LOW IMPACT DEVELOPMENT POLICY ADOPTION IN MS4 PHASE I STORMWATER MANAGEMENT PROGRAMS WEST OF THE CONTINENTAL DIVIDE

Exit Project
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May 2014

SUMMARY

Low impact development is recognized as an effective means of controlling the impacts of urban stormwater. The majority of research on low impact development (LID) discusses its viability as a stormwater management technology or its challenges to its implementation, but little analysis has focused on its adoption as policy. This paper analyzes the LID policies for MS4 Phase I permittees west of the Continental divide. The analysis identifies significant differences for problem severity, climate, geographic, socioeconomic and political variables with respect to LID policy selection. Through multinomial logistic regression, this paper expands the analysis and explores the determinant effects the variables have on permittee LID policy choice. The results demonstrate that more stringent LID policy adoption arises in jurisdictions where climate influences higher levels of runoff levels. In addition, jurisdictions with higher education and higher income are more likely to have more stringent LID policies. These results suggest a higher willingness to pay for more increased regulation among jurisdictions with greater affluence.

INTRODUCTION

Urban stormwater is a major contributor to water quality degradation in streams in the United States. Low impact development (LID) is a new approach to addressing the effects of stormwater, but it requires on-site implementation, which increases the focus on stormwater management during the project planning process. This differs from conventional stormwater best management practices (BMPs), which may be designed later in the planning process because they do not require on-site implementation. To be effective, LID requires extensive re-writing of local guidance. Such guidance not only provides developers with design standards, but it also provides a means to quantify the level of treatment achieved through the use of LID. As a result, it is difficult and discouraging for project planners to use LID without robust local guidance. And, it is challenging for jurisdictions to increase LID implementation because it requires prioritization of stormwater management early in the project planning process.

Despite these challenges, LID has gained acceptance and support throughout the United States because it provides cost-effective results (US EPA 2007). Demonstrations and related research supported by the US EPA has encouraged and promoted LID. The growing literature suggesting that LID is effective as a stormwater treatment approach (USEPA 2000) has also contributed to its increased acceptance and adoption.

West of the continental divide, a region where all water flows toward the Pacific Ocean, nearly all of the Municipal Separate Stormwater Sewer System (MS4) permitting programs have added conditions requiring permittees to develop and implement policy relating to LID. The flexibility granted to permittees in their policy implementation approach for LID has resulted in many distinct policy approaches. But, the underlying characteristics of permittees, and how those characteristics have shaped different outcomes in LID policy selection are not clearly understood.

This analysis uses chi-square, and analysis of variance (ANOVA) to characterize how permittees differ between three categories of LID policy approaches based on *incorporating*, *preferring*, or *requiring* LID. To explain the role local characteristics have on LID policy selection, I use multinomial logistic regression to determine the effect variables have on permittees selecting either a *prefer LID* approach or a *require LID* approach with reference to an *incorporate LID* approach. I develop a preferred model incorporating only significant results for a selection of problem severity, climate, geographic, and socioeconomic variables.

The results of the analysis indicate problem severity and climate conditions play a large role in shaping the type of policy permittees select. Jurisdictions with higher regional quantities of impaired streams were more likely to opt for a less stringent approach. In addition, jurisdictions with higher income levels and educational attainment adopt more stringent regulation, which indicates not only a higher ability to pay but also a possibly higher willingness to pay for stronger environmental protection.

This analysis sets out to identify independent variables influencing choice in LID policy approaches for stormwater permittees west of the Continental Divide in the United States. This study (1) characterizes the current state of LID policy in the region, (2) identifies differences in characteristics based upon policy choice, and (3) develops a model describing how independent variables explain LID policy approach selection. I present the findings and discuss the results of the analysis and the predictive implications of the model. I conclude with a discussion of the implications this analysis has with regard to policymakers evaluating, promoting and implementing LID in the future.

LITERATURE REVIEW

POLICY FRAMEWORK

The EPA enacted the National Pollutant Discharge Elimination System (NPDES) program under the Clean Water Act in 1972 to regulate construction, industrial and municipal stormwater discharges draining directly or indirectly into surface waters (US EPA 1999). In 1990, the EPA required NPDES permits for medium to large metropolitan areas (100,000 or more). These individual permits, known as Municipal Separate Storm Sewer Systems (MS4) Phase I permits, required implementation of stormwater management programs to control the water quality impacts from urban runoff (US EPA 2001). The Phase I program now has approximately 750 individual MS4 Phase I permittees throughout the United States (US EPA 2013). Through implementation of its stormwater management program, each permittee is responsible for controlling the impacts of stormwater within water quality standards.

OVERVIEW OF URBAN STORMWATER IMPACTS

Urban stormwater has water quality impacts and water quantity impacts. These impacts are summarized as (1) those resulting generally in urban environments, and (2) those unique to specific regions of the country. Overall, this characterizes a need to address urban stormwater based on general management practices to address the overall impacts and unique management practices based on local and regional priorities.

Urban stormwater runoff contributes a number of effects arising from contamination of aquatic resources. Close proximity of impervious surfaces to streams increases the negative effects on stream water quality (Brabec 2002). Because of low water quality, stream ecosystems develop ecology lacking in biodiversity (Meyer et al 2005). High nutrient loads in urban stormwater runoff contribute to eutrophication of streams (Taylor et al 2004). Urban stormwater runoff from connected impervious surfaces is the constraining factor to success in urban and near-urban stream restoration (Walsh et al 2005). And, current restoration practices are ineffective because of the impacts of urbanization and impervious surfaces (Stranko et al 2012).

Urban stormwater also has several impacts to characteristics resulting from increased impervious surfaces in urban watersheds. Past research has demonstrated urbanization of watersheds increases peak flow rates (Leopold 1968) and runoff volumes (Hollis 1975). Bledsoe and Watson (2001) found that even low levels increases (10% to 20%) of impervious surfaces increase the likelihood of channel instability through higher discharge levels that increases erosivity. Urban catchments also contribute thermal impacts during warm weather months, which negatively affect cold-water environments, and conventional stormwater management practices are inconsistent in addressing these thermal impacts (Jones et al 2012).

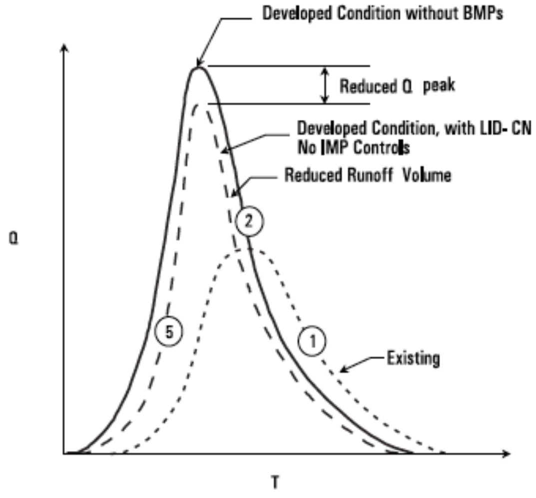
Regionally, urban stormwater in the northwestern United States affects aquatic species highly sensitive water quality degradation. In the Puget Sound region, researchers observed high percentages of Coho salmon suffered premature spawning mortality when returning to spawn in Seattle-area streams from 2002 to 2009. Evidence demonstrated the cause of mortality was the toxicity of urban stormwater runoff (Scholz et al 2012).

The higher intensity of runoff events in urbanized environments has unique effects in semi-arid climates of California and Arizona. In coastal California, stormwater runoff from the Santa Ana watershed is a significant source of near-shore pollution (Ahn 2005). The problem is compounded in southern California's semi-arid climate, where runoff events are more infrequent, allowing contamination to accumulate and concentrate, resulting in higher levels of contamination during runoff events (Noble et al 2003). Also in California, Hawley and Bledsoe (2011) found that semi-arid stream flow regimes have higher-level peak flows compared to those in humid climates, which indicates greater stream sensitivity resulting from development. In semi-arid environments in Arizona, the channels are highly modified and managed, and water limitation leads to soil desiccation, which increases its erodibility during runoff events (Gallo et al 2012).

LOW IMPACT DEVELOPMENT

To deal with the many aforementioned problems of stormwater, new approaches have been devised to reduce impacts of stormwater runoff and increase water quality. Low Impact Development (LID) was pioneered in the 1990s, providing an array of methods and techniques designed to reduce impervious surface impacts (US EPA 2000). A definition of LID with examples is included in Appendix A. LID methods allow on-site stormwater management of impacts resulting from increases in impervious surfaces.

