Policy Learning for Flood Mitigation: A Longitudinal Assessment of the Community Rating System in Florida

ABSTRACT

Floods continue to inflict the most damage upon human communities among all natural hazards in the United States (U.S.). Because localized flooding tends to be spatially repetitive over time, local decision makers often have an opportunity to learn from previous events and make proactive policy adjustments to reduce the adverse effects of a subsequent storm. Despite the importance of understanding the degree to which local jurisdictions learn from flood risks and under what circumstances, little if any empirical, longitudinal research has been conducted along these lines. This article addresses the research gap by examining the change in local flood mitigation policies in Florida from 1999 to 2005. We track 18 different mitigation activities organized into four series of activities under the Federal Emergency Management Agency's (FEMA) Community Rating System (CRS) for every local jurisdiction in Florida participating in the FEMA program on a yearly time step. We then identify the major factors contributing to policy changes based on CRS scores over the seven-year study period. Using multivariate statistical models to analyze both natural and social science data, we isolate the effects of several variables categorized into the following groups: hydrologic conditions, flood disaster history, socioeconomic and human capital controls. Results indicate that local jurisdictions do in fact learn from histories of flood risk and this process is expedited under specific conditions.

KEY WORDS: Florida, Flood Mitigation, Community Rating System, Adaptive Management

1. INTRODUCTION

Floods continue to pose the greatest threat among all natural hazards to the property and safety of human communities in the United States (U.S.). According to data extracted from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), the average annual flood count has increased six-fold from 394 floods per year in the 1960s to 2,444 flood events a year in the 1990s. SHELDUS data also show increasing property damage from floods over time. In the 1960s, floods caused $45.65 million dollars a year; by the 1990s, average annual property damage from flooding increased to $19.13 billion dollars a year (inflation adjusted at 1960 dollars). These damage estimates are consistent with other studies on flood damage[1-5] and help confirm what has been tacitly understood by local policy makers for years: that floods pose a major risk to the health and safety of the U.S. population and that the problem is getting worse.[i]

Increasingly, local communities are resorting to policy-based mitigation measures (as opposed to purely structural or engineering-based) to stem risk trends in property damage and casualties from localized flooding. No longer is flood control the sole province of the federal government. Mitigation strategies have become embedded in local land use plans, zoning ordinances, building codes, and local education programs. Because localized flooding tends to be chronic and spatially repetitive over time, local planners often have an opportunity to learn from previous events and make proactive policy adjustments to buffer the adverse effects of subsequent storms. In the context of flood risk management, we define jurisdictional learning as *a change in policy or the strength of a policy in response to flood events or some other factor*. Despite the importance of understanding the degree to which local jurisdictions learn from repetitive flood events and under what circumstances, little if any empirical, longitudinal research has been conducted on this topic.

Our study addresses this lack of research by examining the change in local flood mitigation policies in Florida from 1999 to 2005. We seek to empirically answer the following research questions related to the extent to which decision makers adjust policies and for what reasons: *to what degree do local communities engage in flood policy learning over time? Which flood mitigation activities change more than others? What hydrological, flood disaster, economic, and* *human capital characteristics influence flood policy learning or change?* Specifically, we track 18 different mitigation activities organized into four activity classes under the Federal Emergency Management Agency's (FEMA) Community Rating System (CRS) for every local jurisdiction in Florida participating in the FEMA program on a yearly time step. We then identify the major factors contributing to policy changes based on CRS scores over the seven-year study period. Using multivariate statistical models to analyze both natural and social science data, we isolate the effects of several variables categorized into the following groups: hydrologic conditions, flood disaster history, socioeconomic and human capital controls. Results from the study provide valuable information on the specific conditions motivating local jurisdictions to alter their flood mitigation policies over time. Systematically addressing these issues help identify the levers to policy learning and change and facilitate proactive approaches to risk mitigation.

The following section examines the existing literature on policy learning and change and presents the FEMA CRS program as an ideal empirical target for investigating learning associated with repetitive floods. Next, we describe our sample selection, variable measurement, and data analysis procedures. Results are reported in two phases. First, we examine the degree to which policies change over the study period. Second, we analyze a series of Generalized Least Squares (GLS) panel models for the four classes of CRS activities. Then, we interpret our findings and discuss their policy implications for expediting the learning or change process when it comes to flood risk mitigation policies as the local level. Finally, we lay-out an agenda for future research on examining the effectiveness of flood reduction programs in the U.S. and better understanding how planners can minimize the rising costs of floods nationwide.

1.1. Adaptive Management and Flood Policy Learning

An adaptive approach to environmental risk management is one of the most effective decision frameworks for facilitating policy learning.[6-8] Adaptive management is an evolving concept in which policies are designed as hypotheses and management tools are implemented as experiments to test hypotheses. In most cases, hypotheses are predictions about how existing conditions will respond to management actions. The rule of good experimentation, however, is that the consequences of the actions be potentially reversible and that the experimenter learns from the experiment.[9] Under adaptive management, local level policy makers must be able to react to constantly changing environmental conditions, sudden shifts in political interests and objectives, and a continuous barrage of new and often ambiguous information. Flood risk mitigation plans and policies, from an adaptive management perspective, must be flexible instruments geared toward varying levels of uncertainty and surprise.

In its broadest sense, adaptive management ensures that local jurisdictions are responsive to the variations, rhythms, and cycles of change in the system (both ecological and human) and are able to react quickly with appropriate management techniques.[10] The process is relatively straightforward: new information and events are identified, evaluated, and used to adjust strategies or goals.[11] Adaptive management is a continuous process of action-based planning, monitoring, researching and adjusting with the objective of improving future management actions.[12, 13] By embracing an adaptive approach to management, local decision makers and flood managers can learn incrementally over time and adjust policies accordingly to reduce the adverse risks and impacts of repetitive floods.

For example, development restrictions in the 100-year floodplain to limit human costs can be designed experimentally, with features of reliable and valid measurement. If a policy succeeds in meeting intended outcomes, hypotheses are affirmed and human safety is protected. If the policy fails, an adaptive design still permits learning so that future decisions can proceed from a better base of understanding. In this sense, experiments can bring surprises, but “management is recognized to be inherently uncertain, the surprises become opportunities to learn rather than failures to predict" (p. 56).[13]

1.2. Factors Influencing Policy Learning

May[14-16] describes adaptive management as an “instrumental” form of policy learning where the planner takes a rational-analytic view to improve designs for reaching existing policy goals. Instrumental learning results from testing the feasibility of policy interventions or conducting systematic policy experiments. Based on the work of Heclo,[17] Sacks,[18] and others, the most important influence in this type of learning is previous policy. The goals and objectives that policymakers pursue at any given time are largely influenced by “policy legacies” or “meaningful reactions to previous policies”.[19] As Hall[20] summarizes, the principal factors affecting policies at time 2 are existing policy conditions at time 1. Brody[21] confirmed this hypothesis in a longitudinal study on hazard mitigation planning in Florida and Washington by showing that the best predictor of plan quality in 1999 was the quality of plans in 1991.

Another critical factor influencing policy learning in the context of flood risk mitigation is the nature and severity of past events.[22, 23] Insofar as learning stems from the ability to adapt to perturbations in the existing system,[24] the degree of flooding in a community and the amount of damage or casualties resulting from these events, may expedite the learning process. Hazard events can act as triggers to the policy system and become catalysts for adaptation. Although natural disasters can be very damaging, they open windows of opportunity for policy change and action.[25] For example, as far back as the late 1970’s researchers found that past flooding was a significant factor in the decision of local communities to participate in the National Flood Insurance Program even when controlling for other community characteristics.[26, 27] More recently, Browne and Hoyt[28] find that flood insurance purchases are highly correlated with the level of flood losses the previous year. Similarly, Burby[29] demonstrates that chronic property loss from hazards (as measured by the number of NFIP repetitive loss properties) is a significant predictor of plan quality change for natural hazards, controlling for other factors. Also, in a recent study of policy change in England and Wales, Johnson et al.[30] find that the magnitude of flood disasters act as a catalyst for local policy change with respect to flood mitigation.

