Economic impacts of urban flooding in South Florida: Potential consequences of managing groundwater to prevent salt water intrusion

Authors:
Jeffrey Czajkowski
Vic Engel
Chris Martinez
Ali Mirchi
David Watkins
Michael C. Sukop
Joe Hughes

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Abstract

High-value urban zones in coastal South Florida are considered particularly vulnerable to salt water intrusion into the groundwater-based, public water supplies caused by sea level rise (SLR) in combination with the low topography, existing high water table, and permeable karst substrate. Managers in the region closely regulate water depths in the extensive South Florida canal network to control closely coupled groundwater levels and thereby reduce the risk of saltwater intrusion into the karst aquifer. Potential SLR adaptation strategies developed by local managers suggest canal and groundwater levels may have to be increased over time to prevent the increased salt water intrusion risk to groundwater resources. However, higher canal and groundwater levels cause the loss of unsaturated zone storage and lead to an increased risk of inland flooding when the recharge from rainfall exceeds the capacity of the unsaturated zone to absorb it and the water table reaches the surface. Consequently, higher canal and groundwater levels are also associated with increased risk of economic losses, especially during the annual wet seasons. To help water managers and urban planners in this region better understand this trade-off, this study models the relationships between flood insurance claims and groundwater levels in Miami-Dade County. Via regression analyses, we relate the incurred number of monthly flood claims in 16 Miami-Dade County watersheds to monthly groundwater levels over the period from 1996 to 2010. We utilize these estimated statistical relationships to further illustrate various monthly flood loss scenarios that could plausibly result, thereby providing an economic quantification of a “too much water” trade-off. Importantly, this understanding is the first of its kind in South Florida and is exceedingly useful for regional-scale hydro-economic optimization models analyzing trade-offs associated with high water levels.
I. Introduction

The counties of the Lower East Coast (LEC) of Florida – Palm Beach, Broward, and Miami Dade – are the three most populous in the state with a population of over 5.6 million people, forecast to rise to over 8.4 million in 2040 (BEBR, 2013). Consequently, the LEC is a significant end-user of publically supplied groundwater withdrawn from Florida aquifers today and into the foreseeable future (USGS, 2010). Moreover, canal water levels in the LEC are managed in part to create a positive hydraulic gradient that continually recharges the Biscayne aquifer with freshwater, thereby lowering the risk of salt water intrusion from the Atlantic Ocean and coastal embayments into groundwater supplies (Carter et al., 2010). However, ensuring there is enough potable groundwater supply to meet the existing and growing needs of the urban areas of the LEC comes at a potential simultaneous and unintended cost to urban users.

Because the urban canal network is also used to receive and discharge excess water during the wet season and extreme rain events, the efforts to prevent salt water intrusion through the manipulation of canal water levels also represent a source of flood risk. And Florida has one of the highest risks of flooding in the United States, ranking 3rd highest in the number of National Flood Insurance Program (NFIP) claims incurred since 1978 U.S., behind Louisiana and Texas (NFIP, 2015). Miami-Dade and Broward are the top two Florida counties to have incurred flood claims in the state (Palm Beach is 6th), with all three LEC Counties representing 36 percent of the total Florida flood claims incurred (NFIP, 2015).

It is these types of system-wide tradeoffs associated with meeting the water demands while also providing flood control for the already large and growing urban areas in the LEC and the Everglades Agricultural Area (EAA), as well as maintaining the ecological integrity of the natural wetland habitats including the Everglades, that characterize South Florida’s water management system (e.g., Watkins et al., 2004). Moreover, as sea level rises, South Florida water managers will increasingly face potentially more severe trade-offs associated with maintaining, on one hand, the high canal and groundwater levels needed to meet the increasing demands of the growing population and to stave off saltwater intrusion; and on the other, the requirements to meet both flood protection goals for urbanized areas and environmental water demands. Extreme rainfall events such as tropical storms or changes in seasonal rainfall patterns associated with climate change may increase the challenges of meeting these potentially conflicting objectives, and quantitative economic analyses are needed to inform water resource management decisions in this region. Given this, the purpose of this study is to provide such a quantitative analysis of the flood risk to better ascertain the associated economic trade-off with maintaining higher groundwater levels.