FIGURE 1: EFFECT OF LID CONSTRUCTION ON POSTDEVELOPMENT HYDROGRAPH WITHOUT STORMWATER BMPS (US EPA 1999)



LID differs from conventional stormwater management techniques. LID includes Integrated Management Practices (IMPs) designed for on-lot implementation to eliminate the need for currently more conventional large-scale treatment (US EPA 1999). The LID approach to stormwater management aims to maintain pre-development on-site hydrologic functions (USEPA

1999). As a result, the use of LID reduces the factor of peak stormwater discharge for developed areas as shown in Figure 1 (USEPA 1999). The use of LID techniques in retrofitting developed sites has succeeded in improving hydrologic impacts as well (Ahiablame et al 2013).

LID Barriers to Policy Implementation

Though LID is an effective stormwater management strategy, it must overcome a number of technical challenges before integration into the existing stormwater management framework. The lack of an accurate reference model to give credit for LID site planning is a challenge for greater adoption of LID (Dietz et al 2007). Also, the design standards for LID techniques require refinement and analysis based on regional and site-specific characteristics (Gilroy et al 2009). These aspects form barriers to adoption of LID at the local level because of the effort required to rewrite stormwater guidance manuals, fee-rebate programs, and local ordinances.

The EPA categorizes stormwater runoff as non-point source pollution, and it treats stormwater as a watershed scale problem (US EPA 2007). Barriers to the success of watershed-scale urban stormwater management include: (1) improving understanding of its cost and benefit; (2) developing model ordinances and guidance based on maintaining hydrologic conditions; (3) integrating management across governments at a watershed scale; (4) educating professionals involved in stormwater; (5) improving support for regulations and ordinances; (6) developing fee-rebate approaches encouraging mitigation of runoff; and (7) educating the community through demonstration and outreach (Roy et al 2008). Because stormwater is a non-point source, watershed-scale problem, the same barriers of success are likely to apply to the implementation of LID as a stormwater management approach. As a result, addressing these seven aspects with regard to LID would greatly improve the success of its adoption and acceptance.

On-site development using LID is not necessarily cost-prohibitive. Implementation of LID may result in both a fiscally and environmentally effective means to manage stormwater runoff (US EPA

2007). Cost-benefit analysis conducted by USEPA across 17 development case studies indicated the majority of the developments implementing LID had more cost-effective outcomes when compared to conventional alternatives to stormwater treatment (US EPA 2007).

But, the adoption of LID policy may be influenced by other local or regional factors. For example, the increasing costs of infrastructure, ecological impacts and water shortages have influenced the adoption of localized water treatment and recycling in Australia (van Roon 2007). In the United States, the EPA has increased its support for LID by actively promoting it to state governments (USEPA 2013). But, the EPA has delegated NPDES permitting authority to State agencies for NPDES permits, including individual MS4 Phase I permitting. This has opened the door to the divergence of the NPDES State programs. As a result, any difference or divergence in permitting programs and resultant implementation of LID amongst MS4 Phase I permittees may also be influenced by other factors at the local or regional level.

DATA & METHODS

ANALYTIC APPROACH

This study explores and interprets the potential influences several independent variables have on the implementation of LID policy. The study analyzes LID policy approach selection, a categorical variable, in comparison to categorical variables and scale variables. I identified three categories of LID policy for the sample of permittees: *incorporate LID*, *prefer LID*, and *require LID*. Categorical variable analysis includes several approaches to identify differences and predict results. Baggett et al (2008) utilize ANOVA and Chi-square analysis to characterize differences in stakeholder opinion on water resource management (Baggett et al 2008). When comparing the policy groups, I used chi-square analysis and ANOVA to test the null hypotheses that policy groups are no different from one another with respect to the individual test variables.

For categorical-to-categorical variable analysis, this study tests performs chi-square analysis to test the null hypothesis that there is no distinction indicated between test variable categories (i.e. Coastal/non-coastal, County/Place) and the LID policy approach categories. The significance of Pearson's chi-square test determines whether one rejects a null hypothesis that the distribution between two categorical variables is indistinguishable (Wackerly et al 2008). The acceptance of each alternate hypothesis indicates there is a relationship between the tested categorical variables and the selected LID policy approach, that is, they are not independent of one another. For scale-to-categorical variable analysis, I use ANOVA to test the null hypotheses that the means of the scale variables are the same for the different categories of LID policy approaches. Significant results in ANOVA determine whether one rejects a null hypothesis that the means of scale variables are the same across groups in a categorical variable (Wackerly et al 2008). Acceptance of each alternate hypothesis indicates the means for the scale variables are different between LID policy approaches.

Multinomial Logistic Regression allows one to determine the predictive effects of independent variables on environmental policy outcomes. Daley (2008) used multinomial logistic regression to analyze independent variable in relation to State public participation procedures in hazardous waste programs (Daley 2008). Mahatma and Kant (2005) used ordinary least squares (OLS), binary logistic regression, and multinomial logistic regression models to identify linkages between a qualitative variable for deforestation levels and collection of independent variables. They developed a categorical variable to represent deforestation to address irregularities resulting from data source differences. The results demonstrate that multinomial logistic regression provided more stable results than the OLS model and clearer results than the binary logistic model (Mahapatr and Kant 2005).

I include each variable in the preliminary multinomial logistic regression model (stepwise entry) with the exception of highly correlated variables (e.g. population density is included, but population and area of land are not). The significance of the chi-square likelihood ratio (LR) indicates whether the variable's inclusion in the model would give different results or have no effect. The Wald test provides similar results to the LR test, but a significant result indicates the effects of the variable for each class of the dependent variable (Long 1997). Only, the variables having significant results for LR and Wald tests are in the preferred model. So, the final regression model only includes the variables having a significant effect on policy choice.

PRIMARY DATA: COMPLIANCE DOCUMENT VARIABLES

To develop the primary data, I obtained copies of Individual Phase I Permits through searching the NPDES State agency website for states with MS4s west of the Continental Divide. I selected this group of states because: they are hydologically linked on a regional level; they include conditions relating to LID for nearly all of permittees (96.7%); and, their stormwater permitting agency websites exhibited apparent differences in their discussion of LID and stormwater management priorities.

Each website and/or permit noted a list of permittees subject to the requirements of an individual NPDES MS4 Phase I permit. Permittees included state transportation agencies, regional agencies, counties, cities, towns, and institutional organizations. I compiled the list making up the most relevant permittees—the Counties, cities and places—to develop the sample group composed of 352 permittees. I omitted institutional organizations and State Transportation agencies because the focus of this study is on jurisdictional entities enacting policy affecting post-construction development and redevelopment of sites within MS4 boundaries.

After tabulating a complete list of permittees, I searched each State and permittee website to obtain the permittee's plan to comply with the permit. In most cases the permittee's compliance plan is the Stormwater Management Plan (SWMP). All MS4 Phase I permittees developed a SWMP during the first permit term. The SWMP is the plan outlining how the permittee(s) implement a stormwater management program (US EPA 2010). However, in other cases the compliance plan is incorporated into the permit itself or in additional documents other than a SWMP. The resultant divergence of compliance documents may have resulted due to delegation of permitting authority to States. In particular, some of the permits in California use alternate documents to provide the same content of a SWMP, but these documents have additional compliance requirements relating to other facets of the overall water quality program.

The SWMP or other compliance document generally indicates the approach the permittee will undertake during the permit term to meet the permit requirements. In many cases, one document was shared amongst dischargers falling under the same permit. I evaluated each SWMP or other compliance document to tabulate the status of the permittee(s)' LID policy as either: *omission* (0), *development* (1) or *implementation* (2). Permittees having no LID or related policies were categorized as omission. Permittees in any phase of policy evaluation or development were categorized as *development*. This included permittees evaluating LID policies, developing guidance, or having completed draft guidance. Permittees having adopted policy were placed in the implementation category.

Table 1: Frequencies of LID Policy Status

	Frequency	Percent
Development	194	55.1
Implementation	136	38.6
Omitted or missing	22	6.3

N=352

Table 2: Frequencies of LID Policy Approach

	Frequency	Percent
Incorporate	46	13.1
Prefer	20	5.7
Require	264	75.0
Omitted or missing	22	6.3

N=352

Next, I tabulated the permittee(s)' LID policy approach as either: *omit* (0), *incorporate* (1), *prefer* (2), or *require* (3). The 14 missing permittees were dropped from the sample. Values for the 8 permittees not indicating any LID policy in their SWMP or other compliance document were coded as omit (0). The permittees not indicating a LID policy are the same as those labeled *omit* in the aforementioned implementation status variable. These permittees not indicating a LID policy were later dropped from the sample to maintain an adequate sample count for analysis.