Understanding adaptive management within the context of flood mitigation planning is ideal because hazards are recurring events spaced-out through time. Decision makers have an opportunity to learn and improve policies from one flood to the next, since these events tend to recur in the same geographic area. If policies are regularly updated or changed, they can reflect the learning that takes place within a planning organization and community at large. That is, one can estimate the extent to which changes in flood mitigation policies correlate with flood histories, adjusting for features of local hydrology and socioeconomic composition that may also influence mitigation activities.

Most of the emphasis on adaptive management, however, assumes that the experimenter (i.e. flood planner) is a rational individual supported by a responsive management structure ready to test hypotheses and implement the results of the experiment. Yet, in the local planning arena (particularly in Florida), the experimenter usually is not a lone scientist or technician, but a member of an organization embedded within a larger community composed of a network of relationships. Local comprehensive planning in Florida is achieved with the participation of a diverse set of stakeholders and community members including environmental NGOs, neighborhood groups, development associations, and businesses. Adaptive management may be based on the principles of scientific experimentation, but it is ultimately about collective human values and a political culture that tolerates learning from mistakes.

This type of management is often called "social policy learning." This type of learning comes from aggregating and reconciling a plurality of interests and influences, rather than a single expert or individual.[(17)] According to May[(15)] "policies with publics" have greater potential for learning because their adoption involves the constant questioning of assumptions and existing policy outcomes by competing advocacy coalitions. Therefore, it is important to consider the socioeconomic and human capital characteristics of a local community as external influences on policy learning. Community-wide levels of income or wealth, education, and population composition may shape the type and speed of learning or change in flood risk mitigation efforts. For example, wealthy communities may have higher valued property at risk from flooding and thus a greater stake in ensuring protective policy measures are taken. Also, high income jurisdictions will most likely have the financial resources to implement costly strategies, such as structural relocation, or drainage improvements. These and other characteristics related to the social and human capital of a locality determine the way rational planners calculate the expected costs and benefits of an intervention, shaping the willingness and capacity of a local jurisdiction to be responsive enough to alter their policies over time.

1.3. CRS as a Framework for Policy Learning

FEMA's Community Rating System (CRS) adopted in the early 1990s encourages communities to go beyond the NFIP's minimum standards for floodplain management by providing discounts of up to 45 percent on flood insurance premiums for residents of participating communities. Credit points are assigned for 18 activities organized into the following 4 broad categories of floodplain planning and management: public information, mapping and regulation, flood damage reduction, and flood preparedness. Premium discounts correspond to credit points accrued by each participating community. Discounts range from 5 (class 9) to 45 percent (class 1) depending on the degree to which a community plans for the adverse impacts of floods (for more information see http://training.fema.gov/EMIWeb/CRS/). As of June, 2006 Florida had over 1.8 million NFIP policies in participating CRS communities. Property owners living within these communities saved approximately $98.5 million per year in insurance premiums from involvement in the CRS program.(31)

The CRS program is an ideal regulatory mechanism with which to track and understand how and why local flood policies may change over time. First, CRS certification requires a genuine commitment on behalf of the jurisdiction receiving credits because each stated activity must be implemented. Each community in the program is evaluated by external reviewers (assigning points on the basis of detailed guidelines) to ensure activities are put into practice, not simply stated in a document. Second, each participating community must recertify by October 1 that it is continuing to implement the activities for which it has earned credit. Thus, the CRS is an ongoing program renewed on a yearly basis. Third, a participating community can modify its application on a yearly basis by adding or changing specific activities to earn more credits and potentially move to a higher class rating (thereby receiving a greater discount on insurance premiums), or a community can choose to scale back interventions in light of new scientific information suggesting lower than expected flood event probabilities. All communities begin at the 5 percent discount level and can move up in subsequent years until a 45 percent discount is achieved. In this way, the CRS is a dynamic program, enabling a community to adapt its flood policies over time as new biophysical and socioeconomic circumstances arise.

2. RESEARCH DESIGN

2.1. Why Florida?

Due to its low elevation, large coastal population, and frequent storm events, Florida experiences significant annual economic losses from floods. Recent estimates indicate that from 1990 to 2003, Florida suffered almost $2.5 billion (in current US$) in losses. Based on a composite risk score accounting for floodplain area and the number and value of households, Florida ranked as the state with the highest risk for flooding, followed by California, Texas, Louisiana, and New Jersey.[32] In general, the combination of rapid population growth and related development, the alteration of hydrological systems through building and channeling activities, and large amounts of annual precipitation associated with a tropical and sub-tropical climate has made many local jurisdictions across the state vulnerable to repetitive flooding and flood damage. With the risk of damaging storms and flooding so high, it is not surprising that 52 of Florida's 67 counties participate in FEMA's Community Rating System program. This high level of community participation coupled with high flood risk make Florida an ideal laboratory for testing ideas of policy change, and to identify variables that influence the behavior of flood management systems.

2.2. Dependent Variables

We measure and analyze five CRS outcome variables summarized at the county scale: *series 300 activities (public information), series 400 activities (maps and regulation), series 500 activities (damage reduction), series 600 activities (flood preparedness), and overall points earned in CRS*. Series 300 and 400 activities are policy solutions that address non-structural interventions, while series 500 and 600 activities involve policy mechanisms addressing structural issues.

Series 300 activities measure the extent to which a locality informs local populace about flood hazards, insurance, and protection measures. Six specific public information activities comprise series 300: *310 elevation certificates; 320 map information service; 330 outreach projects; 340 hazard disclosure; 350 flood protection information; and 360 flood protection assistance*. Each specific activity in series 300 is evaluated by a point system, with point maximums varying by specific action. To measure *series 300 activities*, we simply totaled the points earned by a county and divide by the maximum points available (variable operations are summarized in Table I).[iii]

Series 400 activities (maps and regulation) measure regulatory enactment and enforcement behaviors that exceed the NFIP minimum standards. Specific activities that constitute series 400 include: *410 additional flood data; 420 open space preservation; 430 higher regulatory standards; 440 flood data maintenance; and 450 storm-water management*. *Series 400 activities* are measured as the total points earned by a county divided by the maximum points earnable. Series 500 activities (damage reduction) involve damage reduction measures like acquiring, relocating, or retrofitting existing buildings and maintaining drainage and retention basins. Four specific activities summarize series 500: *510 floodplain management planning; 520 acquisition and relocation; 530 flood protection; and 540 drainage system maintenance.* Series 500 activities are measured as the total points earned divided by the maximum points available. Series 600 activities (flood preparedness) coordinate local managerial efforts to minimize the effects of a flood on people, property, and building contents. Specific activities in series 600 are: *610 flood warning program; 620 levee safety; and 630 dam safety*. Following the same procedure as before, we measure *series 600* activities as the total points earned by a locality divided by the maximum points. Finally, *overall points in CRS* summarize points earned for all class activities divided by the maximum points available.

Most counties in Florida earn their own CRS scores. In many cases, independent municipalities nested in a county earn separate scores for mitigation work. In such cases, we population adjust and summarize the mitigation activities of nested municipalities and the county itself. By this procedure, our adjusted county CRS scores reflect the number of people that directly benefit from mitigation efforts. Fig. 1 shows the measurement logic, with Lee County and the nested municipalities of Bonita Springs, Cape Coral, Sanibel, and Fort Meyers Beach and City. Each municipality has earned different point totals for the specific activity of 430 (higher regulatory standards). First, we subtract the combined population of nested municipalities from the total county population of Lee County to derive the balance of persons belonging to Lee County. Second, the population of each municipality is divided by the total county population to derive a weight. Third, we multiply this municipal weight by the observed CRS score for each municipality. Fourth, we summarize weighted scores to derive our population corrected county score. This procedure was performed for all participating counties (and nested entities), across 18 activities in 4 classes for the period 1999-2005.