Specifically we examine the relationship between groundwater levels and the rate of flood insurance claims in urbanized areas of Miami-Dade County, the most populous and most flood-impacted county of the LEC. Significantly, this relationship is not particularly well understood by South Florida residents and water management experts alike (Bolter, 2013), with the typical SLR flood risk focus primarily related to more intense storm surge impacts or direct waterfront coastal areas and rising tides (Lemonick, 2012). Flood losses herein are represented by the number of actual flood claims incurred during the study period of 1996 to 2010. We benefit from access to the entire policy and claim portfolio of the NFIP. We first relate via panel data regression analyses (Dell et al., 2014) the incurred number of flood claims to corresponding monthly groundwater levels for individually managed watersheds in Miami-Dade County. By controlling for relevant flood hazard, land-use, and other exposure variables in the
regression analyses, a predictive model of the number of urban residential flood claims per varying groundwater levels is obtained at a given managed watershed location.

This information is expected to be useful in urban planning and water resource forums in South Florida where new strategies for managing the region’s water resources are being sought during this period of rapidly changing environmental and land use conditions. The predictive model is particularly relevant to applications of water resources systems analysis, including hydro-economic optimization (HEO, Mirchi et al., 2017 this issue), trade-off analysis, and collaborative modeling (e.g., Brown et al., 2015). In particular, hydro-economic modeling provides a solution-oriented framework for integrated analysis of complex water resources systems and for assessing potential economic impacts of management decisions and resource development options on different system sectors (Heinz et al. 2007; Harou et al. 2009, Mirchi et al. 2010). These models are most frequently applied to assist in water resources management under conditions of water scarcity (Jenkins et al., 2004; Marques et al., 2006; Pulido-Velazquez et al., 2006; Ward et al., 2006; Maneta et al., 2009; Harou et al., 2010; Tilmant et al., 2014). However, they are similarly useful for regions where economic performance is also dependent on managing flood risk (Harou et al. 2009). The economic relationship we are modeling here has not previously been readily available for such uses.

Beyond South Florida, coastal areas around the world are increasingly exposed to flooding due to higher water tables caused by high tides and sea level rise. The National Climate Assessment (Melillo et al., 2014) reports that sea levels may rise between 0.3 and 2 m by 2100. This will cause increases in coastal groundwater levels and the potential for exacerbating sea water intrusion (Werner and Simmons, 2009; Chang et al, 2011). Subsurface storage of stormwater is reduced by higher water tables and the water table can rise above the land surface leading to flooding. The National Climate Assessment (Melillo et al., 2014) points out that erosion and inundation in some portions of Alaska, Louisiana, the Pacific Islands, and other coastal regions, have already forced communities to relocate away from their historical homelands. Miami Beach Florida and Norfolk Virginia (Corum, 2016) are two prime examples of areas experiencing tidally-driven “sunny-day” or “nuisance” flooding while Hawaii and California will likely lose land to sea level rise. Wdowinski et al. (2016) found that tidal and rain-based flooding became more frequent in Miami Beach between 2006 and 2013. Habel et al. (2017) and Rotzoll and Fletcher (2013) investigated groundwater inundation in Hawaii, while Hoover et al. (2016) assess potential groundwater emergence on the California coast. Our work here importantly adds to this literature.

The remainder of the paper is organized as follows. Section II provides further detail on the managed South Florida water system and its connection to urban residential flooding from groundwater. Section III details the study area, methodology, and data used for the flood claim statistical analyses. Section IV presents the regression results. Section V discusses potential HEO application of these results. Section VI provides concluding comments.

II. South Florida Water Management System

The South Florida Water Management District (SFWMD) operates and maintains the regional water management system (Figure 1) known as the C&SF Project (SFWMD Drought and Flood 2015). The system’s primary operating goals of providing flood control, water supply, and environmental preservation (Watkins et al., 2004) are accomplished through the management of over 2,600 miles of
canals and levees as well as approximately 1,300 water control structures and 66 pump stations (SFWMD 2010; 2015b). It is a three-tiered system of water management where: 1) the primary drainage system of SFWMD-operated water control structures (including pumps) route water through the major canals into and out of impounded storage areas, including the Everglades Water Conservation Areas (WCAs) and Lake Okeechobee, and toward coastal discharge points; 2) the primary drainage system receives discharge from a secondary system of more local-level (county, city) canals, water control structures; and 3) the secondary system receives discharge from a tertiary drainage system, which is a localized system of drainage grates, ditches, and smaller canals (SFWMD 2010). Overall, surface water drains or is pumped from the WCAs to canals in the urbanized areas to facilitate groundwater recharge, particularly near municipal well fields. Especially during the November to May dry season, this system, along with periodic restrictions on residential water use, is used to maintain groundwater tables at target depths (typically less than 1 m) below the surface of the lowest land elevations in order to prevent salt water intrusion. Coastal discharge structures are normally kept closed during the dry season, except during those periods when increased capacity to absorb stormwater is needed. During the June through October wet season, the water levels in the canal systems may be maintained at target levels by storing excess surface water in inland impoundments (e.g. the WCAs) or by discharge to the coast. The coastal discharge structures typically remain open to tidal exchange during the wet season.

