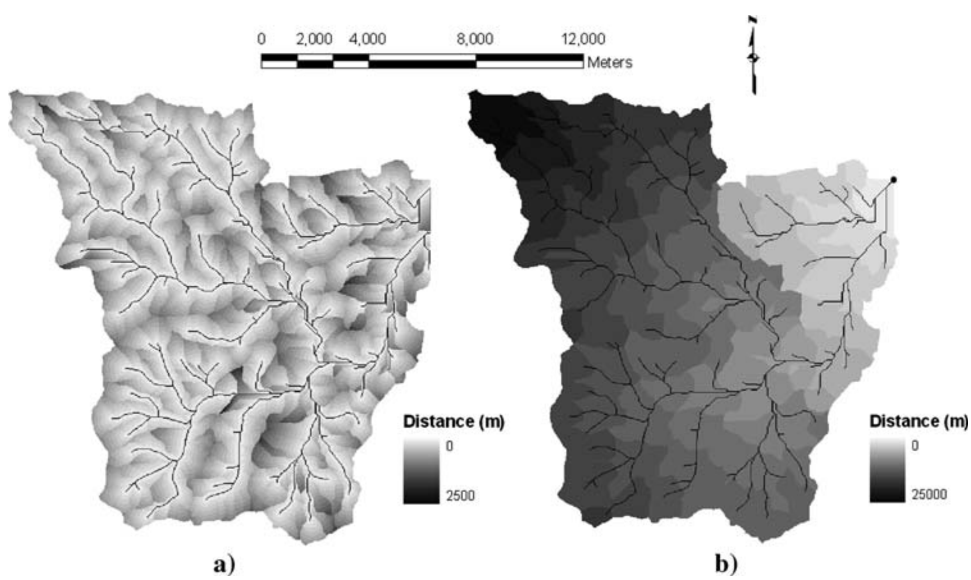

Fig. 2 Calculated distances for each cell in the Muddy Creek Watershed: (**a**) out-of-stream distance and (**b**) in-stream distance

Three general model forms were created to describe the various models. The first general model form is

$$\log(NO_3^-) = a_0 + a_1(F_{eff}) + a_2(A_{eff}) + b_1(TI_{eff}) \tag{3}$$

where a_0 is the intercept, a_1 and a_2 are land use coefficients, and b_1 is the TI coefficient. F_{eff}, A_{eff}, and TI_{eff} are the effects of forested land use, agricultural land use, and TI, respectively, which can be percentage land use, total inverse-distance ($Total^{-1}$), or total inverse-distance squared ($Total^{-2}$). Total inverse-distance and inverse-distance squared were calculated by summing in-stream and out-of-stream inverse-distance and inverse-distance squared, respectively. For the in-stream and out-of-stream models, the general model form is

$$\log(NO_3^-) = a_0 + a_1(F_{eff1}) + a_2(F_{eff2}) + a_3(A_{eff1}) + a_4(A_{eff2}) + b_1(TI_{eff1}) + b_2(TI_{eff2}) \tag{4}$$

where the subscripts *eff*1 and *eff*2 denote the in-stream and out-of-stream effects, respectively. Variables with the *eff*1 subscript can be in-stream inverse-distance (1/d) or in-stream inverse-distance squared ($1/d^2$), and variables with the *eff*2 subscript can be out-of-stream inverse-distance (1/d) or out-of-stream inverse-distance squared ($1/d^2$). Models were created incorporating the in-stream and out-of-stream inverse-distance ($In + Out^{-1}$) and the in-stream and out-of-stream inverse-distance squared ($In + Out^{-2}$). To determine the relationship between in-stream and out-of-stream effects, a multiplicative model was also tested:

$$\log(NO_3^-) = a_0 + a_1(F_{eff1}) * (F_{eff2}) + a_3(A_{eff1}) * (A_{eff2}) + b_1(TI_{eff1}) * (TI_{eff2}) \tag{5}$$

The multiplicative models were depicted as $In*Out^{-1}$ for inverse-distance and $In*Out^{-2}$ for inverse-distance squared. To include HLR in the models, the TI variables were replaced with the HLR group variables, i.e.,

$$\log(NO_3^-) = a_0 + a_1(F_{eff1}) + a_2(F_{eff2}) + a_3(A_{eff1}) + a_4(A_{eff2}) + b_1(Group\,3) + b_2(Group\,9) + b_3(Group\,16) + b_4(Group\,19) + b_5(Group\,20) \tag{6}$$

Each watershed was assigned a group number based on the provided maps. We did not use a percentage or inverse-distances for these models because HLRs categorize the watersheds and do not vary within the watershed. In all models, elevation, slope, and watershed area were separately substituted for TI variables to compare with HLR and TI models. The same model forms were used for the chloride models.

Since nitrate data in western Oregon are highly skewed toward zero (and not normally distributed), nitrate data were $\log_{10}$-transformed. Chloride data were also $\log_{10}$-transformed.