2.3. Independent Variables

To estimate the extent to which localities learn or change behavior from flood histories (or prior probabilities of flooding), we measure two variables: *flood frequency* and *flood property damage*. Both variables are measured at the county scale (the finest spatial resolution available). *Flood frequency* is measured as a ten-year rolling average of the annual number of flood events recorded in a county. To estimate the intensity of flood events experienced, we calculate a ten-year rolling average[iv] of the annual property damage incurred from flood events. Property damage figures are expressed in $10,000 dollar increments, adjusted for the time value of money fixed to the year 2000. Both data on flood frequency and property damage are derived from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), 1990-2005[v]. All things held equal, from a pure risk standpoint, we presume that localities with rolling histories of high flood frequency and intensity will be more vigilant in their risk mitigation efforts as reflected in CRS scores.

To assess local responsiveness to flood risk, we analyze three families of control measures: natural hydrologic variables; economic variables; and measures of human and social capital. Two hydrology variables are tested: *floodplain percentage*, and *stream length*. *Floodplain percentage* is measured as the total land area of a county (in square kilometers) located in the 100-year floodplain (delineated areas that have a one percent chance of flooding in any one year), divided by the total land area. Floodplain estimates were derived from the most recent FEMA Digital Q3 flood data. Theoretically, localities with high floodplain overlap face higher flood mitigation costs relative to expected gains. That is, more is required (in time, effort, and money) of such localities to stem the risks of repetitive flooding, and to acquire points and accompanying benefits in the CRS program. Insofar as localities are constrained by their hydrological conditions, we expect counties with high floodplain overlap to possess lower CRS scores across all activity series. Our *stream length* variable was calculated in a GIS using the

National Hydrography Dataset (NHD), and measured as the total length of all streams (in meters) in a county jurisdiction. Localities that are highly dissected by streams experience rapid hydrologic response to rainfall events.[(33)] Both floodplain percentage and stream length are time invariant variables.

Two socioeconomic control variables are tested: *population density* and *reductions per policy holder*. *Population density* is measured as the total population in a county divided by the county area in square kilometers. Population values from the 1990 and 2000 U.S. Censuses are used to estimate missing years. A linear rate of population change is assumed between decadal censuses and for extrapolation beyond 2000.[vi] *Reductions per policy holder* is measured as the total monies saved by a county area from CRS discounts divided by the total number of NFIP policy holders residing in a county. Theoretically, this variable captures both the benefits that flow to individual residents from local government efforts to attenuate flood outcomes, and the value of protected by insurance instruments. Insofar as local officials are economically rational, we assume that higher expected benefits per policy holder will induce more comprehensive flood management efforts. Annual data on monies saved per policy holder are collected from FEMA CRS files.

We measure three control variables of human and social capital: *median household income; percent college educated; and non-profit assets per capita*. *Household income* is measured as the sum of money received in a year by all household members 15 years old and over. The midpoint in the distribution of household income is used to characterize counties. *Percent college educated* is measured as the total number of persons age 25 and over with a bachelor's, master's, professional, or doctorate degree divided by the total population 25+ years of age. Values for the 1990 and 2000 Censuses are used to estimate intervening years, assuming equal interval of change. Income and education values from 1990 and 2000 Censuses are used to estimate intervening years, assuming equal intervals of change. We assume that counties with higher median household income and percent college educated will have higher CRS scores. Analyses show that the odds of purchasing an NFIP instrument increase with income and education. The estimated elasticity of income is .492 percent, adjusting for the price of insurance, mortgage size, and hurricane interval.[(34)] Incentives to mitigate flood risks are higher in localities with residents that have higher propensities to purchase NFIP instruments, as discount gains are more plentiful.

Finally, *non-profit assets per capita* is measured as the total assets reported by all non-profit organizations of tax-exempt status with $25,000 dollars in gross receipts required to file Form 990 with the IRS in a county area, divided by the total population. Data are derived from the National Center for Charitable Statistics (NCCS), Core Files that merge data from three cumulative files compiled by the IRS: the Business Master File, the Return Transaction File, and the Statistics of Income file. All things held equal, we hypothesize that counties characterized by higher civic engagement will have higher CRS scores.

2.4. Specification and Logic of Analysis

Five separate panel regression models, one for each CRS series described above, were estimated by loading each suite of independent variables incrementally. Because communities entered or left the CRS program at different times, we analyzed unbalanced panels, ranging from a minimum of 48 panels to a maximum of 52. The time-step for each model was annual, ranging from 1999 to 2005 (t = 7; t-bar = 6.8).

Initial model diagnostics revealed two specification issues. First, four of the five panel regression models demonstrated serial autocorrelation.[35, 36] Second, all five models tested significant with respect to groupwise heteroskedasticity following the calculation of a modified Wald statistic. As a consequence, we analyzed Feasible Generalized Least Squares (FGLS) regression models corrected for groupwise heteroskedasticity. Where tests were significant for serial autocorrelation, a panel-specific AR(1) correlation was specified. The use of panel-specific AR(1) correlation is driven by the assumption that changes in CRS scores over time are not the same within each panel (county); these changes are more likely to be different within each geographic unit as the flood risk of each county is place-specific.

3. RESULTS

Descriptive analysis of series activities from 1999 to 2005 show the degree to which policy learning or change occurs for specific policies. Table II averages points earned by Florida localities for each activity series as a percentage of total points available. From 1999 to 2005, we observe an upward trend[vii] in flood risk mitigation efforts across all activity series. Data indicate that Florida localities perform best at public information activities (series 300), earning (on average) 28.49 percent of total series 300 points available. Over the time period examined, Florida localities showed greatest improvement in series 400 (maps and regulations) activities. Series 400 scores increased from 5.38 percent in 1999 to 11.00 percent of obtainable points in 2005. In contrast, as shown in Table II, participating CRS localities score substantially lower on series 500 (damage reduction) and 600 (flood preparedness) activities. Over the study period, average scores for both 500 and 600 series activities improved modestly. Series 600 scores increased from 5.97 percent in 1999 to 7.00 percent of earnable points in 2005.

When considering all series together, Florida localities (on average) earn less than 10 percent of total CRS points available. Overall scores are trending upward, but there is considerable room for improvement. The top performing localities are Charlotte, Lee, St. Johns, Manatee, and Hillsborough counties, earning between 14 and 17.5 percent of total CRS points. Top performers cluster geographically on the Gulf side of Florida, around the Charlotte Harbor Estuary and the Tampa Bay region.

Next, we explain the spatial and temporal variation in CRS scores using feasible generalized least squares regression. As with all models, we load parameters incrementally by variable domain, beginning with hydrologic conditions, then flood disaster measures, and finally socioeconomic and human capital estimates. We concentrate interpretation on fully saturated models in column 4. As shown in Table III, results indicate that public information activities (series 300) decrease significantly with floodplain percent overlap (where $p = <.01$) and stream length (where $p = <.1$). Series 300 scores are reduced by 9.35 percent as counties move from zero percent of land area in the 100 year floodplain to full floodplain coverage.

On flood disaster variables, we find that a unit increase in the rolling average of annual flood events increases series 300 scores by 3.784 percent (where $p = <.01$). Our measure of flood intensity, a 10-year rolling average of property damage (in $10,000 increments) caused by flood events, is also positively associated with public information scores (b = .002217, p = <.01). On average, CRS participating localities experience $2.46 million dollars in flood related property damage annually. A doubling of this figure to $4.92 million would move series 300 scores by half a percentage point.