The differences in the *incorporate*, *prefer* and *require* LID policy approaches are diverse, but I categorized them by overall characteristics of the language used in the permit compliance document. Examples of sample language are provided in Appendix A. The *incorporate LID policy* approach amends the existing stormwater management approach. Incorporation approaches were characterized as the addition of LID BMPs alongside other BMPs. This approach expands the menu of BMPs but does not provide preference to or requirements for implementation of those BMPs. A LID *preference approach* provides developers with options to implement LID BMPs and encourages their implementation through mechanisms such as expedited review, fees, incentives, or quotas. A *preference approach* would include the requirement that developers evaluate LID during plan development, but leave implementation solely up to the developer. Incentives included adding higher fees to the use of conventional approaches or providing higher credits to developers implementing LID instead of other approaches. A quota would require developers to implement a small number of LID BMPs based on development type but allow for more general BMP selection for development. The LID *requirement approach* involves a mandate to implement LID as the principal approach to stormwater management. The *requirement approach* mandates the use of LID planning and/or BMP implementation when practicable before considering the use of non-LID structural or non-structural BMPs. Often language would indicate that LID must be implemented to the maximum extent possible (MEP).

Table 3: Frequencies of Compliance Document Year

	Frequency	Percent	# removed from sample
1998	1	.3	1
2003	1	.3	1
2006	1	.3	0
2007	2	.6	0
2008	4	1.1	3
2009	8	2.3	0
2010	12	3.4	0
2011	27	7.7	1
2012	54	15.3	0
2013	153	43.5	0
2014	75	21.3	2
Missing	14	4.0	14
N = 352,	n = 330		

I also tabulated the year the permit compliance document was published. Several documents not indicating a LID policy were removed from the sample. These are the same 8 permittees that omit LID from the document. The compliance document year variable is not included in the regression analysis, but it is included as a variable in the selection of LID policy in the alternate models in Appendix E. I expect that if a compliance document is more recent, then the selected LID policy will be more stringent.

SECONDARY DATA[1]

PROBLEM SEVERITY

Research by Daley and Garand (2005) indicates that states are more to develop policy when they are responding to an identified problem. With the input of states, the US EPA publishes a list of impaired and threatened waters under Section 303(d) of the Clean Water Act. The impaired and threatened waters list is used to link water quality goals to NPDES permit requirements (EPA 2012). One caveat arising from the use of this dataset is that the methods for collecting data on impaired streams and designating Total Maximum Daily Loads (TMDL) varies from state-to-state, which leads to different listings of the cause of impairment. For this reason, the data for this variable is aggregated by watershed sub-region and all impairments are aggregated regardless of identified source. This provides a broad summary of the problem, which includes urbanized stormwater and other impacts to water quality. I expected jurisdictions to select a *prefer LID* or *require LID* approach where there are increases in problem severity. That is, jurisdictions would choose a more stringent policy because of greater pollution levels.

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[1] I used ArcGIS to link secondary datasets to the primary data in SPSS. Geoprocessing techniques are described in greater depth in Appendix C.

CLIMATE

I include climate variables because the literature indicates different stormwater impacts by climate (Scholz et al 2012, Noble et al 2012, Hawley and Bledsoe 2011, Gallo et al 2012) are likely to influence how permittees choose stormwater management policy. I obtained mean precipitation and mean high temperature values from the National Weather Service (NWS) of the National Ocean and Atmospheric Administration (NOAA). The precipitation and temperature variables convey fundamental and general aspects of the hydrologic cycle, which would impact a permittee's choice to select LID policies. The abundance or shortage of runoff events from precipitation along with high temperatures may influence the policy selection. I expect jurisdictions with wetter and cooler climates to adopt stronger policies than the *incorporate LID policy* approach because higher magnitude and more frequent runoff events increase the mobilization of pollution deposited on impervious surfaces.

GEOGRAPHIC

Coastal environments provide a multitude of social and economic opportunities, which may be negatively impacted by poor water quality. The data indicates that a large segment (75.9%) of the permittees are located within coastal sub-region basins. The U.S. Department of Agriculture's (USDA) National Resource Conservation Service (NRCS) provided the Watershed Boundary Dataset. I identified sub-region basins as major geographical features with shared geographic characteristics relative, such as bounding by the ocean or mountain ranges. Among these sub-regions, I identified coastal sub-regions as the final watersheds before contributing flows into coastal waters. A coastal basin collects and aggregates polluted runoff from upstream watersheds before discharging into the ocean. One can expect a more stringent LID policy approach amongst coastal watersheds because the levels of water pollutants increase due to upstream aggregation.

A municipal discharger's jurisdiction type also may have a relationship with permittee LID policy approach selection. Counties (9.1%), and cities/towns (90.9%) compose the sample. All of the towns and cities in the sample are incorporated; they are each responsible for discharges within their own jurisdictions. On the other hand, counties are responsible for areas outside of incorporated boundaries, which also contribute to the stormwater runoff of the MS4. These jurisdictional distinctions would likely lead to differences in LID policy selection. One issue that is of concern is that there are differences in the amount of authority and responsibility counties have for management of stormwater. These differences were not always clear through review of stormwater documents. To compensate for this issue, I include population density in the analysis. However, I expect that counties, which typically have lower density than cities or towns, would have a less stringent level of LID policy selection.

I calculuated population density by dividing estimated population (Census 2012) by the jurisdiction's land area in square miles (Census TIGER 2010). Areas with higher density were more likely to have greater levels of environmental degradation because a jurisdiction's source of stormwater pollution is its population, and the increase in impervious land cover results from increased density of development. I expected an increased likelihood for permittees to select more stringent approaches where population density is higher.

SOCIOECONOMIC

The 2012 American Community Survey is the source for the variables: estimated population, median household income, percent living below the poverty line, percent high school education or greater, percent college education or greater and home ownership. Population for counties includes the incorporated and unincorporated portions[2]. These variables would potentially indicate the demand for LID policy resulting from the social and economic characteristics of the population. Many of these variables are highly correlated with one another. For example, median

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[2] Population and population density values may be estimated to include only unincorporated populations and it was considered. However, the role counties play in stormwater management is in many cases the primary role of responsibility. In some cases, a permit may designate a county as the principal permittee, and a principal permittee has differing responsibilities. In other cases, cities defer stormwater policy entirely to a county. Examples of this are Clean Water Services in Washington County, Oregon.

household income was highly correlated with college education (.778). So, only one or two of the socioeconomic variables are included in the regression. I link the variables in socioeconomic results of the preferred regression model. Permittees requiring LID were expected to have higher household incomes and education levels. These higher income levels and education levels likely translate to a higher demand for stronger environmental regulation. Areas where poverty and education attainment is low are likely to have weaker controls for environmental regulation.

POLITICAL

To characterize the political makeup of the jurisdictions, I used from the results of the 2010 Congressional Election for all the States (Federal Electoral Commission 2010). These results provided both the percent of people voting Democrat or Republican within the congressional district. This characterizes the overall political environment within the region at the district scale. A jurisdictional scale would have been more appropriate, however, election results at that scale were not available. One would expect that the effect of greater percentages of people voting Democrat to lead to selecting higher regulation in LID policy than those with greater percentages of people voting Republican.