Model Determination

Using the model forms described above, SAS version 9.1 (SAS Institute, Inc. 2003) was used to perform linear regressions. Variable correlations were performed to determine which independent variables other than the HLRs being tested have the potential to predict nitrate and chloride concentrations. Correlations between nitrate/chloride and all available data (HLR, percentage land use, slope, elevation, watershed area, watershed road density, mean annual flow rate, and total length of all upstream streams) were initially calculated for the western Oregon datasets. Correlations between nitrate/chloride and explanatory variables >0.2 were considered large enough to include the variables in the models; correlations <0.2 will likely be too weak to have significance.

The significance of the addition of HLR and the other terrain analysis measures to the models was evaluated using the partial-F test. Models from each region were compared using Akaike's Information Criterion (AIC), which is a measure of how well a model fits the data, with an added penalty for the number of estimated model coefficients (Burnham and Anderson 1998). Thus, the AIC helps identify small (parsimonious) models that fit the data better than other models. The difference in the AIC of the model subtracted from the minimum AIC among all candidate models (ΔAIC) was used to compare models. Models with a $\Delta AIC < 2$ are considered good and models with a $\Delta AIC < 7$ are considered okay compared to the best model (Burnham and Anderson 1998).

Results

Parameter Correlations

Table 2 lists correlations with all available parameters. HLRs were moderately correlated with chloride and nitrate. The highest correlations with nitrate were with slope, elevation, natural/forested, agriculture, developed land use, and HLR variables ($r > 0.2$). Slope, elevation, agriculture, natural/forested, developed land use, and HLR had the highest correlations to chloride. This indicates that HLR, TI (which is derived from slope), and land use variables might successfully predict nitrate and chloride. Both site and mean elevation were highly correlated with nitrate and chloride. Models were created with site and mean elevation to determine which variable predicts nitrate and chloride better. Because of the high collinearity between the agricultural and the forested variables (on average, $r = -0.900$ for area, 1/d, and $1/d^2$ variables), it is difficult to interpret the resulting coefficients. Thus, models using only the forested variables are presented and discussed.

Table 2 Correlation matrix

Variable	log(NO_3^-)	log(Cl^-)	%Ag	%For	%Nat Veg	%ADA	%Ag + ADA	%Ag + LDD	Rd Den	Site Slope	Site Elev	Mean Slope	Mean Elev	Wshd Area	Strm Len	Mean Q	HLR
log(NO_3^-)	1.000	0.473	0.475	-0.398	-0.523	0.287	0.531	0.516	0.024	-0.394	-0.574	-0.467	-0.618	-0.029	-0.008	-0.100	-0.378
log(Cl^-)	0.473	1.000	0.630	-0.529	-0.636	0.263	0.652	0.661	0.008	-0.632	-0.754	-0.655	-0.793	0.027	0.037	-0.098	-0.699
%Ag	0.475	0.630	1.000	-0.822	-0.842	0.111	0.898	0.977	-0.183	-0.546	-0.590	-0.725	-0.657	0.007	0.034	-0.116	-0.671
%For	-0.398	-0.529	-0.822	1.000	0.906	-0.461	-0.902	-0.880	-0.241	0.486	0.504	0.659	0.583	0.077	0.057	0.195	0.613
%Nat Veg	-0.523	-0.636	-0.842	0.906	1.000	-0.589	-0.976	-0.925	-0.207	0.566	0.567	0.715	0.625	0.054	0.048	0.165	0.735
%ADA	0.287	0.263	0.111	-0.461	-0.589	1.000	0.537	0.315	0.726	-0.269	-0.259	-0.368	-0.316	-0.090	-0.114	-0.120	-0.396
%Ag + ADA	0.531	0.652	0.898	-0.902	-0.976	0.537	1.000	0.968	0.166	-0.585	-0.619	-0.778	-0.697	-0.034	-0.022	-0.151	-0.755
%Ag + LDD	0.516	0.661	0.977	-0.880	-0.925	0.315	0.968	1.000	-0.023	-0.579	-0.621	-0.767	-0.694	-0.013	0.008	-0.136	-0.731
Rd Den	0.024	0.008	-0.183	-0.241	-0.207	0.726	0.166	-0.023	1.000	-0.040	-0.076	-0.132	-0.136	-0.100	-0.121	-0.101	-0.125
Site Slope	-0.394	-0.632	-0.546	0.486	0.566	-0.269	-0.585	-0.579	-0.040	1.000	0.744	0.546	0.711	-0.421	-0.433	-0.269	0.450
Site Elev	-0.574	-0.754	-0.590	0.504	0.567	-0.259	-0.619	-0.621	-0.076	0.744	1.000	0.630	0.952	-0.329	-0.352	-0.113	0.626
Mean Slope	-0.467	-0.655	-0.725	0.659	0.715	-0.368	-0.778	-0.767	-0.132	0.546	0.630	1.000	0.740	0.035	0.017	0.170	0.692
Mean Elev	-0.618	-0.793	-0.657	0.583	0.625	-0.316	-0.697	-0.694	-0.136	0.711	0.952	0.740	1.000	-0.094	-0.114	0.043	0.704
Wshd Area	-0.029	0.027	0.007	0.077	0.054	-0.090	-0.034	-0.013	-0.100	-0.421	-0.329	0.035	-0.094	1.000	0.981	0.926	0.014
Strm Len	-0.008	0.037	0.034	0.057	0.048	-0.114	-0.022	0.008	-0.121	-0.433	-0.352	0.017	-0.114	0.981	1.000	0.925	0.013
Mean Q	-0.100	-0.098	-0.116	0.195	0.165	-0.120	-0.151	-0.136	-0.101	-0.269	-0.113	0.170	0.043	0.926	0.925	1.000	0.182
HLR	-0.378	-0.699	-0.671	0.613	0.735	-0.396	-0.755	-0.731	-0.125	0.450	0.626	0.692	0.704	0.014	0.013	0.182	1.000