For the LEC, the WCAs (Figure 1) provide wet season flood protection, while also providing dry-season recharge of the regional groundwater resources needed to meet LEC residential demands (SFWMD, 2015a). In conjunction with the WCAs, four primary canals (Figure 2 left panel) provide flood control and water supply/groundwater recharge to the LEC. Flood control is provided by discharging local LEC runoff to the coast. These canals are also used to lower the WCA water levels and hence provide flood protection along the East Coast Protective (ECP) levee, the main barrier between the WCAs and the LEC (Figure 2, middle panel). The discharge capacity of these canals relative to inflows is thus a critical parameter regulating the effectiveness of flood protection in the LEC. Seepage beneath the ECP levee is a major source of groundwater in adjacent areas (Strowd, 2011). Similarly, seepage beneath the levees bordering Everglades National Park (ENP) is a significant source of groundwater for adjacent agricultural and urbanized lands, and without active management could represent a potential flood risk for these areas. (Figure 2 right panel). During wet periods or when high LEC groundwater levels present an increased flood risk, levee seepage from the WCAs and ENP is pumped back into the storage areas or routed to coastal discharge structures. The influence of Everglades’ water depths on groundwater levels in adjacent parcels indicates that the higher water levels and increased flows in the Everglades generated through restoration (USACE and SFWMD, 1999) will continue to require active management strategies to maintain current groundwater targets in the LEC.

Canal water levels in the LEC are managed to create a positive hydraulic gradient that continually recharges the Biscayne aquifer with freshwater, thereby lowering the risk of salt water intrusion from the Atlantic Ocean and coastal embayments into groundwater supplies. This risk is especially significant in the LEC given the high porosity and hydraulic conductivity (>0.1 m s\(^{-1}\)) of the surficial Biscayne aquifer underlying the region (Cunningham and Sukop, 2011; Lemonick, 2012; Prinos et al., 2014; Weissmann, 2015). This high porosity complicates efforts to protect the region from SLR and salt water intrusion since more traditional methods, such as sea wall construction, cannot prevent the upward percolation of seawater into the aquifer (Weismann, 2015). Because the urban canal network is also used to receive and
discharge excess surface water during the wet season and extreme rain events, the efforts to prevent salt
water intrusion through the manipulation of canal water levels also represent a source of flood risk.
Global mean sea level is expected to rise at least 1.6 m above current levels by the end of the century,
with substantially greater increases possible (Strauss et al. 2015; IPCC 2013). Sea level has already risen
~2 mm yr\(^{-1}\) since the completion of the C&SF system with a corresponding decrease in hydraulic gradient
and overall efficiency of gravity drainage through the canal network.

III. Study Area, Methodology, and Data

Study Area and Methodology

The study area for this analysis is 16 SFWMD-defined watersheds within Miami Dade County
(Figure 3). The boundaries for these watersheds were provided from the SFWMD’s Arc Hydro Enhanced
Database (AHED, 2015). These specific watersheds were chosen for this analysis because of the high
quality hydrologic data available and also the intensity of water management along the environmental
and urban border in this area leading to potentially higher flood risk. Much of the developed land of South
Florida is characterized by a shallow groundwater table that rises rapidly in response to rainfall events
due to the high permeability of the aquifer and of the overlying unsaturated zone. In a companion paper
(Sukop et al. 2017, this issue), we analyze the rate of water table rise in response to rainfall events and
the correlation between flooding and groundwater levels in the Arch Creek repetitive loss area in Miami-
Dade County. Close coupling of the ground and surface water (Hughes and White, 2016) is leveraged by
the South Florida Water Management District to aid in flood control (Carter et al., 2010). Before the arrival
of possible large storm events, surface and groundwater levels are sometimes lowered to increase local
basin storage and reduce flood risk. Lowering the water table provides more unsaturated zone storage
that buffers the flooding potential of storm events. Widespread flooding events are strongly associated
with the highest groundwater levels and occur when the water table reaches the ground surface. The low
relief of South Florida, similarly to the recent experiences in Houston, is not conducive to high runoff rates
and much of the water that falls as rain ultimately makes its way to the canals via groundwater flow.
Canals generally replaced natural stream channels as South Florida developed and are now effectively the
only surface water/stream channels in the area. Because they are intensively managed by water control
structure operations, their stages are likely to reflect those operations. In contrast, the more natural effect
of rainfall on the water table can be measured by the observation well network. The management of canal
levels, the strong observed correlation of flooding events with high groundwater levels, and the loss of
unsaturated zone buffer against flooding that comes with higher groundwater levels suggest that
groundwater levels are the best available gauge of flooding events in the area.