Table 4: Secondary data source variables with description, source, and expected relationship to LID policy

Variable by type	Description	Source	Expected Sign
Problem Severity			
# TMDL by HUC4	Number of TMDLs within sub-region (HUC4)	US EPA 2013	+
# Impaired by HUC4	Number of 303(d) within sub-region (HUC4)	US EPA 2013	+
Climate			
Precipitation	Mean annual precipitation	NOAA 2010	+
Temperature	Mean annual high temperature	NOAA 2010	-
Geographic			
Coastal Watershed	Coastal subregion (HUC4)	NRCS 2014	+
Place/County	Census TIGER County and Place	U.S. Census Bureau 2010	-
Land Area	Census TIGER polygon land area	U.S. Census Bureau 2010	-
Water Area	Census TIGER polygon water area	U.S. Census Bureau 2010	+
Socioeconomic			
Population	Estimated Population	U.S. Census Bureau 2012	+
Population Density	Population per square mile	U.S. Census Bureau 2010, 2012	+
Median Household Income	Estimated median household Income	U.S. Census Bureau 2012	+
% Poverty	Percent below the poverty line	U.S. Census Bureau 2012	-
% Own	Percent of household ownership	U.S. Census Bureau 2012	+
% High School	Percent with a high school diploma or greater	U.S. Census Bureau 2012	+
% College	Percent college or greater	U.S. Census Bureau 2012	+
Political			
% Voting Democrat	Percent voting Democrat in 2010 Congressional election by district	Federal Electoral Commission 2010	+
% Voting Republican	Percent voting Republican in 2010 Congressional election by district	Federal Electoral Commission 2010	-

Table 5: Descriptive statistics for variables tested for relationships with choice in LID policy approach

	Minimum	Maximum	Mean	Std. Deviation
Compliance Document				
LID policy status	0	1	.41	.493
Policy year	1998	2014	2012.51	1.669
Problem Severity				
Total TMDL by Watershed (HUC4)	0	31178	816.99	2350.979
Total Impaired by Watershed (HUC4)	262	119441	8520.89	8947.789
Climate				
Mean Annual Precipitation	3.05	113.73	19.1632	11.22517
Mean Annual High Temperature	53	88	72.38	6.220
Geographic				
Coastal Watershed	0	1	.76	.429
County	0	1	.09	.288
Area of Land (sq mi)	.07	20056.94	324.3367	1536.39081
Area of Water (sq mi)	.00	693.06	13.0016	55.10088
Population Density	12	23326	4600.84	3686.223
Socioeconomic				
Population	59	9840024	228756.60	695806.382
Median Household Income	0	231898	74410.89	32919.029
Percent below poverty line	.0100	.3060	.118108	.0640602
Percent own	.0370	.9810	.616838	.1514053
Percent HS or greater	.3890	.9970	.849239	.1215241
Percent College or greater	.0390	.8420	.351065	.1863849
Political				
Percent Voting Democrat	.00	.86	.5200	.17319
Percent Voting Republican	.00	1.00	.4465	.17004

N = 352

RESULTS

CHI-SQUARE ANALYSIS

Chi-square analysis tested the null hypothesis that cross-tabulated variable groups, the test variable and the LID policy approach variable, were indistinct. The null hypothesis is rejected for all of the test variables. However, the LID Policy Status, and Coastal variables did not have expected cell counts over five (5) for all cells, which violates the sample requirements for chi-square. This increased the potential for errors in the subsequent regression model testing, so these variables were not included in the regression. All of the variables met the critical value test, $\chi^2_{2DF} = 5.99$, $p < .05$) or $\chi^2_{8DF} = 15.51$, $p < .05$), which indicates a significant relationship between groups.

LID POLICY DOCUMENT CHARACTERISTICS

There is a significant relationship between LID Policy Status and LID policy approach, χ^2 (2, N = 330) = 18.18, p <.001). The association between the LID Policy Status and the selected LID Policy is small (Φ=.235). The LID policy status variable is not included in the preferred model regression analysis. It is included within the alternate model.

GEOGRAPHIC

The jurisdictions by type, city/town versus county, differed by their selected LID policy approach, χ^2 (2, N = 330) = 14.396, p <.001. The strength of the association between the jurisdiction type and the LID policy approach is small (Φ=.235). Jurisdiction type has a significant relationship with selected policy approach. The results suggest counties are more likely to select an *incorporate* or *prefer LID policy* approach rather than a *require LID policy* approach. But, this variable is excluded from the regression analysis, because it lacks adequate cell counts to ensure validity. The variable is included in the alternate model.

The coastal/non-coastal permittee differed by their selected LID policy approach, χ^2 (2, N = 330) = 178.387, p =.000. The strength of the association between Coastal subregion is high (Φ=.735). The results suggest permittees in non-coastal sub-regions are more likely to select an *incorporate LID* *policy* approach. As mentioned before, the coastal/non-coastal variable did not have an adequate expected cell count to ensure the validity of the chi-square analysis, and it is excluded from the preferred model of regression analysis. It is included in the alternate model in Appendix E.

Table 5: Chi-square results

	Incorporate	Prefer	Require	Total	DF	χ^2	Φ
Compliance Document							
LID Policy Status							
Development	37 (1.9)	17 (1.5)	140 (-1.2)	194	2	18.18***	.235
Implementation	9 (-2.3)	3 (-1.8)	124 (1.5)	136			
Geographic							
Coastal Sub-Region							
Non-Coastal	31 (7.5)	19 (7.8)	13 (-5.3)	63	2	178.39***	.735
Coastal	15 (-3.6)	1(-3.8)	251(-2.6)	267			
Jurisdiction Type							
City/Town	38 (-0.6)	15 (-0.8)	249 (0.5)	302	2	14.40**	.209
County	8 (2.1)	5 (2.5)	15 (-1.6)	28			

* p < .05. ** p < .01. *** p < .001

ONE-WAY ANALYSIS OF VARIANCE

One-way ANOVA of scale variables and their relationship to LID Policy Approach tested the null hypothesis that the means of the scale variables were the same across the categories of the LID policy approach variable. ANOVA indicated that the problem severity, climate, geographic, and socioeconomic variables exceeded the critical value for the F-test statistic ($F_{crit}(2,327) = 3.02$, $p < .05$). However, the political variables failed to meet the critical value test.

COMPLIANCE DOCUMENT

The year the compliance document was published has a significant relationship with the selected LID policy approach, $F(2,327) = 48.878$, $p < .001$. The strength of the relationship between the selected LID policy and the compliance document is moderate ($\eta^2 = .230$). Comparing the means indicates that the most recent documents written in (2012-2013) have permittees selecting a r*equire LID policy* approach. This suggests that some unknown factor has triggered this increase in requiring LID. Such factors could be a local or state mandate to meet new standards. The year of the compliance document is eliminated from the preferred model. But, it is included as a control variable in an alternate model in Appendix E.

PROBLEM SEVERITY

The quantity of impaired sites within a sub-basin has a significant relationship with policy choice $F(2,327) = 5.542$, $p <.01$. The number of sites designated a TMDL within a sub-basin also has a significant relationship with policy choice ($F(2,327) = 5.531$, $p <.01$). The scale of the relationship LID policy selection has on impaired ($\eta^2= .033$) and TMDL sites ($\eta^2 = .023$) within a watershed is small. Results of ANOVA for the problem severity variables suggest the selected LID policy's relationship with pollution in streams is not profound. The analysis only includes impaired sites variable in the regression analysis because of the effects of multicollinearity.

CLIMATE

The climate variables of mean annual precipitation ($F(2, 327) = 72.299$, $p < .001$) and mean annual high temperature ($F(2, 327) = 57.862$, $p < .001$) have a significant relationship with policy choice. The results indicate a greater relationship between LID policy selection and the dependent variables, precipitation ($\eta^2 =.307$) and temperature ($\eta^2 =.261$). Through comparing the means of groups, one can see the group of permittees adopting an *incorporate LID policy* approach has a higher temperature mean along with a lower precipitation mean. Overall, this demonstrates that the selected LID policy type is different by climate type. The suggested possibility that both climate variables are the strongest variables affecting LID policy selection in comparison to the other variables is investigated further in the regression analysis.

GEOGRAPHIC

The effects of geography are mixed. The results indicate a failure to reject the null hypothesis that the area of water ($F(2, 327) = .543$, ns) is different by LID policy approach. The results for area of land ($F(2, 327) = 3.872$, $p < .05$) indicate that the LID Policy selection groups are significantly different in their areas. But, the size of relationship between LID policy and the area of land variable is small ($\eta^2 = .023$). Population density has a significant relationship with LID policy approach selection ($F(2, 327) = 6.91$, $p < .001$). The strength of population density's relationship with LID policy choice is small (η^2 =.067). Area of land is highly correlated with population density, so it is not included individually in the regression analysis.

SOCIOECONOMIC

ANOVA results for population (F(2, 327) = .323, ns) and home ownership (F(2, 327) = .469, ns) failed to reject the null hypothesis. So, population was not determined to be an indicator of LID policy choice. The percentage of people owning homes also was not different by LID policy approach selection.

On the other hand, median household income (F(2, 327) = 11.857, $p < .001$) and the percent of people living below the poverty line (F(2, 327) = 13.1, $p < .001$) indicated significant differences between the LID policy selection groups. The strength of the relationship is weak between LID policy and the income variables, household income variable (η^2 =.067) the poverty variable (η^2 =.074). The two variables are based on the same data, leading to high correlation between variables; median household income is the only income variable included in the regression analysis. But, the percentage of people living below the poverty line suggests an inverse relationship with more stringent LID policy selection, while household income suggests a positive relationship with more stringent policy selection.