Note: Ag, agriculture; For, forest; Nat veg, natural vegetation; ADA, all developed areas; LDD, low-density development; Rd density, road density (m roads/m^2 watershed area); elev, elevation (m); Wtrshd area, watershed area (ha); stream length, length (m) of stream in watershed upstream of site; mean Q, estimated mean annual discharge (cfs). Shaded areas identify significant correlations for nitrate and chloride

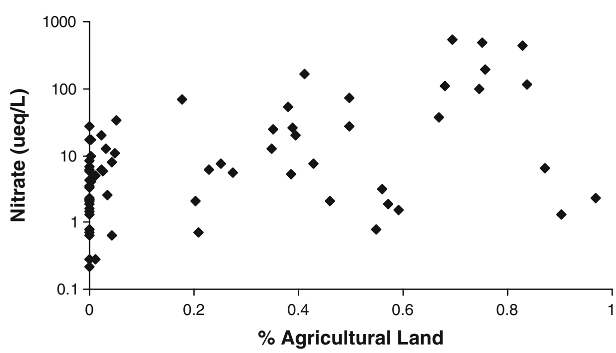

Fig. 3 Nitrate variation with percentage agricultural land

Figure 3 shows the variation in nitrate concentrations with proportion of agricultural land use in each watershed. This figure reveals the lack of any clear pattern that can be easily modeled, and indicates that additional variables are needed to predict nitrate.

Table 3 lists the correlations between nitrate/chloride and the individual HLR parameters. Since we did not have access to the same datasets that the originators of the HLR system (Wolock and others 2004) used to determine HLR parameters, we examined parameters that would best mimic the original parameters used. We used slope as a surrogate for percentage flatland, geologic type for bedrock permeability class, hydrologic soil type for percentage sand, and precipitation for precipitation minus PET. Nitrate and chloride were correlated with slope, precipitation, soil, and geology.

Table 3 Correlations of HLR grouping parameters with stream nitrate and chloride concentrations for the western Oregon dataset

Variable	Pearson's coefficient
Nitrate	
Mean precipitation	−0.460**
Mean slope	−0.467**
%Type D hydrosoil	0.367*
Calc-alkaline volcanics	−0.446**
Lake sediments	0.377*
Glacial drift	−0.372*
Chloride	
Mean precipitation	−0.683**
Mean slope	−0.655**
%Type D hydrosoil	0.580**
Calc-alkaline volcanics	−0.655**
Lake sediments	0.484**

Note: * $p < 0.001$; ** $p < 0.0001$

Nitrate Modeling

Table 4 shows the nitrate modeling results. The partial *F*-test ($\alpha = 0.05$) indicated that including HLR did not significantly improve nitrate models. Combining HLR with land use improved R^2 values compared to using just HLR or land use, however, the percentage land use (%land use) model had a lower ΔAIC value than the HLR and %Land Use HLR models. The ΔAIC revealed that the inverse-distance HLR models also did not improve prediction of

Table 4 Nitrate modeling results

Model	Terms (Coefficient, SE)	R^2	ΔAIC
HLR	Group 3 (−0.0126, 1.87); Group 9 (0.690, 1.13); Group 16 (−0.418, 1.16); Group 19 (−0.776, 1.12); Group 20 (−0.488, 1.53)	0.16	26.3
%Land Use	Forested (−2.51, 0.503)	0.26	8.7
%Land Use HLR	Forested (−2.89, 0.834); Group 3 (−2.46, 1.87); Group 9 (−0.577, 1.10); Group 16 (−0.212, 1.08); Group 19 (−0.508, 1.04); Group 20 (−0.0721, 1.42)	0.29	16.1
%Land Use TI	Forested (−2.88, 0.873); TI (−0.122, 0.205)	0.29	10.6
%Land Use Elevation	Forested (−1.33, 0.535); Site elevation (−0.00179, 0.000530)	0.38	0.0
$Total^{-1}$ Land Use HLR	Forested (−2.52, 0.806); Group 3 (−2.10, 1.88); Group 9 (−0.469, 1.12); Group 16 (−0.275, 1.09); Group 19 (−0.534, 1.05); Group 20 (−0.0776, 1.44)	0.27	18.2
$Total^{-1}$ Land Use TI	Forested (−2.80, 0.865); TI (−0.134, 0.215)	0.28	11.8
$Total^{-1}$ Land Use Elevation	Forested (−1.14, 0.552); Site elevation (−0.00184, 0.000560)	0.37	1.8
$Total^{-2}$ Land Use HLR	Forested (−1.02, 0.699); Group 3 (−0.930, 1.96); Group 9 (0.268, 1.16); Group 16 (−0.527, 1.15); Group 19 (−0.749, 1.11); Group 20 (−0.384, 1.52)	0.18	25.9
$Total^{-2}$ Land Use TI	Forested (−1.68, 0.563); TI (0.0246, 0.0785)	0.15	23.7
$Total^{-2}$ Land Use Elevation	Forested (−0.474, 0.512); Site elevation (−0.00234, 0.000521)	0.34	5.3
In + out^{-1} Land Use HLR	IS forested (0.0332, 2.26); OS forested (−2.77, 2.50); Group 3 (−2.30, 1.91); Group 9 (−0.454, 1.13); Group 16 (−0.202, 1.10); Group 19 (−0.514, 1.05); Group 20 (−0.0923, 1.45)	0.27	19.6