Socioeconomic and human capital controls perform as expected. An increase in population density by 100 people increases series 300 scores by 2.53 percent (b = 0.0253, p = <.01). Likewise, a $10 increase in savings per NFIP policy holder increases the percentage of series 300 points earned by 1.71 percent. A $10 increase constitutes a 30 percent increase over current average savings per policy holder ($33 dollars). Results show that public information activities are sensitive to median income values. A $10,000 increase in median household income increases series 300 scores by 1.45 percent (where, p = <.01). Both the percentage of college educated persons (b = .0776, p = <.05) and non-profit assets per capita (b = .0005, p = <.01) increase public information interventions by localities.

Table IV presents modeling results for series 400 (mapping and regulation) activities. As with series 300, mapping and regulation activities are constrained negatively by hydrologic conditions. A 10 percent increase in county land area in the 100 year floodplain decreases the percentage of series 400 points gained by just under 1 percent (b = -.08299, p = <.01). Similarly, stream dissected localities have lower series 400 scores. Mapping and regulation activities are significantly and positively influenced by rolling histories of flood intensity (b = .00158, p = <.01), but not flood frequency. A $1 million dollar increase in 10-year rolling average of property damage incurred from flooding increases scores for mapping regulation activities by about a tenth of a percentage point. As with series 300 activities, localities are more likely to undertake mapping and regulation activities as the monies saved per NFIP policy holder increases. A $10 dollar increase in monies saved increases the percentage of series 400 points netted by 1.06 percent. Similarly, a $10,000 dollar increase in median household incomes corresponds to an increase in series 400 scores by 1.2 percent. A percentage point gain in this instance is quite substantial given that, on average, counties during the study period accumulated only 8.5 percent of all points available in class 400.

Table V reports model results for series 500 (flood damage reduction) activities. As mentioned above, series 500 activities address more structural issues involving capital-intensive fixes to existing buildings and maintenance of drainage basins. While hydrological variables are significant predictors of non-structural efforts (series 300 and 400), they are insignificant for series 500 scores. However, flood frequency (b = .124) is positively associated with flood damage reduction activities at the .1 level of statistical significance. All socioeconomic and human capital variables significantly increase series 500 scores. Again, the average amount of monies saved by a NFIP policy holder increases the percentage of obtained points in series 500 (b = .0215, p = <.01). Results also show that unit increases in college educated population (b = .0338, p = <.01), non-profit assets per capita (b = .00006, p = <.05), and median household income (b = .000018, p = <.05) increase the likelihood and degree of flood damage reduction activities by Florida counties.

Results for series 600 (flood preparedness) activities in Table VI indicate that both disaster variables - flood frequency (b = .663, p = <.01) and flood property damage (b = .00009, p = <.01) - are significant predictors of flood preparedness. A two unit increase in the rolling average of flood frequency increases series 600 scores by about 1.3 percent. A doubling of the rolling average of flood-related property damage from $2.46 million to $4.92 million increases the percentage of achieved points in flood preparedness activities by about two-tenths of a percentage point. As with all series examined, the size of savings per insurance holder (b = .0498, p = <.01) is a significant predictor of series 600 behaviors. Results also show that a 10 percent increase in the percentage of college educated adults residing in a locality increases the class 600 scores by almost 1 percent (b = .0836, p = <.01).

Finally, Table VII presents results for overall CRS scores as measured by the total points for each locality divided by the total possible CRS points. Our fully saturated model in column 4 shows that increasing amounts of land area in the 100-year floodplain actually deters flood mitigation. Moving from zero land area in the floodplain to 100 percent overlap decreases overall CRS score by 4.65 percent. In contrast, both measures of flood history significantly increase overall CRS scores. A unit change in flood frequency increases the percentage of obtained points by roughly three-tenths of a percent ($b = .281$, $p = <.10$). A $1 million dollar increase in annual flood related property damage raises the overall measure of flood mitigation activities by a modest .00785 percent.

Results in Table VII also indicate that population density is a strong positive predictor of flood mitigation. For example, an increase in population density of 100 people raises the percentage of earned points by almost half a percent. Likewise, lower costs for NFIP insurance significantly increase overall CRS scores. With respect to human and social capital controls, results indicate that mitigation efforts increase with levels of civic vitality, median household income, and the percentage of adult residents with a university degree or higher.

4. DISCUSSION AND POLICY IMPLICATIONS

Our study shows that local jurisdictions in Florida are improving their flood risk mitigation policies over time and that specific contextual characteristics act as catalysts for policy learning. Identifying which mitigation activities improve more than others and why provides important information for decision makers in Florida and other states interested in reducing property loss and human casualties from repetitive flood events. Pinpointing the levers of policy learning and change can help policy makers expedite the process and curtail the adverse risks associated with flooding.

Our descriptive results suggest that Florida localities are pursuing a form of least-cost learning where they appear to disproportionately select or engage in point-earning activities that are less expensive and more politically viable. For example, CRS participants appear to favor series 300 and 400 activities which involve primarily information provision, public outreach, and tightening of existing regulations. Points in these series are considerably easier and cheaper to achieve than 500 and 600 activities that require relocation of structures or address structural issues such as drainage maintenance and dam safety. The high capital costs of structural interventions relative to the expected benefits (i.e., rewards for CRS points, and limiting death, injury and property damage from flooding) may account for why Florida localities gravitate to non-structural solutions.

To the extent that the CRS point scheme is rationally constructed, the effectiveness of each activity series in mitigating flood outcomes is implied by the maximum points earnable per series. As shown in Table VIII (as of 2005), localities could earn 835 points for series 300 (5.69 percent of total), 5894 points for series 400 (40.18 percent of total), 6639 points for series 500 (45.26 percent of total), and 1300 points for series 600 activities (8.86 percent). Table VIII demonstrates that Florida localities disproportionately pursue series 300 (public information) and series 400 (mapping and regulation) activities. For example, in 2005, almost 74 percent of total points earned (on average) came from series 300 and 400 interventions, a figure 28 percent higher than the proportional weight assigned to these activities. These gains probably benefited most from technological advances in the collection, storage, and accessibility of data associated with the Internet revolution. Although the trend lines are very modest, results in Table VIII indicate that Florida localities have been increasing their use of activities associated with structural issues to stem flood risks. For example, series 500 scores (on average) increased from 180.62 points in 1999 to 226.15 points in 2005. Florida localities (on average and over the time period assessed) deviate below the proportional weight of series 500 scores by 23.49 percent. This result indicates local jurisdictions are underperforming for this series of activities and that in general CRS participants are pursuing a “low-hanging fruit” strategy for accumulating points.

Taken together, the under-pursuit of series 500 and 600 activities and the over-pursuit of series 300 and 400 activities may reflect shortcomings in the CRS reward structure. To broaden the depth of activities pursued (if such a thing is desirable, given the considerable deviations between points earned and the proportion of points obtainable by activity class), CRS decision-makers may consider re-calibrating the reward structures to reflect the political and economic difficulties associated with undertaking series 500 and 600 activities. One strategy could entail sub-dividing interventions into smaller, more incremental steps, with points attached to each step. This approach could facilitate momentum toward policies that address structural issues. Another strategy could be to simply increase the weighting of each point earned in series 500 and 600 activities.

Factors influencing CRS policy learning differ by activity series, but several general patterns emerge from the results above. With respect to hydrologic variables, we find that stream dissected localities with sizeable land area in the 100-year floodplain are significantly disadvantaged in the CRS system. Among CRS participants, moving from zero to all land in the 100-year floodplain decreases observed scores from about 2 to 9 percent, depending on the activity series examined. These results are reinforced by mean comparison tests showing that localities with at least 25 percent of land area in the 100-year floodplain perform significantly worse across all activity series. In fact, gains in overall CRS scores (points earned divided by points available) are stunted for localities with a quarter of land area in the floodplain (moving from 6.2 to 7.2 percent, compared to 7.2 to 9.7 percent of earnable points for localities with less than 25 percent of land area in the floodplain).