We spatially joined 2010 Miami-Dade census tracts to the 16 watersheds such that if the center
of the census tract is located within the watershed, it was assigned to that watershed. A total of 328
census tracts were spatially joined to these 16 watersheds containing over 1.7 million people and 602,000
housing units. Thus, we captured 70 percent of the total Miami-Dade County 2010 population (61 percent
of housing units) and 31 percent of the total LEC 2010 population (24 percent of housing units) (Miami
Dade County Research Section, 2011), or a significant portion of the urban residential area of the LEC
exposed to inland flood risk. Many of the eastern areas of Miami Dade County not included in this analysis
are primarily exposed to coastal storm surge flood risk, which we excluded from the analysis in order to
focus on claims associated with increased groundwater levels as part of the SFWMD managed system. Table 1 lists the study area’s 16 watersheds as well as relevant census data collected. We conducted a regression analysis of the number of flood claims incurred per watershed per month during the timeframe of 1996 to 2010. We focused our statistical analysis on the number of claims as opposed to the dollar value of the individual losses since the extent of damages given a claim has first been incurred is complicated by a number of detailed property exposure and vulnerability factors. For this study we were primarily interested in establishing the statistical relationship between groundwater levels and whether or not flood losses occur; for this reason we modeled the number of claims, which resulted in a more straightforward analysis. As the study of residential flood losses is a multi-causal hazard, exposure, and vulnerability issue, our multivariate regression analysis appropriately captures and quantifies these effects jointly. That is, watershed residential flood claims are a function of a vector of relevant watershed flood hazard, exposure, and vulnerability variables described in more detail below. Our monthly observations for each watershed over the 15-year time period provided a panel estimation structure that emphasizes variation over time within our watershed-defined spatial area and, importantly, is appropriate to isolate the impact of groundwater levels on the occurrence of flood losses (Dell et al., 2014). Though groundwater levels rise rapidly in response to recharge from rainfall, the effects of large rainfall events on the water table typically persist for 15 days or more (Sukop et al, 2017). This suggests that the monthly average stages we use here are likely to be a reasonable measure of higher groundwater levels and consequently of the potential for flooding. Thus the monthly time-step allowed for the capture of both large events such as tropical cyclones, but also more frequent yet still significant non-tropical-cyclone precipitation events.

**Insured Flood Claim and Policy Data**

Economic losses due to flooding were represented by the actual insurance claims incurred per watershed per month by the U.S. NFIP. In the U.S., coverage for flood damage resulting from rising water is explicitly excluded in homeowners’ insurance policies, but such coverage has been available since 1968 through the federally managed NFIP. Thus, the NFIP is the primary source of residential flood insurance in the U.S. (Michel-Kerjan, 2010; Michel-Kerjan and Kunreuther, 2011). We benefited from access to its entire policy portfolio from 2000 to 2010, as well as individual policy claim data from 1996 to 2010.

For each watershed, we determined the total number of residential flood claims incurred per month per year from 1996 to 2010. The NFIP portfolio data does not contain individual residential location (street address); therefore, we aggregated NFIP claims incurred at the US census tract level, the lowest level of geographic identification in the NFIP dataset. Again, as we spatially joined the Miami-Dade census tracts to the 16 watersheds, this allowed for an aggregation of the collected census tract claims to the individual watershed level. “Residential” equates to single-family, two- to four-family, and other residential structures. Non-residential (i.e., primarily commercial) structures covered by the NFIP, which represent less than 5 percent of the total insured portfolio, were excluded from this analysis. Since we focused on analyzing inland freshwater flood losses, we excluded all claims explicitly due to “tidal water overflow” as classified by the NFIP (i.e., storm surge losses).