Table 4 continued

Model	Terms (Coefficient, SE)							R^2	ΔAIC
In + out^{-1} Land Use TI								0.33	10.2
	IS forested	OS forested	IS TI	OS TI					
	(1.51, 2.40)	(−4.56, 2.39)	(0.710, 0.386)	(−0.963, 0.409)					
In + out^{-1} Land Use Elevation								0.38	2.3
	IS forested,	OS forested,	Site elevation						
	(1.33, 1.78)	(−2.56, 1.82)	(−0.00200, 0.000574)						
In + out^{-2} Land Use HLR								0.26	20.7
	IS forested	OS forested	Group 3	Group 9	Group 16	Group 19	Group 20		
	(0.771, 1.07)	(−3.28, 1.37)	(−2.02, 1.91)	(−0.173, 1.13)	(−0.090, 1.11)	(−0.463, 1.06)	(−0.0930, 1.46)		
In + out^{-2} Land Use TI								0.31	12.8
	IS forested	OS forested	IS TI	OS TI					
	(−0.0385, 1.02)	(−3.50, 1.09)	(0.0980, 0.134)	(−0.483, 0.216)					
In + out^{-2} Land Use Elevation								0.38	2.2
	IS forested	OS forested	Site elevation						
	(0.960, 0.795)	(−2.03, 0.899)	(−0.00210, 0.000554)						
In*out^{-1} Land Use HLR								0.28	17.5
	IS*OS forested	Group 3	Group 9	Group 16	Group 19	Group 20			
	(−2.13, 0.660)	(−1.52, 1.81)	(−0.351, 1.10)	(−0.122, 1.09)	(−0.347, 1.05)	(0.124, 1.44)			
In*out^{-1} Land Use TI								0.29	10.1
	IS*OS forested	IS*OS TI							
	(−2.47, 0.639)	(−0.00997, 0.0112)							
In*out^{-1} Land Use Elevation								0.36	2.0
	IS*OS forested	Site elevation							
	(−0.987, 0.487)	(−0.00178, 0.000589)							
In*out^{-2} Land Use HLR								0.23	21.4
	IS*OS forested	Group 3	Group 9	Group 16	Group 19	Group 20			
	(−1.61, 0.633)	(−1.10, 1.85)	(−0.0418, 1.12)	(−0.220, 1.12)	(−0.431, 1.08)	(0.00824, 1.48)			
In*out^{-2} Land Use TI								0.28	11.8
	IS*OS forested	IS*OS TI							
	(−2.62, 0.566)	(−0.0176, 0.00947)							
In*out^{-2} Land Use Elevation								0.35	4.1
	IS*OS forested	Site elevation							
	(−0.677, 0.485)	(−0.00203, 0.000596)							

Note: AIC, akaike's information criterion; HLR, hydrologic landscape region; TI, topographic index; IS, in-stream; OS, out-of-stream nitrate; the best model was the %Land Use Elevation model.

Adding TI did not significantly ($\alpha = 0.05$) improve nitrate predictions and accounting for inverse-distance or inverse-distance squared did not improve the overall model results. A slight improvement was observed when just looking at forested land use and TI as independent variables; nitrate predictions improved from $R^2 = 0.29$ and $\Delta AIC = 10.6$ using area proportions to $R^2 = 0.33$ and $\Delta AIC = 10.2$ using in-stream and out-of-stream inverse-distance squared ($1/d^2$). Except for the In*Out^{-1} Land Use Elevation model, the additive models predicted nitrate better than the multiplicative models.

Site elevation was consistently a better predictor of nitrate than the other measures (i.e., %Land Use TI had an R^2 of 0.29 and ΔAIC of 10.6 compared to %Land Use Elevation, which had an R^2 of 0.38 and ΔAIC of 0.0) and significantly ($\alpha = 0.05$) improved nitrate models. Slope did not significantly improve nitrate models ($\alpha = 0.05$).

Chloride Modeling

Chloride modeling results using land use, HLR, TI, and site elevation are reported in Table 5. The partial-F test ($\alpha = 0.05$) indicated that the models were significantly improved with HLR. Combining HLR with land use improved the results compared to using just HLR or land use.