We offer several plausible explanations for this finding. First, local jurisdictions with large floodplain area may have less land available for development or people living in the floodplain, reducing incentive to engage in CRS activities. In other words, the floodplain acts as a deterrent for development so there is less of a need to adopt rigorous flood mitigation policies. Second, and more likely, increasing floodplain area within a locality makes it more difficult to sufficiently protect residents living within these areas. Mitigating the adverse impacts of floods in these cases requires more significant, expensive, and politically less desirable interventions. As a consequence, there is less available "low-hanging fruit" for jurisdictions wanting to maximize their CRS scores, making it difficult to accumulate points over time (without making significant policy investments). In these instances, the economic benefit of reduced insurance premiums may not be equal to the cost of obtaining more CRS points. Third, even if localities with large floodplain area wanted to increase their point total (e.g. move from a CRS class 6 to a 5), they most likely will not have the financial resources to implement policies that involve land acquisition, relocation, drainage system maintenance, etc. The fact that all of our measures of wealth and income are negatively correlated with floodplain area ($p < .001$) support this explanation. The CRS program should thus be more sensitive to the contextual conditions and capabilities of local jurisdictions to provide sufficient incentive to adopt flood risk mitigation policies.

Our results suggest that rolling averages of both flood history measures induce flood policy change, but only by modest amounts. The strongest effect of flood frequency was on public information activities (series 300), increasing the observed percentage of points earned by 3.784 percent for every unit increase in the 10-year rolling average. Flood related property damage was significant in 4 of the 5 models executed, but the coefficient sizes were comparatively small. Only extremely large changes in the rolling average of flood-related property loss induce rather small changes in policy learning. Taken together, our flood disaster history measures suggest that the frequency of events may be more influential than their intensity in terms of driving CRS policy adoption.

The most consistently significant variable in our predictive models is the socioeconomic measure of monies saved per policy holder. Recall, this measure estimates both the size of the constituency that benefits from local involvement in the CRS, and the value of property protected by NFIP instruments. Local officials appear motivated by the per capita gains that flow to this constituency from mitigation activities. The same dynamic holds for population density. As the number of persons per square kilometer increases, local institutions have more to gain by their costly actions in terms of protection of human life and property. A significant negative correlation between floodplain area and population density ($p < .05$) provides further support for why local jurisdictions with large floodplain area do not advance to the same degree on CRS point totals.

All of these findings support the implication that local jurisdictions seek economic utility and are very sensitive to potential economic gain for their institutions and residents. In short, we find that Florida localities are economically rational – working to mitigate flood outcomes as the expected benefits of interventions increase in terms of the density of the beneficiary pool, and the monies saved per policy holder. The knowledge gained from our study can be used by FEMA CRS officials to provide incentives that expedite policy adoption for flood risk mitigation at the local level and ensure the development of more resilient and sustainable communities over the long term.

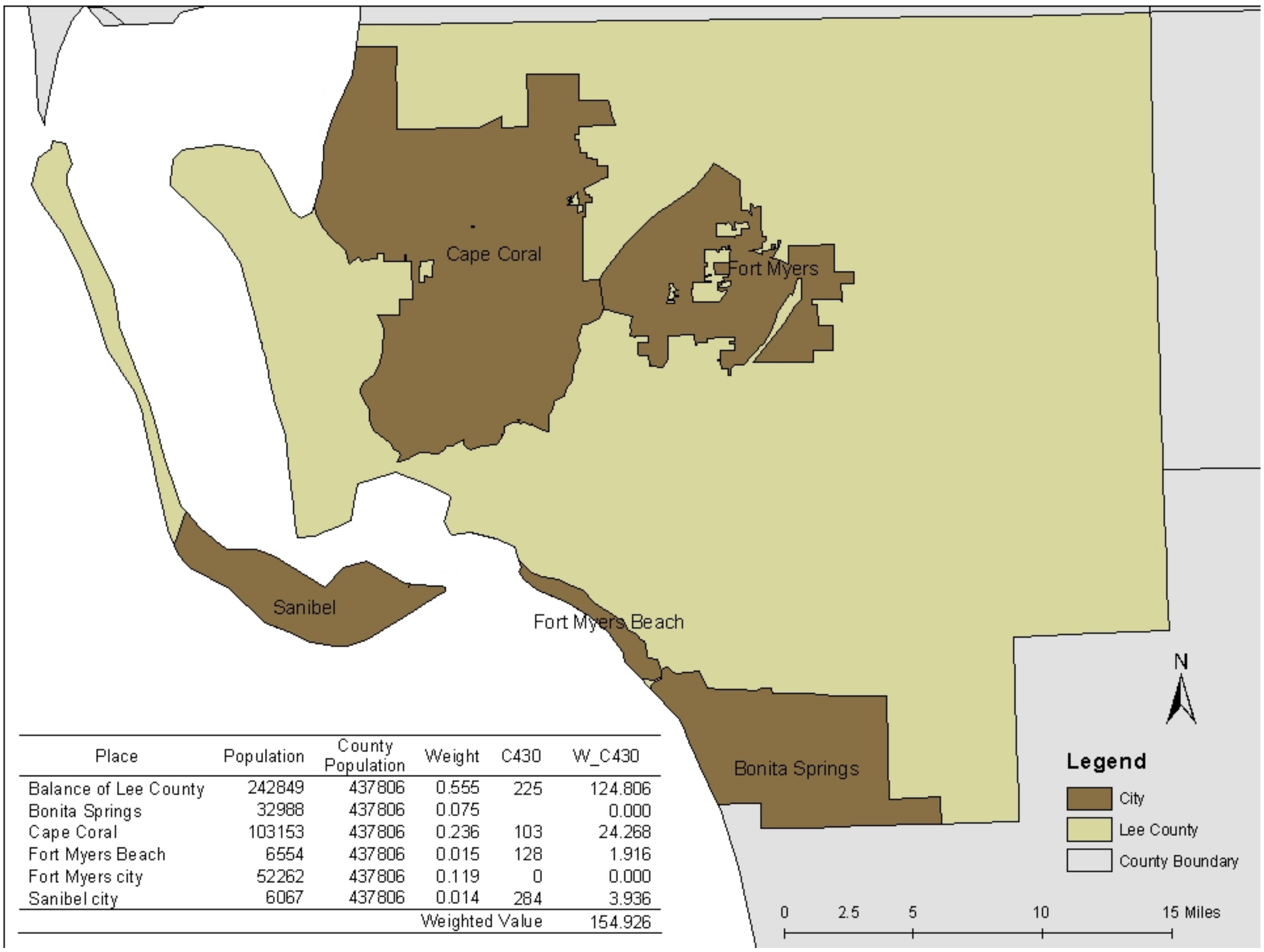
5. CONCLUSION

Our study provides initial empirical evidence on how and why local jurisdictions adopt flood mitigation policies over time. While our analysis provides some important insights into the relationship between local contextual characteristics and CRS policy learning, it should only be considered a first step in investigating the topic. Further research is needed in several areas. First, we only consider a seven year time period when examining policy change. As the longitudinal record of data continues to expand, longer study periods should be analyzed to better gauge the policy learning time horizon. Second, we only examine one state, which limits the ability to externalize our results to other parts of the country. A multi-state study would help us better understand how jurisdictions learn via policy change, particularly from a comparative perspective. Third, we examine the entire state of Florida, but miss the possible influence of very local or difficult to measure characteristics. Case study analysis of both fast and slow learning communities would better contextualize our statistical findings. Fourth, we identify appropriate incentives as a key aspect for CRS participation and learning. More research needs to be conducted on the mechanics of these incentives, and the thresholds at which local jurisdictions are most willing to adopt aggressive flood risk mitigation policies. Finally, our analysis is limited to the local jurisdictional level. Given that institutional CRS learning is partly a function of the number of policy holders, future research should investigate the factors motivating individuals and households to purchase flood insurance from the federal government.