Permittee's educational attainment percentages of at least a high school level (F(2, 327) = 7.656, $p < .001$) and at least a college level (F(2, 327) = 10.344, $p < .001$) indicate a significant difference with respect to LID policy selection. The strength of the relationship is weak between LID policy selection and the education attainment variables, high school (η^2 =.045) and college (η^2 =.059). The differences in means suggest that people with higher levels of education will select more stringent policy approaches other than the incorporate approach.

POLITICAL

The results for the political variables, percent voting Democrat and percent voting Republican in the 2010 congressional election, indicate a failure to reject the null hypothesis. The failure to reject the hypothesis suggests that political voting behavior is not different across the groups. But, the selected data does not allow one to accept the null hypothesis that the groups are the same. Regardless, the data is tested in the regression even though it fails the ANOVA test.

Table 6: Means, Standard Deviations and One-way ANOVA Results for LID Policy Approach and Scale Variables

	Incorporate		Prefer		Require			
	M	SD	M	SD	M	SD	F(2, 327)	η^2
Compliance Document								
Year document published	2011.65	1.494	2010.85	1.814	2012.92	1.018	48.878***	.230
Problem Severity								
# TMDL by Watershed	1933.	6394.	772.	311.	669.	181.	5.542**	.033
# Impaired by Watershed	10315.	23883.	2736.	1763.	9169.	1356.	5.431**	.032
Climate								
Precipitation	14.65	12.22	43.23	22.32	18.13	6.97	72.299***	.307
Temperature	76.98	8.43	61.95	2.33	72.85	4.63	57.862***	.261
Geographic								
Area of Land (sq mi)	852.78	2188.11	325.76	631.54	195.42	1368.21	3.872*	.023
Area of Water (sq mi)	20.98	55.47	9.04	24.90	12.04	58.42	.543	.004
Population Density	3527	3729	2633	1447	5079	3777	6.906***	.041
Socioeconomic								
Population	307398	479147	201473	256605	217784	769885	.323	.002
Median HHI	56264	15570	62657	19189	79691	35217	11.857***	.068
% below poverty line	.1580	.0608	.1219	.0601	.1086	.0606	13.1***	.074
% own	.6044	.1173	.6431	.1287	.6130	.1576	.469	.003
% HS or greater	.7992	.1252	.9230	.0380	.8510	.8481	7.656***	.045
% College or greater	.2416	.1126	.3645	.1272	.3753	.1971	10.344***	.059
Political								
% Voting Democrat	.5030	.1494	.5261	.1529	.5407	.1651	1.086	.007
%Voting Republican	.4563	.1423	.4322	.1521	.4280	.1618	.626	.004

* $p < .05$. ** $p < .01$. *** $p < .001$

MULTINOMIAL LOGISTIC REGRESSION

Several models were tested before choosing a preferred model. The final model eliminated highly correlated variables to control for multicollinearity. Variables were also removed step-wise based on their failure to meet the likelihood ratio test with significant at a 95% confidence interval. Unselected models may be referenced in Appendix E. For brevity, I report the direction of the variable's effect on LID policy selection, and the strength of the relationships indicated by the Wald test.

The multinomial logistic regression model is a nonlinear model, which allows for analysis of categorical variables. One interprets its results in relation to a base category omitted from the analysis (Long 1997). This analysis uses the *incorporate LID policy* approach as the base category for the model. The *incorporate LID policy* approach is the least stringent LID policy option, that is, it is the easiest manner to include LID BMPs without major revision of existing stormwater management approaches.

Overall, the final model's goodness of fit had a high level of significance, which indicates the model has more predictive power than an empty model, $\chi2$ (12, N =330) = 158.00, $p < .001$). The LR tests indicated all the variables in the preferred model were significant at the 99% confidence interval ($p < .01$).

PROBLEM SEVERITY

No significant effect could be found between problem severity, the number of impaired streams, and the *require LID policy* approach. On the other hand, problem severity had a significant negative effect on the selection of a *prefer LID* approach. This pattern appears counter to the expected effect that increases in problem severity would be the impetus to adopt more developed environmental policy. The results indicate that permittees choosing an incorporate approach would adopt a preference LID approach if the impaired waters were at lower levels. This indicates hesitance to adopt more stringent policy because impaired waters are a major hurdle to adopting a more stringent policy. For example, the higher cost of managing more impaired waters may be prohibitive to permittees.

CLIMATE

Climate had a significant effect on for permittee selection of both the *prefer* and *require LID policy* alternatives. Precipitation and temperature were integrated into the model as one interaction variable (precipitation*temperature) because of their strong linkage in the hydrologic cycle. The climate variable had significant effects on LID policy approach selection. The results suggest that positive changes in the climate interaction increase the likelihood to select a more stringent LID policy than the *incorporate LID policy*. In particular, a lower value for mean high temperature, and a higher value for mean annual precipitation had a significant effect on choosing either more stringent alternative.

GEOGRAPHIC

Area of water was not a significant variable identified in the previous ANOVA analysis. However, the regression model indicates decreased water areas increase the selection of a *prefer LID policy* approach. Area of water was highly correlated with Counties (.646). One possible explanation is that, smaller, urbanized jurisdictions may require more stringent requirements because they contribute more impacts from impervious surface runoff in relation to their proportion of area of water.

Higher density jurisdictions are significantly more likely to adopt a *require LID policy* alternative. Also, population density and the county jurisdiction variables were strongly negatively correlated (-.314). So, high-density jurisdictions were more likely to select more stringent policy. Explanations for this are twofold. The first is that high density is an indirect indicator of problem severity, which increases the need to strongly regulate the impacts of stormwater.

Another explanation indicates the high-density jurisdictions have different outcomes based on the characteristics of the stakeholders within the region. For example, there is a strong negative correlation between population density and other socioeconomic indicators, such as household income, high school and college educational attainment, and home ownership. Residents with the financial means and higher education levels inhabit jurisdictions where environmental degradation is lower and environmental regulation is more stringent. This population is the most able to migrate from the region, so one may infer that the population has a higher willingness to pay for more stringent regulation.

SOCIOECONOMIC

Household Income showed a significant positive effect on the selection of a *require LID policy* approach. A change in income did not have a significant relationship with selection of a *prefer LID policy* approach. Approaches requiring LID are more likely to have a higher need to modify existing stormwater management approaches to reflect the primacy of LID project planning and BMP selection. Because requiring LID requires a major shift in stormwater management approach, a higher amount of economic resources is necessary to implement modifications to existing guidance. Banzhaf and Walsh (2008) demonstrate that community migration is environmentally motivated with increased demand for communities with improved air quality. And, the migration resulted in a demographic shift between higher-income versus lower-income households (Banzhaf and Walsh 2008). So, mean household income is an indicator of the overall ability for permittees to pay to make the major changes needed to require LID, but it also suggests a higher willingness to pay, which may be demonstrated by migration of high-income residents to jurisdictions where stormwater policy is more rigidly regulated and also where there are fewer levels of environmental impacts.

Attainment of a college education level was not included in the regression analysis because it was expected that college education attainment would not improve the model because it is highly correlated with income (.778). On the other hand, attainment of a high-school education level resulted in a higher likelihood to select a *prefer LID policy* approach even when controlling for the effects of income. This also suggests that any greater level of education attainment, high school or college, within jurisdictions translates to a greater willingness to pay for more stringent regulation.

POLITICAL

The political variables were not included in the preferred model. They did not meet the LR test requirements of the preferred model. So, the inclusion of these variables would have no effect in comparison to a model that did not include the variables. The selected variable may not adequately characterize the effect politics has on the dependent variable. There may be a large difference between district-wide voting and local jurisdiction voting patterns. Addressing this issue through the use of data providing voting behavior by jurisdiction would provide a more reliable result.

Table 7: Multinomial logistic regression results (stepwise model)

	β	SE	Exp(β)	Wald
Incorporate/Prefer				
Intercept	-29.6262	9.86747		9.014**
Problem Severity				
Count of 303(d) by HUC4	-.000422	.00012	1	11.857***
Climate				
Precipitation*Temperature	.002452	.00062	1.002	15.817***
Geographic				
Area of Water	-.046273	.02323	.955	3.966*
Population Density	.000021	.00023	1.000	.009
Socioeconomic				
Household Income	-.000010	.00002	1.000	.235
Percent High School	.318	11.23877	1.375	8.012**
Incorporate/Require				
Intercept	-3.562	1.514		5.536*
Problem Severity				
Count of 303(d) by HUC4	-.000027	.00001	1.000	3.380
Climate				
Precipitation*Temperature	.001004	.00044	1.001	5.158 *
Geographic				
Area of Water	-.000855	.00254	.999	.114
Population Density	.000196	.00006	1.000	9.810**
Socioeconomic				
Household Income	.000048	.00001	1.000	14.097***
Percent High School	.004	1.9657	1.004	.047

Pseudo R^2: .398 (Cox and Snell), .558(Nagelkerke), .407 (McFadden). LR χ2 = 158.000***.
* p < .05. ** p < .01. *** p < .001.