The partial-F test ($\alpha = 0.05$) showed that adding TI significantly improved the results. Site elevation also significantly improved ($\alpha = 0.05$) prediction of chloride. The inverse-distance (1/d) and inverse-distance squared ($1/d^2$) calculations slightly improved the model results; on average the ΔAIC values were lower compared to those in the proportional models. The model with the highest R^2 value (0.65) was the In*Out^{-2} Land Use HLR model. However, according to the ΔAIC values, the best model was the In*Out^{-1} Land Use Elevation model ($R^2 = 0.64$), which is likely due to the higher number of variables in the In*Out^{-2} Land Use HLR model.

Site elevation was consistently a better predictor of chloride than the other measures (i.e., %Land Use TI had an R^2 of 0.45 and ΔAIC of 30.9, compared to %Land Use Elevation, which had an R^2 of 0.61 and ΔAIC of 4.6).

From these results, it appears that TI, HLR, and site elevation are strong variables for predicting chloride. As site elevation increases, chloride concentrations gradually decrease (Fig. 4). Site elevation and mean elevation were found to produce very similar modeling results, because they are so closely related ($r = 0.952$). In this study, site elevation produced better model results, but either site elevation or mean elevation could be used in model simulations. Slope also significantly improved chloride models ($\alpha = 0.05$) but not as much as elevation (R^2 of 0.51, compared to 0.61 for the %Land Use Slope and %Land Use Elevation models, respectively).

Discussion

Why HLR Parameters Did Not Capture Low-Flow Nitrate

While the HLR parameters significantly improved the chloride predictions, they did not improve the nitrate predictions ($\alpha = 0.05$ significance level). The difference between the efficacy of the chloride and that of the nitrate models may be due to land class groupings; HLR groupings are based on land surface form, geologic texture, and climate in terms of percentage flatland, bedrock permeability class, percentage sand, and precipitation minus PET. In some cases, slope was used instead of percentage flatland. Correlations with slope, precipitation, soil, and geology were consistently lower for nitrate compared to chloride (Table 3), which coincides with the ability of HLR to improve chloride predictions but not nitrate. The higher correlation between chloride and slope indicates that chloride is more tightly coupled to the flow paths (water transport) of the catchment, and nitrate is possibly affected by additional processes. Soil type predicts the ease with which water is transported through soil, whether it is percentage sand or percentage Type D hydrosoil. Nitrate, which is often removed from the soil via plant uptake and microbial denitrification, is not transported with water as efficiently as chloride. Since these parameters were used to determine hydrologic settings, a better correlation with chloride (as a quasi-conservative tracer) appears more tightly linked to hydrological flow paths.

Land Use Controls on Low-Flow Nitrate

Relationships found in this study are similar to those found in other studies using percentage area of land use, with a negative correlation between forested area and nitrate (Norton and Fisher 2000; King and others 2005; Arheimer and Liden 2000; Herlihy and others 1998). The reason for the relatively poor nitrate model performance in this study could be the low-flow sampling conditions or the lack of variability in land use. Mixed results have been shown on the relative importance of wet versus dry sampling conditions. In contrast to Heisig (2000), who saw a significant relationship between nitrate concentrations and land use during low-flow conditions, Johnson and others (1997) saw no relationship between nitrate and land use during dry conditions but were able to produce a significant nitrate model for wet weather data using percentage agriculture. It

Table 5 Chloride modeling results

Model	Terms (Coefficient, SE)							R^2	ΔAIC
HLR								0.55	25.7
	Group 3	Group 9	Group 16	Group 19	Group 20				
	(−0.296, 0.541)	(0.367, 0.326)	(−0.365, 0.336)	(−0.670, 0.323)	(−1.05, 0.442)				
%Land Use								0.42	34.8
	Forested								
	(−1.25, 0.176)								
%Land Use HLR								0.59	20.5
	Forested	Group 3	Group 9	Group 16	Group 19	Group 20			
	(−0.653, 0.249)	(−0.848, 0.559)	(0.0812, 0.331)	(−0.319, 0.322)	(−0.611, 0.310)	(−0.961, 0.425)			
%Land Use TI								0.45	30.9
	Forested	TI							
	(−1.83, 0.314)	(−0.174, 0.0739)							
%Land Use Elevation								0.61	4.6
	Forested	Site elevation							
	(−0.518, 0.176)	(−0.00108, 0.000170)							
Total^{-1} Land Use HLR								0.63	14.6
	Forested	Group 3	Group 9	Group 16	Group 19	Group 20			
	(−0.817, 0.228)	(−0.975, 0.532)	(−0.00864, 0.318)	(−0.319, 0.309)	(−0.594, 0.297)	(−0.922, 0.408)			
Total^{-1} Land Use TI								0.51	22.1
	Forested	TI							
	(−1.87, 0.292)	(−0.177, 0.0723)							
Total^{-1} Land Use Elevation								0.63	1.7
	Forested	Site elevation							
	(−0.607, 0.177)	(−0.000990, 0.000180)							
Total^{-2} Land Use HLR								0.59	20.7
	Forested	Group 3	Group 9	Group 16	Group 19	Group 20			
	(−0.503, 0.195)	(−0.746, 0.548)	(0.160, 0.323)	(−0.419, 0.322)	(−0.658, 0.309)	(−1.00, 0.424)			
Total^{-2} Land Use TI								0.32	47.6
	Forested	TI							
	(−0.783, 0.208)	(0.0549, 0.0290)							
Total^{-2} Land Use Elevation								0.58	10.3
	Forested	Site elevation							
	(−0.282, 0.174)	(−0.00124, 0.000171)							
In + out^{-1} Land Use HLR								0.64	13.7
	IS forested	OS forested	Group 3	Group 9	Group 16	Group 19	Group 20		
	(−1.49, 0.629)	(0.782, 0.695)	(−0.867, 0.530)	(−0.0270, 0.314)	(−0.346, 0.305)	(−0.599, 0.293)	(−0.911, 0.402)		