A total of 43,551 NFIP flood claims (Table 1) were incurred in these 16 watersheds from 1996 to 2010, or an average of 241 flood claims per month in the entire study area (approximately 15 flood claims per watershed per month). While we modeled the count of flood claims incurred, total damage (building
and content) from these claims was $327.3 million in 2010 dollars, or a straightforward average of $7,515 per claim. Ninety percent of the total claims over the 15-year time period were incurred during the June to October wet season, although this did vary in any one year with only 50 percent or less of the annual claims occurring in the wet season in 1997, 1998, 2002, 2006, 2009 and 2010. While 96 percent of total flood claims occurred prior to 2006 (87 percent of total in 1999, 2000, and 2005 alone), the median number of annual flood claims was 461 per year, or a median value of 29 claims per watershed per year. So although there is clearly some skewness to the flood claim data stemming from anomalous wet periods during this timeframe, the median annual claim amounts reflect a significant flood risk issue in the study area. For example, the 461 median annual flood claims would cost over $3.5 million dollars per year (= 461 x $7,515) based upon this NFIP insured loss data. A study on the entire NFIP claims database by Kousky and Michel-Kerjan (2015) indicates that this $7,515 loss amount is fairly representative, with their median claim value being $12,555 across the whole country and all years. In South Florida, extreme flood/rainfall events significantly increased these median claim values, as evidenced by the data. We provide a more detailed analysis of the dollar value of losses in Section V below in the context of the use of our empirical results in a HEO application.

From 1996 to 2010, flood claims were incurred in every watershed and in 312 of the 328 underlying census tracts, or 95 percent of the Miami-Dade study area. Figure 4 illustrates our defined relatively high flood claim watersheds in the study area (i.e., total of 4500 claims or greater from 1996 to 2010), which are coincident with development characterized as single-family housing units. As we dealt with insured flood claims, claims were only incurred where there were NFIP policies in force. NFIP flood insurance is only required in a designated high-risk flood zone and if the homeowner has a federally backed mortgage. This is certainly not the case for all areas, even though groundwater flooding may be an issue. Across the 16 watershed study area in 2010, there were 181,680 NFIP residential policies in force, or an average NFIP market penetration rate of 30 percent (= total NFIP policies in force / total housing units), approximately equal to the NFIP market penetration rates in this region from Michel-Kerjan and Kousky (2010). NFIP market penetration rates were as high as 51 percent (Table 1) in some watersheds, reflective of Florida’s relatively large participation in the NFIP (Michel-Kerjan and Kousky, 2010). Despite the relatively high NFIP market penetration in the study area, the number of NFIP claims and associated losses can be considered a lower-bound estimate of the actual (insured and uninsured) flood losses during this timeframe. However, since the vast majority of flood insurance in the US is obtained through the NFIP, our data are expected to be a good representation of the number of insured claims.

Flood Hazard data – Watershed Groundwater Levels

Daily groundwater levels (in feet above the 1929 National Geodetic Vertical Datum, or NGVD29) for the period 1996-2010 were obtained from the DBHydro database (DBHydro, 2014) maintained by the SFWMD. Only wells with less than 10 percent missing daily data were used in this analysis. We incorporated monthly watershed groundwater levels in two distinct ways: first, as standardized groundwater levels in each watershed; and second, as distance (i.e. depth) below the ground surface to the groundwater relative to the mean watershed elevation. For the first approach, daily groundwater levels were standardized by subtracting the long-term mean water level measured in the well and dividing by the standard deviation (resulting in time series with a mean of zero and a standard deviation of unity).
For the second approach, the mean elevation of each watershed was calculated from a digital elevation model (SFWMD, 2009). In both approaches, we combined the well data by an inverse-distance-squared weighting approach to the centroid of each watershed, for the watersheds with multiple wells. The interpolated daily groundwater values were then averaged to monthly values. The depth to groundwater relative to the mean elevation (for the second approach) is then equal to the watershed mean elevation minus the mean groundwater level. The potential advantage of using standardized groundwater levels is that each well (in the case of watersheds with multiple wells) is given equal weight prior to interpolation, and thus one well with large variance does not overly bias results. The potential advantage of using unstandardized groundwater depths is that this emphasizes the impact of differences between watersheds where some may be of higher elevation than others (where the term “higher” is on the order of 10s of centimeters in this region). In addition, using unstandardized values accounts for differences in soil hydraulic properties as represented in the groundwater measurements (i.e., a unit input of rainfall will cause different water table responses depending on the specific yield of the soil in question). This second approach does not treat each well equally per its variance, but rather accounts for the magnitude of changes in depths at each well.