CONCLUSION

This analysis examined the differences of jurisdictions making LID policy and how those differences lead to different policy approach outcomes using alternative mechanisms for implementation of LID standards. The analysis showed which factors have a relationship with LID policy choice and how those factors influence policy choice. The negative relationship between problem severity and selection of a more rigorous policy alternative was unexpected, but it suggests that greater problem severity leads to other potential drivers of reluctance to adopt more stringent LID policy not included in this analysis, such as the number of point-source polluters along with the number of industrial firms within jurisdictions. Additional research focusing on the effect commercial interests have on development and implementation of LID policy may help explain why areas with higher pollution have less rigorous LID stormwater regulation. Additional analysis including migration patterns between jurisdictions and growth rates would validate the implication that people choose to settle according to their regulatory preferences—in particular, people with higher incomes migrate from regions of weak environmental policy to stronger environmental policy.

Jurisdictions selecting a *prefer LID* policy approach had comparatively higher levels of high school attainment than the *incorporate LID* reference group. This also demonstrates that even while controlling for income levels, high school education attainment influences jurisdictions to select more stringent policy. This suggests that a jurisdiction having higher education attainment level may provide policymakers with greater opportunities to engage the public on stronger regulation. So, an educated population, whether they have higher median incomes or not, leads to greater support and success in implementing more stringent regulation.

Either policy alternative increases regulation in comparison to the *incorporate LID* approach. The regression model indicates that arid climate and lower problem severity have the largest effect on a jurisdiction's selection of a *prefer LID* policy approach. On the other hand, income and population density were the dominant influences for jurisdictions selecting a *require LID* policy approach. The differences of these overall effects are of particular value to policymakers because the first phase of MS4 permittees have laid the groundwork for implementation of LID. So, the relationships identified in this analysis provide a valuable reference point for those developing guidance in the future such as Phase I permittees in the early stages of policy development and the Phase II permittees recently subject to general permit conditions requiring LID policy. The information in this study provides a backdrop of several influencing factors affecting other jurisdictions in their LID policy approach selection. As a result, this analysis provides value as a reference to facilitate discussions on LID policy approach alternatives.

Public interest organizations and agencies conducting outreach in support of LID would also stand to benefit from the results of this analysis. The results provide a snapshot of what LID policies are more likely based on jurisdictional characteristics. This information herein may serve as a facilitation tool for approaching discussions with stakeholders to enhance acceptance of LID policies. Consequently, one could increase the acceptance and adoption of LID by suggesting policy approaches having a greater likelihood of stakeholder support in a community. Conversely, it would also help to avoid presenting unpopular LID policy approaches as well. By offering LID policy approaches stakeholders would likely develop and adopt, engagement of stakeholders could be more productive, and outreach organizations would have a better basis to form better relationships with residents, developers and policymakers.

In the end, the results indicate a potential to save time in policy development process by showing what policies are suitable for a community or a region based on the independent factors investigated herein. The relevance of these factors provides an opportunity to inform the public review process on LID policy rather than conducting ground-up policy development. Such policy development would not only increase the financial cost to jurisdictions developing policy, but it may also reduce the threat of losing early support because LID proponents would be more aware of what policies are unsuitable.

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APPENDIX A: LOW IMPACT DEVELOPMENT DEFINITION AND EXAMPLES

Low Impact Development (LID) is an urban stormwater management approach, which is unlike conventional stormwater management practices. It differs because it manages stormwater using small-scale, cost-effective landscape features on each lot instead of in large off-site facilities (such as detention ponds). LID uses "reduced impervious surfaces, functional grading, open channel sections, disconnection of hydrologic flowpaths, and the use of bioretention/filtration landscape areas" to influence "infiltration, frequency and volume of discharges, and groundwater recharge" (US EPA 1999).

Specific LID techniques are called Integrated Management Practices (IMPs), which can:

- Reduce runoff by integrating small-scale stormwater controls throughout the site
- Eliminate the need for large-scale off-site best management practice (BMP) facility by being placed near the source of impacts, in a small area of each lot (US EPA 1999).

Examples of LID IMPs:

- Bioretention is the use of a soil bed and vegetation to filter runoff in shallow depressions
- Dry wells are excavated pits filled with aggregate to capture runoff and allow it to filter and infiltrate.
- Filter strips are bands of vegetation between pollutant sources and streams
- Vegetated buffers are strips of vegetation around areas sensitive area to runoff
- Level spreaders take concentrated runoff and disperse it through sheet flow
- Grassed swales are vegetated, shallow channels that provide quantity and quality treatment of stormwater
- Rain barrels collect stormwater from rooftops and store it for future use
- Cisterns provide underground storage from impervious surfaces for future use.
- Infiltration trenches are excavated trenches backfilled with stone, forming a sub-surface basin where water can infiltrate
- Green roofs replace conventional rooftop materials with vegetated rooftops (US EPA 1999)

APPENDIX B: SAMPLE LANGUAGE FOR LID POLICY STATUS AND LID POLICY APPROACH

Tabulated as Development (1) for LID Policy Status:

> "Conduct a review of policies, practices and regulations to identify potential barriers to implementing low impact development techniques (City of Eugene 2011)."
>
> "During the first four years of the new permit term, the City will continue to evaluate Low Impact Development (LID) practices to assess the feasibility of incorporating additional measures into the City's practices (City of Tucson 2012)."

Tabulated as Implementation (2) for LID Policy Status:

> "The District has incorporated LIDA into its Design & Construction Standards, has provided incentives for using these approaches, and has entered into public/private partnerships to demonstrate the use of these techniques (Clean Water Services 2008)."

Tabulated as Incorporate (1) for LID Policy Approach:

> "As required by the Permit Appendix A.VI.H, the City is evaluating LID practices, applicability, regulatory hurdles, and other factors that would contribute to the reduction of pollutants in stormwater discharges from new construction, significant redevelopment, and retrofits of commercial and residential areas. In the fourth year annual report, the City will include the findings of this evaluation and identify a plan and schedule for incorporation into design standards (City of Scottsdale 2012)."

Tabulated as Prefer (2) for LID Policy Approach

> "The District has incorporated LIDA into its Design & Construction Standards, has provided incentives for using these approaches, and has entered into public/private partnerships to demonstrate the use of these techniques (Clean Water Services 2008)."
>
> "ACHD will use the term Green Stormwater Infrastructure (GSI) to replace Green Infrastructure/Low Impact Development (GI/LID) terminology used in the Permit. ACHD is required to develop a strategy to provide incentives for the increased use of GSI techniques in private and public sector development projects. When the strategy is submitted to the EPA it must include descriptions and a narrative report on the pilot projects it has implemented (Ada County 2013)."

Tabulated as Require (3) for LID Policy approach:

> "The SWDM requires the use of a minimum amount of LID BMPs (referred to as flow control BMPs) on nearly all projects and allows LID BMPs to be used as the sole means of managing stormwater for many projects (King County 2013)."

APPENDIX C: PROCESSING OF INDEPENDENT VARIABLES

TIGER 2010 BOUNDARIES FOR PLACES AND COUNTIES

The U.S. Census Bureau provided the 2010 TIGER Boundary files for counties and places. Counties and Places are identified using 5-digit county identifier codes and 7-digit place identifier codes respectively (GEOID10). I identified Counties and Places in the seven states west of the continental divide and converted polygons to points based upon polygon centroid values. I cross-referenced the point values names with the list of permittees to sample the other variables using a nearest value for point-to-point or intersected value for point-to-polygon.

PROBLEM SEVERITY

Problem severity data was obtained from the U.S. Environmental Protection Agency. The data included statewide data of 303(d) listed sites for selected reaches of streams. The impaired sites and TMDL sites were consolidated by reach using a pivot table counting the number of impairments/TMDLs per reach. The consolidated data was joined to stream reach point data, which was prepared through converting polyline data to points. These points were intersected with HUC4 polygon features, which included a summation of all impaired and TMDL counts per HUC.

CLIMATE

Climate data was obtained from the National Weather Service (NWS) of the National Ocean and Atmospheric Administration (NOAA). The climate values were cross-referenced with the jurisdiction point data. The precipitation data points were cross-referenced using the nearest data point to the centroid of the jurisdictions. The mean high temperature polygon values were intersected with the centroid points of the jurisdictions.