Table 5 continued

Model	Terms (Coefficient, SE)							R^2	ΔAIC
In + out^{-1} Land Use TI								0.54	21.7
	IS forested	OS forested	IS TI,	OS TI					
	(−1.92, 0.818)	(0.0768, 0.812)	(−0.0141, 0.131)	(−0.186, 0.139)					
In + out^{-1} Land Use Elevation								0.63	3.1
	IS forested	OS forested	Site elevation						
	(−0.382, 0.566)	(−0.241, 0.576)	(−0.000981, 0.000185)						
In + out^{-2} Land Use HLR								0.64	14.0
	IS forested	OS forested	Group 3	Group 9	Group 16	Group 19	Group 20		
	(−0.499, 0.295)	(−0.341, 0.379)	(−0.981, 0.527)	(−0.00125, 0.311)	(−0.325, 0.307)	(−0.587, 0.294)	(−0.912, 0.403)		
In + out^{-2} Land Use TI								0.53	24.1
	IS forested	OS forested	IS TI,	OS TI					
	(−0.440, 0.345)	(−1.31, 0.368)	(0.0477, 0.0455)	(−0.191, 0.0732)					
In + out^{-2} Land Use Elevation								0.64	1.2
	IS forested	OS forested	Site elevation						
	(−0.0181, 0.249)	(−0.661, 0.281)	(−0.000994, 0.000176)						
In*out^{-1} Land Use HLR								0.64	12.4
	IS*OS forested	Group 3	Group 9	Group 16	Group 19	Group 20			
	(−0.723, 0.184)	(−0.805, 0.506)	(0.0148, 0.308)	(−0.265, 0.304)	(−0.527, 0.294)	(−0.848, 0.403)			
In*out^{-1} Land Use TI								0.58	11.3
	IS*OS forested	IS*OS TI							
	(−1.64, 0.202)	(−0.0115, 0.00354)							
In*out^{-1} Land Use Elevation								0.64	0.0
	IS*OS forested	Site elevation							
	(−0.573, 0.154)	(−0.000910, 0.000186)							
In*out^{-2} Land Use HLR								0.65	10.1
	IS*OS forested	Group 3	Group 9	Group 16	Group 19	Group 20			
	(−0.718, 0.169)	(−0.783, 0.495)	(0.0408, 0.300)	(−0.277, 0.299)	(−0.519, 0.289)	(−0.834, 0.397)			
In*out^{-2} Land Use TI								0.54	17.2
	IS*OS forested	IS*OS TI							
	(−1.40, 0.185)	(−0.00692, 0.00309)							
In*out^{-2} Land Use Elevation								0.64	0.4
	IS*OS forested	Site elevation							
	(−0.555, 0.152)	(−0.000919, 0.000186)							

Note: AIC, akaike's information criterion; HLR, hydrologic landscape region; TI, topographic index; IS, in-stream; OS, out-of-stream

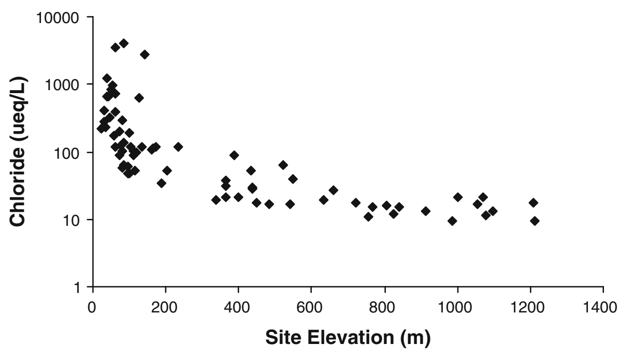

Fig. 4 Variation in chloride concentrations with site elevation

appears that watersheds and rivers are still hydrologically connected during dry conditions in some areas but not in others. Unless sampling is conducted during wet conditions, it is unknown whether or not a more significant model can be produced if wet-season data are used.