ACKNOWLEDGEMENTS

This article is based on research supported in part by the U.S. National Science Foundation Grant No. CMS- 0346673. The findings and opinions reported are those of the authors and are not necessarily endorsed by the funding organizations or those who provided assistance with various aspects of the study.

Fig. 1. The logic of population weighted measurement of the dependent variables.



Place	Population	County Population	Weight	C430	W_C430
Balance of Lee County	242849	437806	0.555	225	124.806
Bonita Springs	32988	437806	0.075		0.000
Cape Coral	103153	437806	0.236	103	24.268
Fort Myers Beach	6554	437806	0.015	128	1.916
Fort Myers city	52262	437806	0.119	0	0.000
Sanibel city	6067	437806	0.014	284	3.936
			Weighted Value		154.926

Table I. Variable operations, data sources, and expected direction on CRS mitigation outcomes.

Variable Name	Variable Operation	Sign	Data Source
Hydrology Variables			
Floodplain percentage	Total land area of a county in the floodplain divided by the total land area (in square kilometers).	-	FEMA Digital Q3 flood data
Stream length	Total length of streams in a county area (in meters).	+/-	National Hydrography Dataset
Flood Disaster Variables			
Flood frequency	Ten year rolling average of the total annual number of flood disasters recorded in a county.	+	Spatial Hazard Events and Losses Database for the U.S., 1990-2005
Flood property damage	Ten year rolling average of the total annual flood caused property damage recorded in a county in \$10,000 increments (in year 2000 inflation adjusted dollars).	+	Spatial Hazard Events and Losses Database for the U.S., 1990-2005
Socioeconomic Variables			
Population density	Total population divided by country area (in square km). Values for 1990 and 2000 Censuses are used to estimate intervening years, assuming equal interval of change.	+	US Census Bureau, 1990, 2000
Reduction per policy holder	Total dollars saved divided by the total number of FEMA National Flood Insurance Program policy holders.	+	FEMA Community Rating System 1999-2005
Human Capital Variables			
Nonprofit assets per capita	The total assets reported by all number non-profit organizations of tax-exempt status with \$25,000 dollars in gross receipts required to file Form 990 with the IRS in a county divided by the total population.	+	National Center for Charitable Statistics, Core Files, 1991-2004
Median household income	The sum of money received in a year by all household members 15 years old and over. Values for 1990 and 2000 Censuses are used to estimate intervening years.	+	US Census Bureau, 1990, 2000
Percent College Educated	Number of persons age 25 and over with a bachelor's, master's, professional, or doctorate degree divided by the total population 25+ years of age. Values for the 1990 and 2000 Censuses are used to estimate intervening years..	+	US Census Bureau, 1990, 2000
Dependent Variables			
Class 300 (Public Information)	Activities that inform the public about flood hazard, insurance, and protection measures, directed toward local populace. Measured as the total points earned divided by the maximum points available.		FEMA Community Rating System 1999-2005
Class 400 (Maps and Regulation)	Activities that enact and enforce regulations that exceed the NFIP minimum standards. Measured as the total points earned divided by the maximum points.		FEMA Community Rating System 1999-2005
Class 500 (Damage Reduction)	Activities that address flood damage to existing buildings. Measures include retrofitting existing buildings and maintaining drainage and retention basins.		FEMA Community Rating System 1999-2005

	Measured as the total points earned divided by the maximum points.	
Class 600 (Flood Preparedness)	Activities coordinated by local emergency managers, including actions taken to minimize the effects of a flood on people, property, and building contents. Measured as the total points earned divided by the maximum points.	FEMA Community Rating System 1999-2005
CRS Overall Points	Summation of points for all activities divided by the maximum points.	FEMA Community Rating System 1999-2005

Table II. Community Rating System points (percent) by series activities, 1999-2005.

Year	N	Series 300 Public Information	Series 400 Maps and Regulation	Series 500 Damage Reduction	Series 600 Flood Preparedness	Overall CRS
1999	48	25.39	5.38	2.75	5.97	5.98
2000	49	28.10	7.36	3.16	6.56	7.18
2001	51	29.09	8.43	3.09	6.58	7.59
2002	52	30.75	9.04	3.35	6.69	8.03
2003	52	27.72	7.61	3.25	6.26	7.37
2004	51	28.43	10.16	3.34	6.40	7.72
2005	51	29.77	11.00	3.41	7.00	8.31
Average		28.49	8.46	3.20	6.50	7.47

Table III. Panel corrected linear regression models using feasible generalized least squares† predicting CRS series 300 flood mitigation activities, 1999-2005**.**

	(1)	(2)	(3)	(4)
Hydrology Variables				
Floodplain percentage	-.2625***	-.1111***	-.1576***	-.09350***
	(.0215)	(.0198)	(.0210)	(.0220)
Stream length	-0.00000312	-0.00000763***	-0.00000272	-0.00000430*
	(0.0000022)	(0.0000016)	(0.0000023)	(0.0000023)
Flood Disaster Variables				
Flood frequency		8.027***	3.314***	3.784***
		(0.42)	(0.45)	(0.45)
Flood property damage ($10,000)		0.00481***	0.00110*	0.00217***
		(0.00056)	(0.00064)	(0.00063)
Socioeconomic Variables				
Population density			0.0372***	0.0253***
			(0.0030)	(0.0026)
Reduction per policy holder			0.184***	0.171***
			(0.017)	(0.018)
Human Capital Variables				
Nonprofit assets per capita				0.000508***
				(0.000098)
Median household income				0.000145***
				(0.000037)
Percent college educated				0.0776**
				(0.037)
Constant	35.25***	23.32***	19.81***	10.38***
	(0.90)	(0.87)	(0.83)	(1.76)
Observations	354	354	354	354
Number of FIPS	52	52	52	52
Log likelihood	-1234.668	-1165.578	-1145.866	-1124.719
Wald χ^2	149.58	544.49	816.31	1254.24

Standard errors in parentheses. Null hypothesis test of coefficient equal zero, *** p<0.01, ** p<0.05, * p<0.1

† Models corrected for heteroskedastic error structure with independent serial autocorrelation

Table IV. Panel corrected linear regression models using feasible generalized least squares† predicting CRS series 400 flood mitigation activities, 1999-2005**.**

	(1)	(2)	(3)	(4)
Hydrology Variables				
Floodplain percentage	-.07278***	-.06240***	-.09269***	-.08299***
	(.0071)	(.0084)	(.0092)	(,0119)
Stream length	-0.000000603	-0.000000186	0.000000171	-0.00000246*
	(0.0000018)	(0.0000019)	(0.0000013)	(0.0000013)
Flood Disaster Variables				
Flood frequency		0.512**	-0.520***	-0.278
		(0.22)	(0.17)	(0.23)
Flood property damage ($10,000)		0.000563	0.00112***	0.00158***
		(0.00043)	(0.00038)	(0.00043)
Socioeconomic Variables				
Population density			-0.00146	-0.00317
			(0.0021)	(0.0030)
Reduction per policy holder			0.115***	0.106***
			(0.0070)	(0.0093)
Human Capital Variables				
Nonprofit assets per capita				0.0000788
				(0.000074)
Median household income				0.000120***
				(0.000035)
Percent college educated				0.00539
				(0.025)
Constant	10.08***	9.212***	7.396***	2.732**
	(0.50)	(0.53)	(0.48)	(1.37)
Observations	354	354	354	354
Number of FIPS	52	52	52	52
Log likelihood	-684.332	-689.7063	-649.9491	-649.4104
Wald χ^2	132.25	128.98	454.70	343.11

Standard errors in parentheses. Null hypothesis test of coefficient equal zero, *** p<0.01, ** p<0.05, * p<0.1

† Models corrected for heteroskedastic error structure and panel-specific AR (1) serial autocorrelation

Table V. Panel corrected linear regression models using feasible generalized least squares† predicting CRS series 500 flood mitigation activities, 1999-2005.