GEOGRAPHIC

Watershed Sub-region (HUC4) data was obtained from the Natural Resource Conservation Service (2013). The Subregions were categorized as either non-coastal (0), or coastal (1). Once categorized, the sub-region (HUC4) polygons were linked through intersecting the sample points. Area of land and area od water were included in the Census TIGER shapefiles for places and counties.

SOCIOECONOMIC

The socioeconomic statistics were obtained from the American Community Survey (2012). Their values were cross-referenced by joining them to their respective 2010 Census TIGER geographic ID code (GEOID10).

POLITICAL

The percentage of voters was obtained from the Federal Electoral Commission (2010). These figures were linked by intersecting the 2010 Census TIGER congressional district and the spreadsheet data with the outcomes by district.

APPENDIX D: CORRELATION MATRIX OF VARIABLES

	Require (dummy)	Preference (dummy)	Adopted (dummy)	Year of Compliance Document	Count of TMDL by HUC4	Count of Impaired by HUC4	Climate	Mean Annual Precipitation	Mean Annual High Temperature	Coastal Watershed	County	Area of Land (sq mi)	Area of Water (sq mi)	Population Density	Median Household Income	Population	% HS or greater	% below poverty line	% own	% College or greater	% Voting Democrat	% Voting Republican
Require (dummy)	1	-.508**	.234**	.463**	-.152**	.051	-.141*	-.184**	.028	.721**	-.134*	-.134*	-.038	.195**	.257**	-.032	.046	-.245**	-.008	.204**	.076	-.053
Preference (dummy)	-.508**	1	-.135*	-.344**	-.008	-.174**	.497**	.543**	-.454**	-.491**	.111*	.005	-.018	-.142*	-.097	-.010	.154**	.023	.050	.011	-.013	.000
Adopted (dummy)	.234**	-.135*	1	-.247**	-.027	-.051	-.258**	-.245**	.129*	.046	-.044	.053	.041	-.118*	-.190**	.066	-.038	.126*	.016	-.220**	-.556**	.572**
Year of Compliance Document	.463**	-.344**	-.247**	1	-.233**	-.074	-.059	-.078	.021	.594**	.009	-.040	-.010	.181**	.275**	-.020	-.001	-.210**	-.025	.206**	.275**	-.256**
Count of TMDL by HUC4	-.152**	-.008	-.027	-.233**	1	.944**	.154**	.128*	-.055	.084	.056	-.010	.103	-.023	-.043	-.005	-.017	.017	-.046	-.032	.056	-.062
Count of Impaired by HUC4	.051	-.174**	-.051	-.074	.944**	1	.105*	.059	.011	.312**	.031	-.079	.088	.044	.068	-.030	-.019	-.073	-.040	.048	.165**	-.168**
Climate	-.141*	.497**	-.258**	-.059	.154**	.105*	1	.983**	-.469**	-.044	.285**	-.039	.180**	-.137*	.074	.043	.181**	-.128*	.093	.128*	.174**	-.183**
Mean Annual Precipitation	-.184**	.543**	-.245**	-.078	.128*	.059	.983**	1	-.569**	-.093	.307**	-.019	.187**	-.142**	.060	.048	.197**	-.120*	.082	.125*	.175**	-.180**
Mean Annual High Temperature	.028	-.454**	.129*	.021	-.055	.011	-.469**	-.569**	1	.103	-.176**	.089	-.095	-.009	-.115*	.032	-.271**	.175**	.022	-.218**	-.228**	.222**
Coastal Watershed	.721**	-.491**	.046	.594**	.084	.312**	-.044	-.093	.103	1	-.168**	-.254**	-.007	.320**	.262**	-.075	-.070	-.239**	-.091	.198**	.309**	-.284**
County	-.134*	.111*	-.044	.009	.056	.031	.285**	.307**	-.176**	-.168**	1	.535**	.560**	-.351**	.129*	.488**	.090	-.024	.093	.088	-.062	.063
Area of Land (sq mi)	-.134*	.005	.053	-.040	-.010	-.079	-.039	-.019	.089	-.254**	.535**	1	.383**	-.224**	-.109*	.449**	-.050	.136*	-.007	-.109*	-.165**	.170**
Area of Water (sq mi)	-.038	-.018	.041	-.010	.103	.088	.180**	.187**	-.095	-.007	.560**	.383**	1	-.186**	-.058	.799**	-.005	.041	-.053	-.026	-.035	.036
Population Density	.195**	-.142*	-.118*	.181**	-.023	.044	-.137*	-.142**	-.009	.320**	-.351**	-.224**	-.186**	1	-.249**	-.136*	-.480**	.325**	-.530**	-.225**	.416**	-.402**
Median Household Income	.257**	-.097	-.190**	.275**	-.043	.068	.074	.060	-.115*	.262**	.129*	-.109*	-.058	-.249**	1	-.114*	.572**	-.728**	.572**	.778**	.067	-.076
Population	-.032	-.010	.066	-.020	-.005	-.030	.043	.048	.032	-.075	.488**	.449**	.799**	-.136*	-.114*	1	-.064	.149**	-.108*	-.068	-.053	.042
% HS or greater	.046	.154**	-.038	-.001	-.017	-.019	.181**	.197**	-.271**	-.070	.090	-.050	-.005	-.480**	.572**	-.064	1	-.764**	.523**	.772**	-.205**	.173**
% below poverty line	-.245**	.023	.126*	-.210**	.017	-.073	-.128*	-.120*	.175**	-.239**	-.024	.136*	.041	.325**	-.728**	.149**	-.764**	1	-.579**	-.724**	.023	-.008
% own	-.008	.050	.016	-.025	-.046	-.040	.093	.082	.022	-.091	.093	-.007	-.053	-.530**	.572**	-.108*	.523**	-.579**	1	.359**	-.326**	.310**
% College or greater	.204**	.011	-.220**	.206**	-.032	.048	.128*	.125*	-.218**	.198**	.088	-.109*	-.026	-.225**	.778**	-.068	.772**	-.724**	.359**	1	.067	-.094
% Voting Democrat	.076	-.013	-.556**	.275**	.056	.165**	.174**	.175**	-.228**	.309**	-.062	-.165**	-.035	.416**	.067	-.053	-.205**	.023	-.326**	.067	1	-.983**
% Voting Republican	-.053	.000	.572**	-.256**	-.062	-.168**	-.183**	-.180**	.222**	-.284**	.063	.170**	.036	-.402**	-.076	.042	.173**	-.008	.310**	-.094	-.983**	1

** Correlation significant at the .01 level (2-tailed)
* Correlation significant at the .05 level (2-tailed)

Appendix E: Multinomial Logistic Regression Alternate Models

Table D1: Multinomial logistic regression results including year of compliance document variable (stepwise model)

								95% Confidence Interval for Exp(B)	
LID Policy^{a}		B	Std. Error	Wald	df	Sig.	Exp(B)	Lower Bound	Upper Bound
Prefer	Intercept	312.337	617.424	.256	1	.613			
	Year	-.170	.308	.306	1	.580	.843	.461	1.542
	HUC4_303	.000	.000	6.106	1	.013	1.000	.999	1.000
	Precip * Temp	.002	.001	9.829	1	.002	1.002	1.001	1.003
	PopDense	.000	.000	.121	1	.728	1.000	1.000	1.000
	HHI	.000	.000	.730	1	.393	1.000	1.000	1.000
	PCT_HS	.334	.110	9.263	1	.002	1.396	1.126	1.731
Require	Intercept	-1167.504	313.770	13.845	1	.000			
	Year	.578	.156	13.769	1	.000	1.783	1.314	2.420
	HUC4_303	.000	.000	.014	1	.907	1.000	1.000	1.000
	Precip * Temp	.001	.000	4.026	1	.045	1.001	1.000	1.002
	PopDense	.000	.000	5.282	1	.022	1.000	1.000	1.000
	HHI	.000	.000	8.326	1	.004	1.000	1.000	1.000
	PCT_HS	.016	.021	.599	1	.439	1.016	.976	1.058

a. The reference category is: Incorporate. Pseudo R^2: .398 (Cox and Snell), .558 (Nagelkerke), .407 (McFadden). LR χ2 = 167.281***

Table D2: Multinomial logistic regression results including year of compliance document, county and coastal watershed variables (stepwise model)

								95% Confidence Interval for Exp(B)	
LID Policy^{a}		B	Std. Error	Wald	df	Sig.	Exp(B)	Lower Bound	Upper Bound
Prefer	Intercept	-35.568	11.681	9.272	1	.002			
	HUC4_303	.000	.000	1.433	1	.231	1.000	1.000	1.000
	Precip * Temp	.002	.000	11.950	1	.001	1.002	1.001	1.003
	Coastal	-2.270	1.844	1.515	1	.218	.103	.003	3.838
	HHI	.000	.000	2.564	1	.109	1.000	1.000	1.000
	PCT_HS	.402	.137	8.598	1	.003	1.494	1.142	1.955
Require	Intercept	-4.880	1.495	10.661	1	.001			
	HUC4_303	.000	.000	6.476	1	.011	1.000	1.000	1.000
	Precip * Temp	.000	.000	.796	1	.372	1.000	1.000	1.001
	Coastal	3.938	.535	54.211	1	.000	51.315	17.988	146.391
	HHI	.000	.000	1.557	1	.212	1.000	1.000	1.000
	PCT_HS	.033	.021	2.315	1	.128	1.033	.991	1.077

a. The reference category is: Incorporate. Pseudo R^2: .498 (Cox and Snell), .699 (Nagelkerke), .553 (McFadden). LR χ2 = 227.214***.