Poor model results could also be due to the lack of variability in land use. Studies have found that models created by watersheds dominated by forest land cover do not predict nitrate concentrations as well as watersheds in lowland areas where agriculture is more common and land cover is more diverse (Herlihy and others 1998). To determine whether or not we could improve the model results for western Oregon, the dataset was split into "valley" and "upland" datasets. The resulting models had a poorer performance than the models using the entire dataset (best R^2 of 0.18). Poor model performance when modeling valley and upland sites separately may be due to the narrow range of site elevations (21–170 and 109–1213 m for the valley and upland sites, respectively). Since site elevation explains the most variability in nitrate concentrations, a better model using site elevation was produced when using the entire dataset.

Chloride as a Tracer of Water

As a conservative tracer, chloride can help determine the effects of hydrology on nitrate. The movement of chloride is similar to the movement of nitrate, without the added microbial reactions and transformations that might occur in catchment positions with different degrees of saturation. Chloride is largely affected by the water cycle, which includes rainout/orographic effects, saturation conditions, and varying contributions of streamwater from different sources such as groundwater, soil water, and rainfall (flow paths). The topography of the study region in western Oregon is dominated by the Willamette Valley, which is bordered by a mountain range on the west side (often called the coast range) and the Cascade Range to the east side. Distance from sampling sites to the coast ranges from 23 to 180 km. Table 6 reports rainwater chloride deposition from three sites in western Oregon, which demonstrates the general decrease in chloride deposition with distance inland and increase with altitude (data from http://nadp.sws.uiuc.edu/nadpdata). A different trend is apparent in stream chloride concentrations with distance inland (Fig. 5). Chloride and distance from the coast were found to be highly correlated ($r = -0.714$). A general decrease in chloride with distance from the coast occurs, but there is a peak along the valley floor where most of the agricultural activity is concentrated. This is similar to findings from other studies, where elevated chloride concentrations in groundwater and streamwater in agricultural areas were observed (Pionke and Urban 1985; Smart and others 1998).

Table 6 Chloride rainfall concentration and deposition data from NADP sites in western Oregon

Site	Elevation (m)	Distance from coast (km)	Avg annual concentration (mg/L)	Avg annual wet deposition (kg/ha)
OR02	104	42.8	1.42	22.64
OR97	69	77.6	0.69	5.97
OR10	436	170.0	0.33	6.60

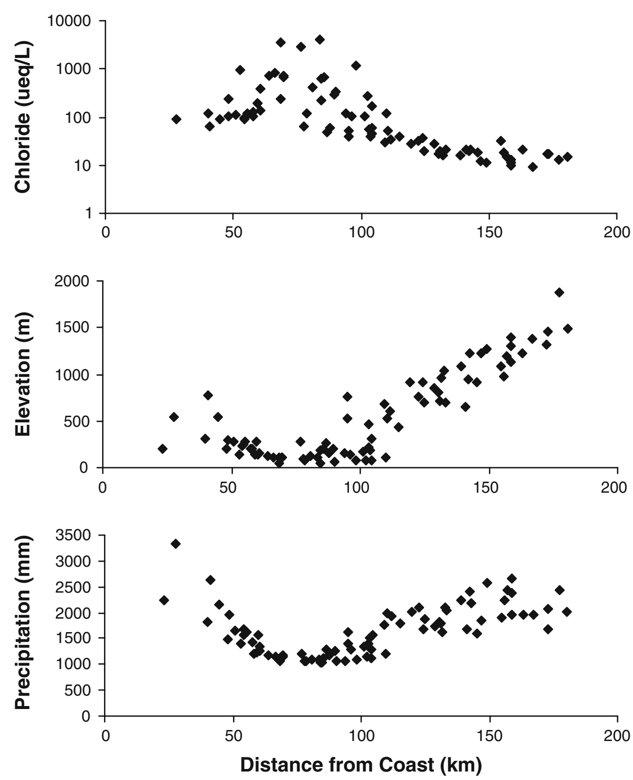

Fig. 5 Variation in chloride concentrations, elevation, and precipitation with distance from the coast

In the Willamette Valley, elevation increases over the coast range, decreases over the valley floor, and increases over the Cascade Range (Fig. 5). Elevation was found to be highly correlated with both chloride and distance from the coast ($r = -0.754$ and $r = 0.801$, respectively). Chloride was modeled using distance from the coast, and model results were about the same as with models using elevation. This same pattern was observed for precipitation (Fig. 5); precipitation amounts decreased with distance inland, with a minimum at the valley floor, then increased as it reached the Cascade Range (where elevation increases). The similarity between elevation and depositional patterns is likely a regional phenomenon due to the unique topography of western Oregon. The difference between stream chloride concentrations and chloride deposition/precipitation trends may be due to the agricultural land use in western Oregon.

This impact of agricultural land use on chloride concentrations may render chloride an inadequate tracer of water. Land use has been found to affect chloride concentrations in other studies (Herlihy and others 1998; Smart and others 1998). Chloride concentrations in groundwater beneath cropland have been found to be five to seven times higher than in forested areas (Pionke and Urban 1985), and watersheds dominated by agriculture have produced elevated concentrations of chloride (Smart and others 1998). Nonetheless, the significance of TI and inverse-distance weighting in the chloride models indicates that some of the catchment processes may be represented (water saturation or hot spots in terms of TI and flow paths in terms of inverse-distance).