	(1)	(2)	(3)	(4)
Hydrology Variables				
Floodplain percentage	-.02101***	-.00918	-.00905	.000721
	(.0061)	(.0058)	(.0071)	(.0066)
Stream length	0.000000521	0.00000171***	0.000000513	0.000000372
	(0.00000060)	(0.00000058)	(0.00000071)	(0.00000070)
Flood Disaster Variables				
Flood frequency		0.699***	0.201***	0.124*
		(0.067)	(0.074)	(0.071)
Flood property damage ($10,000)		0.000603***	-0.0000587	0.0000980
		(0.000052)	(0.000047)	(0.000094)
Socioeconomic Variables				
Population density			0.00568***	0.00459***
			(0.00066)	(0.00092)
Reduction per policy holder			0.0250***	0.0215***
			(0.0023)	(0.0024)
Human Capital Variables				
Nonprofit assets per capita				0.0000633**
				(0.000028)
Median household income				0.0000189**
				(0.0000088)
Percent college educated				0.0338***
				(0.0094)
Constant	3.734***	2.111***	1.893***	0.376
	(0.30)	(0.26)	(0.34)	(0.49)
Observations	354	354	354	354
Number of FIPS	52	52	52	52
Log likelihood	-94.41263	-159.3691	-125.4641	-124.1535
Wald χ^2	25.31	335.04	246.19	316.15

Standard errors in parentheses. Null hypothesis test of coefficient equal zero, *** p<0.01, ** p<0.05, * p<0.1

† Models corrected for heteroskedastic error structure and panel-specific AR (1) serial autocorrelation

Table VI. Panel corrected linear regression models using feasible generalized least squares† predicting CRS series 600 flood mitigation activities, 1999-2005.

	(1)	(2)	(3)	(4)
Hydrology Variables				
Floodplain percentage	-.08508***	-.03683***	-.03237***	-.03730***
	(.0078)	(.0071)	(.0094)	(.0089)
Stream length	0.00000354***	0.00000219***	0.00000223***	0.000000545
	(0.00000065)	(0.00000054)	(0.00000066)	(0.00000072)
Flood Disaster Variables				
Flood frequency		0.744***	0.587***	0.663***
		(0.12)	(0.13)	(0.14)
Flood property damage ($10,000)		0.00130***	0.000329**	0.000941***
		(0.00024)	(0.00016)	(0.00021)
Socioeconomic Variables				
Population density			0.00772***	0.00447***
			(0.00087)	(0.0011)
Reduction per policy holder			0.0448***	0.0498***
			(0.0044)	(0.0046)
Human Capital Variables				
Nonprofit assets per capita				0.000154*
				(0.000079)
Median household income				0.0000184
				(0.000016)
Percent college educated				0.0836***
				(0.018)
Constant	8.064***	5.315***	3.879***	2.014***
	(0.27)	(0.27)	(0.35)	(0.73)
Observations	354	354	354	354
Number of FIPS	52	52	52	52
Log likelihood	-190.2019	-255.0637	-323.8535	-342.993
Wald χ^2	140.02	189.73	505.66	735.50

Standard errors in parentheses. Null hypothesis test of coefficient equal zero, *** p<0.01, ** p<0.05, * p<0.1

† Models corrected for heteroskedastic error structure and panel-specific AR (1) serial autocorrelation

Table VII: Panel Corrected Linear Regression Models using Feasible Generalized Least Squares† Predicting CRS Overall Flood Mitigation Activities, 1999-2005.

	(1)	(2)	(3)	(4)
Hydrology Variables				
Floodplain percentage	-.05419***	-.04249***	-.05544***	-.04645***
	(.0067)	(.0091)	(.0075)	(.0071)
Stream length	0.000000982	0.000000165	0.00000147***	0.00000113
	(0.00000087)	(0.00000097)	(0.00000055)	(0.00000087)
Flood Disaster Variables				
Flood frequency		1.191***	0.140	0.281*
		(0.12)	(0.13)	(0.14)
Flood property damage ($10,000)		0.000721***	0.000382**	0.000785***
		(0.00025)	(0.00019)	(0.00025)
Socioeconomic Variables				
Population density			0.00876***	0.00551***
			(0.0013)	(0.0017)
Reduction per policy holder			0.0768***	0.0704***
			(0.0049)	(0.0056)
Human Capital Variables				
Nonprofit assets per capita				0.000155***
				(0.000038)
Median household income				0.0000518***
				(0.000019)
Percent college educated				0.0256**
				(0.012)
Constant	8.498***	7.004***	5.112***	2.427***
	(0.28)	(0.33)	(0.28)	(0.77)
Observations	354	354	354	354
Number of FIPS	52	52	52	52
Log likelihood	-414.1529	-432.0679	-388.3308	-388.9244
Wald χ^2	69.15	203.02	635.63	829.62

Standard errors in parentheses. Null hypothesis test of coefficient equal zero, *** p<0.01, ** p<0.05, * p<0.1

† Models corrected for heteroskedastic error structure and panel-specific AR (1) serial autocorrelation

Table VIII. Average Community Rating System points earned by class activities, the percent of total points earned, and deviation of percent earned from proportion of class size, 1999-2005.

Year	Points Row %	Series 300 835 pts (5.69)	Dev. %	Series 400 5894 pts (40.18)	Dev. %	Series 500 6639 pts (45.26)	Dev. %	Series 600 1300pts (8.86)	Dev. %	Overall
1999	Pts	193.44	+21.79	256.87	-3.68	180.62	-19.60	72.88	+1.50	703.81
	Row %	(27.48)		(36.50)		(25.66)		(10.36)		(100.00)
2000	Pts	214.09	+19.40	351.44	+1.00	207.77	-20.91	80.07	+0.52	853.37
	Row %	(25.09)		(41.18)		(24.35)		(9.38)		(100.00)
2001	Pts	221.64	+18.74	402.75	+4.21	202.68	-22.92	80.26	-0.01	907.33
	Row %	(24.43)		(44.39)		(22.34)		(8.85)		(100.00)
2002	Pts	234.30	+18.53	431.60	+4.43	219.92	-22.53	81.62	-0.42	967.45
	Row %	(24.22)		(44.61)		(22.73)		(8.44)		(100.00)
2003	Pts	231.42	+18.00	448.36	+5.72	215.64	-23.18	81.35	-0.53	976.77
	Row %	(23.69)		(45.90)		(22.08)		(8.33)		(100.00)
2004	Pts	237.41	+15.11	599.04	+12.29	221.98	-25.82	83.15	-1.58	1141.58
	Row %	(20.80)		(52.47)		(19.44)		(7.28)		(100.00)
2005	Pts	248.54	+14.79	648.07	+13.22	226.15	-26.63	90.94	-1.37	1213.70
	Row %	(20.48)		(53.40)		(18.63)		(7.49)		(100.00)
Avg.	***Pts***	***226.22***	***+17.65***	***450.43***	***+6.29***	***210.99***	***-23.49***	***81.55***	***-0.45***	***969.18***
	Row %	***(23.34)***		***(46.47)***		***(21.77)***		***(8.41)***		***(100.00)***