Table D3: Multinomial logistic regression results including year of compliance document, county and coastal watershed variables (forced model)

								95% Confidence Interval for Exp(B)	
LID Policy^{a}		B	Std. Error	Wald	df	Sig.	Exp(B)	Lower Bound	Upper Bound
Prefer	Intercept	568.389	734.416	.599	1	.439			
	Year	-.300	.365	.675	1	.411	.741	.362	1.516
	HUC4_303	.000	.000	1.788	1	.181	1.000	1.000	1.000
	Precip * Temp	.002	.001	6.761	1	.009	1.002	1.001	1.004
	County	1.118	1.707	.429	1	.513	3.058	.108	86.833
	Coastal	-.755	2.025	.139	1	.709	.470	.009	24.875
	WaterSqMi	-.033	.040	.688	1	.407	.967	.895	1.046
	PopDense	.000	.000	.272	1	.602	1.000	1.000	1.001
	HHI	.000	.000	2.416	1	.120	1.000	1.000	1.000
	PCT_HS	.407	.149	7.440	1	.006	1.503	1.121	2.013
	PCT_DEM_Plus	-.031	.044	.490	1	.484	.970	.890	1.057
Require	Intercept	1233.271	543.633	5.146	1	.023			
	Year	-.616	.270	5.183	1	.023	.540	.318	.918
	HUC4_303	.000	.000	9.824	1	.002	1.000	1.000	1.000
	Precip * Temp	.000	.000	.216	1	.642	1.000	.999	1.001
	County	1.026	.977	1.104	1	.293	2.791	.411	18.934
	Coastal	5.677	1.032	30.238	1	.000	292.042	38.609	2209.009
	WaterSqMi	-.003	.004	.801	1	.371	.997	.989	1.004
	PopDense	.000	.000	.806	1	.369	1.000	1.000	1.000
	HHI	.000	.000	1.429	1	.232	1.000	1.000	1.000
	PCT_HS	.042	.026	2.626	1	.105	1.043	.991	1.097
	PCT_DEM_Plus	-.013	.019	.492	1	.483	.987	.952	1.024

a. The reference category is: Incorporate. Pseudo R^2: .511 (Cox and Snell), .717(Nagelkerke), .574 (McFadden). LR χ2 = 236.144***.

Table D4: Multinomial logistic regression results with county variable forced in step model

								95% Confidence Interval for Exp(B)	
LID Policy^a		B	Std. Error	Wald	df	Sig.	Exp(B)	Lower Bound	Upper Bound
Prefer	Intercept	-30.618971	10.146	9.107	1	.003			
	County	.271296	1.546	.031	1	.861	1.312	.063	27.127
	HUC4_303	-.000426	.000	11.820	1	.001	1.000	.999	1.000
	Precip * Temp	.002462	.001	15.520	1	.000	1.002	1.001	1.004
	PopDense	.000035	.000	.024	1	.878	1.000	1.000	1.000
	WaterSqMi	-.053582	.028	3.674	1	.055	.948	.897	1.001
	HHI	-.000010	.000	.225	1	.635	1.000	1.000	1.000
	PCT_HS	.326941	.115	8.114	1	.004	1.387	1.107	1.737
Require	Intercept	-3.409620	1.513	5.081	1	.024			
	County	-1.017219	.749	1.844	1	.174	.362	.083	1.570
	HUC4_303	-.000027	.000	3.339	1	.068	1.000	1.000	1.000
	Precip * Temp	.001021	.000	5.464	1	.019	1.001	1.000	1.002
	PopDense	.000169	.000	7.384	1	.007	1.000	1.000	1.000
	WaterSqMi	.002062	.004	.290	1	.590	1.002	.995	1.010
	HHI	.000049	.000	14.307	1	.000	1.000	1.000	1.000
	PCT_HS	.003865	.020	.039	1	.844	1.004	.966	1.043

a. The reference category is: Incorporate. Pseudo R^2: .385 (Cox and Snell), .540 (Nagelkerke), .390 (McFadden). LR χ2 = 160.318***.

Table D5: Multinomial logistic regression results with county variable forced and coastal and compliance doc year in step model

								95% Confidence Interval for Exp(B)	
LID Policy^a		B	Std. Error	Wald	df	Sig.	Exp(B)	Lower Bound	Upper Bound
Prefer	Intercept	-35.375	11.836	8.933	1	.003			
	County	-.601	1.225	.241	1	.624	.548	.050	6.051
	HUC4_303	.000	.000	1.425	1	.233	1.000	1.000	1.000
	Precip * Temp	.002	.001	11.903	1	.001	1.002	1.001	1.003
	Coastal	-2.226	1.833	1.474	1	.225	.108	.003	3.926
	HHI	.000	.000	2.598	1	.107	1.000	1.000	1.000
	PCT_HS	.399	.138	8.324	1	.004	1.491	1.137	1.955
Require	Intercept	-4.879	1.495	10.656	1	.001			
	County	.053	.715	.006	1	.941	1.054	.260	4.281
	HUC4_303	.000	.000	6.342	1	.012	1.000	1.000	1.000
	Precip * Temp	.000	.000	.703	1	.402	1.000	1.000	1.001
	Coastal	3.950	.554	50.746	1	.000	51.922	17.514	153.926
	HHI	.000	.000	1.535	1	.215	1.000	1.000	1.000
	PCT_HS	.033	.021	2.330	1	.127	1.033	.991	1.077

a. The reference category is: Incorporate. Pseudo R^2: .498 (Cox and Snell), .699 (Nagelkerke), .553 (McFadden). LR χ2 = 227.517***.

Table D6: Multinomial logistic regression results with precipitation & precipitation with temperature interaction

								95% Confidence Interval for Exp(B)	
LID Policy^a		B	Std. Error	Wald	df	Sig.	Exp(B)	Lower Bound	Upper Bound
Prefer	Intercept	-33.675970	12.937	6.776	1	.009			
	HUC4_303	-.000278	.000	2.207	1	.137	1.000	.999	1.000
	PopDense	-.000147	.000	.242	1	.623	1.000	.999	1.000
	WaterSqMi	-.143589	.080	3.220	1	.073	.866	.741	1.013
	HHI	-.000028	.000	1.147	1	.284	1.000	1.000	1.000
	PCT_HS	.401019	.152	6.926	1	.008	1.493	1.108	2.013
	Precip * Temp	-.016986	.008	4.088	1	.043	.983	.967	.999
	Precip	1.163672	.516	5.076	1	.024	3.202	1.163	8.810
Require	Intercept	-4.403407	1.623	7.358	1	.007			
	HUC4_303	-.000030	.000	4.355	1	.037	1.000	1.000	1.000
	PopDense	.000198	.000	10.420	1	.001	1.000	1.000	1.000
	WaterSqMi	-.000531	.003	.035	1	.851	.999	.994	1.005
	HHI	.000047	.000	13.490	1	.000	1.000	1.000	1.000
	PCT_HS	.010702	.020	.278	1	.598	1.011	.971	1.052
	Precip * Temp	.004073	.002	4.990	1	.025	1.004	1.000	1.008
	Precip	-.195785	.110	3.181	1	.075	.822	.663	1.020

a. The reference category is: Incorporate. Pseudo R^2: .412 (Cox and Snell), .578 (Nagelkerke), .426 (McFadden). LR χ2 = 175.241***.