Chloride, which is largely affected by the hydrology of the catchment, is predicted better with TI and HLR than nitrate. The ability to predict chloride concentrations better than nitrate concentrations using land use and site elevation, HLR, or TI is likely due to rainout/orographic effects and the quasi-conservative nature of chloride. The pattern of chloride deposition can be identified in stream chloride concentrations, which is likely the reason for successful predictions using site elevation (distance to the coast and site elevation were highly correlated). Although agriculture in the Willamette Valley affects the chloride pattern, the pattern of decreasing chloride concentrations with increasing distance to the coast is still discernible. Nitrate and distance to the coast were also found to be correlated, although the correlation is very similar to that between nitrate and chloride ($r = -0.474$ and $r = 0.473$, respectively). These correlations indicate that stream nitrate concentrations may be controlled somewhat by chloride deposition.

Due to the quasi-conservative nature of chloride, the chloride models also reflect the hydrologic setting (primary hydrologic flow paths in the case of HLR, saturated areas in the case of TI, and flow paths in the case of inverse-distance weighting) within the catchment, which likely affects nitrate concentrations as well. Transformation processes, such as denitrification, plant uptake, nitrogen fixation, and nitrification, also affect nitrate concentrations (Sylvia and others 1998). Chloride does not undergo these processes and is generally controlled by atmospheric deposition, anthropogenic inputs (i.e., fertilizer or irrigation in agricultural areas, sewage input in urban areas), and catchment hydrology. The decrease in ability to predict nitrate concentrations compared to chloride is likely due to these transformation processes affecting nitrate concentrations more than land use and catchment hydrology. An in-stream decay coefficient has been used in other models to account for transformation processes (e.g., Smith and others 1997), but we feel that adding a coefficient that needs to be measured in the field or borrowed from the literature would take away from the simplicity of the model.

Conclusion

Our statistical model development tested whether the classified HLRs aid in our ability to predict low-flow nitrate concentrations in watersheds. Comparison of chloride, a conservative tracer, and nitrate provided useful insights. Model results revealed the following.

1. Hydrologic landscape regions were moderately correlated with nitrate. Model results revealed that HLRs did not significantly improve nitrate predictions. This is likely due to the reactive nature of nitrate, which is affected more by transformation reactions than the hydrology of a catchment during low-flow conditions.
2. Site elevation was the most significant predictor of nitrate and chloride concentrations. The identification of hot spots with TI and in-stream, out-of-stream, and total inverse-distance calculations did not significantly improve nitrate predictions. Chloride was successfully predicted using land use and site elevation. Site elevation likely represents regional rainout/orographic effects due to the similarities between precipitation and elevation variations, which is more strongly linked to chloride than nitrate. Correlations between nitrate/chloride and nitrate/distance to the coast indicate that stream nitrate concentrations may be controlled somewhat by chloride deposition. More work needs to be done to determine the mechanism involved.
3. Stream chloride concentrations were elevated in agricultural areas in western Oregon, which differed from the observed rainout/orographic pattern of atmospheric chloride deposition. This may render chloride an inadequate tracer of water. Nonetheless, the use of HLR, TI, and inverse-distance weighting significantly

> improved chloride models, indicating that the hydrologic setting of the catchment (identification of primary hydrologic flow paths in the case of HLR, saturated areas in the case of TI, and flow paths in the case of inverse-distance weighting) is represented. Nitrate models were not significantly improved using HLR, TI, and inverse-distance weighting. Improved predictions of chloride compared to nitrate are likely due to the conservative nature of chloride, which creates a tighter link between chloride and the hydrology of the catchment.

This study has shown that nitrate traveling in the deeper groundwater (the source of streamwater during low flow) is not significantly affected by the identification of hot spots using TI. Hot spots at the interface between the groundwater and riparian water near the stream evidently do not significantly transform groundwater nitrate before it reaches the stream, or groundwater may bypass the riparian area altogether (so there is no interface for a hot spot). The saturated areas (and hot spots) that are formed from shallow flow paths during storm events may be better identified by TI than the hot spots at the interface between groundwater and riparian water. Alternatively, TI may not be adequately identifying these hot spots. TI does aid in the prediction of chloride, which indicates that TI is identifying saturation conditions within the catchment. More work, possibly with a different index and/or using TI to predict nitrate using storm samples, is needed. Hydrologic landscape regions, which identify areas of similar hydrologic settings where similar water quality characteristics may occur, may also be more suitable for predicting water quality parameters when the catchment is saturated or "wetting up" during storm events. Sampling during wet conditions will show whether or not HLR can improve predictions under different conditions. Although a regional classification system would have likely predicted nitrate concentrations better than the national system developed by Wolock and others (2004), we wanted to test the predictive power of the generalized HLRs. A simple, general watershed classification scheme that can accurately categorize and predict hydrologic responses will enable us to understand what mechanisms control the hydrology and water quality of a catchment and improve our ability to competently manage watersheds.

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