REFERENCES

1. Association of State Floodplain Managers (ASPFM). (2000). *National Flood Programs in Review - 2000*. Madison, WI: Association of State Floodplain Managers.
2. Kunreuther, H. and Roth, R. J. (1998). *Paying the price: The status and role of insurance against natural disasters in the United States*. Natural Hazards and Disasters. Washington, DC: Joseph Henry Press.
3. Mileti, D. S. (1999). *Disasters By Design: A Reassessment of Natural Hazards in the United States*. Natural Hazards and Disasters. Washington, DC: Joseph Henry Press.
4. Pielke, R. A. (1996). *Midwest Flood of 1993: Weather, Climate, and Societal Impacts*. Boulder, CO: National Center for Atmospheric Research.
5. Pielke, R. A. and Downton, M. W. (2000). Precipitation and damaging floods: Trends in the United States, 1932-97. *Journal of Climate*, *13*, (20), 3625-3637.
6. Holling, C. S. and United Nations Environment Programme. (1978). *Adaptive environmental assessment and management*. International Series on Applied SystemsAnalysis. Laxenburg, Austria: International Institute for Applied Systems Analysis, Wiley.
7. Lee, K. N. (1992). Ecologically effective social organization as a requirement for sustaining watershed ecosystems. In R. J. Naiman (Ed.), *Watershed Management: Balancing Sustainability and Environmental Change*, (pp. xii, 542). New York: Springer-Verlag.
8. Schön, D. A. (1983). *The Reflective Practitioner: How Professionals Think In Action*. New York, NY: Basic Books.
9. Holling, C. S. (1996). Surprise for science, resilience for ecosystems, and incentives for people. *Ecological Applications*, *6*, (3), 733-735.
10. Westley, F. (1995). Governing design: the management of social systems and ecosystems management. In L. H. Gunderson, C. S. Holling and S. S. Light (Eds.), *Barriers and Bridges to the Renewal of Ecosystems and Institutions*, (pp. 391-427). New York: Columbia University Press.
11. Lessard, G. (1998). An adaptive approach to planning and decision-making. *Landscape and Urban Planning*, *40*, (1-3), 81-87.
12. Holling, C. S. (1995). What barriers? What bridges? In L. H. Gunderson, C. S. Holling and S. S. Light (Eds.), *Barriers and Bridges to the Renewal of Ecosystems and Institutions*, (pp. 3-34). New York: Columbia University Press.
13. Lee, K. N. (1993). *Compass and Gyroscope: Integrating Science and Politics for the Environment*. Washington, DC: Island Press.
14. May, P. J. (1992). Policy learning and failure. *Journal of Public Policy*, *12*, (4), 331-354.
15. May, P. J. (1992). Reconsidering policy design: Policies and publics. *Journal of Public Policy*, *11*, (Part 2), 187-206.
16. May, P. J. (1998). *Fostering Policy Learning: A Challenge for Public Administrators*. Seattle, WA: Department of Political Science, University of Washington.

17. Heclo, H. (1974). *Modern social politics in Britain and Sweden; from relief to income maintenance*. Yale Studies in Political Science. New Haven, CT: Yale University Press.
18. Sacks, P. (1980). State structure and the asymmetrical society. *Comparative Politics*, *12*, (3), 349-376.
19. Weir, M. and Skocpol, T. (1985). State structures and the possibilities for 'Keynesian responses to the great depression in Sweden, Britain and the United States'. In P. B. Evans, D. Rueschemeyer, T. Skocpol, Social Science Research Council (U.S.) Committee on States and Social Structures, Joint Committee on Latin American Studies and Joint Committee on Western Europe (Eds.), *Bringing the State Back In*, (pp. 107-168). Cambridge: Cambridge University Press.
20. Hall, P. A. (1993). Policy paradigms, social-learning, and the state: the case of economic policy-making in Britain. *Comparative Politics*, *25*, (3), 275-296.
21. Brody, S. D. (2003). Are we learning to make better plans? A longitudinal analysis of plan quality associated with natural hazards. *Journal of Planning Education and Research*, *23*, (2), 191-201.
22. Beem, B. (2006). Planning to learn: Blue crab policymaking in the Chesapeake Bay. *Coastal Management*, *34*, (2), 167-182.
23. Sabatier, P. (1995). An advocacy coalition framework of policy change and the role of policy-oriented learning therein. In D. McCool (Ed.), *Public Policy Theories, Models, and Concepts: An Anthology*, (pp. xiii, 412). Englewood Cliffs, NJ: Prentice Hall.
24. Folke, C., Hahn, T., Olsson, P. and Norberg, J. (2005). Adaptive governance of social-ecological systems. *Annual Review of Environment & Resources*, *30*, (1), 441.
25. Berkes, F. (2007). Understanding uncertainty and reducing vulnerability: Lessons from resilience thinking. *Natural Hazards*, *41*, (2), 283-295.
26. Luloff, A. E. and Wilkinson, K. P. (1979). Participation in the National Flood Insurance Program: a study of community attentiveness. *Rural Sociology*, *44*, 137-152.
27. Moore, D. E. and Cantrell, R. L. (1976). Community response to external demands: an analysis of participation in the Federal Flood Insurance Program. *Rural Sociology*, *41*, 484-508.
28. Browne, M. J. and Hoyt, R. E. (2000). The demand for flood insurance: Empirical evidence. *Journal of Risk and Uncertainty*, *20*, (3), 291-306.
29. Burby, R. J. (2003). Making plans that matter - Citizen involvement and government action. *Journal of the American Planning Association*, *69*, (1), 33-49.
30. Johnson, C. L., Tunstall, S. M. and Penning-Rowsell, E. C. (2005). Floods as catalysts for policy change: Historical lessons from England and Wales. *International Journal of Water Resources Development*, *21*, (4), 561 - 575.
31. Federal Emergency Management Agency (FEMA). (2006). *CRS State Profile: Florida*. Washington, DC:
32. Federal Emergency Management Agency (FEMA). (1997). *Multi-Hazard Identification and Risk Assessment*. Washington, DC: Government Printing Office.

33. Horton, R. E. (1932). Drainage-basin characteristics. *Transactions-American Geophysical Union*, *13*, 350-361.
34. Kriesel, W. and Landry, C. (2004). Participation in the National Flood Insurance Program: An empirical analysis for coastal properties. *Journal of Risk and Insurance*, *71*, (3), 405-420.
35. Drukker, D. M. (2003). Testing for serial correlation in linear panel-data models. *Stata Journal*, *3*, 168-177.
36. Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data*. Cambridge, MA: MIT Press.

FOOTNOTES

[i] According to Centers for Disease Control Compressed Mortality Files, 2,196 persons have been killed from floods and cataclysmic storms from 1979 to 1998. The average number of persons killed in the United States per year has remained relatively constant over this time period, despite noticeable improvements in flood mitigation, response, and recovery efforts.

[iii] The maximum points a locality can earn per class and overall has changed twice in the last decade. We use denominators in the 1999 CRS Coordinator's Manual to calculate flood mitigation values for 1999 to 2002, and the 2002 Coordinator’s manual to calculate values for 2003 to 2005.

[iv] A ten-year rolling average is both theoretically and practically reasonable. From theory and empirical evidence, we assume that flood planning is slow and incremental. On the question of institutional change, or change in the rules and procedures that structure institutional behavior, Nobel laureate Douglass C. North (1995: 19-20) maintains that, “the overwhelming majority of change is simply incremental and gradual.” A single flood event may not be enough to induce institutional change - much depends on prior probability distributions. We presume that a locality is more likely to undertake costly mitigation efforts if flood events are recurrent and cumulate in institutional memory. Practically, a ten-year rolling average sufficiently smoothes the noise in estimates of flood frequency and intensity.

[v] The SHELDUS database consists of a county-level inventory of 18 natural hazard types, including hurricanes, floods, wildfires, and drought. Hazard event records include a start and end date, estimated property damage and crop loss, as well as the number of human injuries and deaths. SHELDUS data are derived from public sources like National Climatic Data Center monthly publications and NGDC's Tsunami Event Database. The data are limited to disaster events that cause more than $50,000 in crop loss or property damage.

[vi] With our annual linear rate of growth, we project from a base year (P_1) to a target year (P_2) with the following formula: $P_2 = P_1 * [1 + (rlin * n)]$ where, $rlin$ is the average annual linear rate of growth, and n is the number of years between the base and target years.

[vii] Upward trends in average activity scores are depressed slightly by localities that entered the CRS program after 1999. Late entering localities have substantially lower CRS scores. Localities gain entry into CRS by performing minimum requirements. Scores generally increase with time, as mitigation efforts cumulate.