We expect higher standardized groundwater levels to have a positive relationship with residential flood claims, whereas increased depths to groundwater are expected to have a negative relationship with residential flood claims. Figure 5 illustrates the distribution of our standardized monthly groundwater levels across all 16 watersheds. Standardized monthly groundwater levels range from 1.71 to 3.62 times the long-term mean for a particular watershed.

**Other relevant hazard, exposure, and vulnerability data**

Rainfall exerts a significant influence on groundwater levels in South Florida (Abtew et al., 2010; Sukop et al., 2017, this issue). Therefore, year 1996 to year 2010 monthly rainfall values for each of the 16 watersheds were also included in the analysis. The precipitation data were sourced from PRISM precipitation monthly time series datasets (PRISM, 2015). The PRISM gridded spatial precipitation data were interpolated to the 16 watersheds using the spatial analyst tool in ArcGIS 10.2.2 (ArcGIS® software by ESRI), with the mean zonal statistics as table-returned value utilized for the monthly rainfall amount. Correlation with the corresponding watershed monthly standardized groundwater levels is \( r = 0.67 \).

Table 1 includes the additional flood exposure variables included in the analysis. Census tract population and housing unit information from census data were collected and aggregated to the watershed level. We utilized annual watershed population and housing unit values for the analysis, where census data were linearly interpolated from the year 1990, 2000, and 2010 collected values. Similarly, we utilized the annual number of NFIP policies-in-force per year from 2001 to 2010 at the census tract level aggregated to each of the 16 watersheds. NFIP policy data for the years 1996 to 2000 was determined by taking the 2001 NFIP market penetration percentage (i.e. the total NFIP policies-in-force divided by the number of total housing units) and multiplying this by the year 1996 to year 2000 watershed housing unit amounts. We also included historic SFWMD land-use values representing the areas of each watershed that are agriculture, forestry, high intensity urban, low intensity urban, new rural residential, new suburban, new urban, private conservation, public lands, ranching, semi-natural private, and water (GeoDesignTech, 2015). Historic land use values for years 1990 and 2010 were spatially interpolated to...
the 16 watersheds and then linearly interpolated for annual values. We note that the linear interpolation of the aforementioned data is a potential limitation of the analysis.

Lastly, a number of factors of the managed and natural system itself can lead to increased vulnerability to flooding, including: 1) the physical location of the managed system components (canals, reservoirs) and natural storage areas such as wetlands; 2) how well drained and maintained the system is; and 3) the amount of flood prone area present (Palm Beach County, 2015). We utilized available GIS data to account for the number and length of canals in each watershed (AHED 2015) as well as the percentage of each watershed comprised of reservoirs and wetlands (FGDL, 2015). Likewise, we also utilized available GIS data to determine the percentage of each watershed deemed to have poor drainage (FGDL, 2015) and the percentage of total area of each watershed located in the 100-year floodplain (FGDL, 2015). These values are constant over all 15 years for any particular watershed, but do vary across watersheds.

Statistical Modeling

As the dependent variable in our multivariate regression analysis is the number of flood insurance claims incurred in an impacted watershed per month per year during the timeframe of 1996 to 2010 (including zero value observations), which is a non-negative count, we utilized a negative binomial (NB) count model estimation framework. Zero-inflated negative binomial (ZINB) models were also estimated with similar results. However, Vuong test results comparing the ZINB to the non-zero-inflated NB specification indicate strong support of the NB over the ZINB. Additional model specification tests conducted strongly support the choice of the NB model over zero-inflated Poisson and Poisson estimations as well.

Monthly watershed flood claims were modeled as a function of a vector of flood hazard, watershed exposure, and watershed flood risk vulnerability variables as described above. The data were pooled such that for each of the 16 watersheds there are 180 monthly claim and groundwater level observations over our timeframe, or a maximum of 2880 monthly claim and groundwater observations for the panel regression analysis. Robust standard errors clustered on the watershed were utilized. We controlled for any unobserved time-specific fixed effects through yearly dummy variables, with 1996 being the omitted category. Likewise, we controlled for any watershed-specific time-invariant unobserved heterogeneity between the 16 Miami-Dade watersheds through watershed categorical dummy variables, i.e., a group effect estimator (Bester and Hansen, 2009). Our watershed group effects follow from Figure 4 categories of high-claim watersheds (>4500 incurred flood claims), medium claim watersheds (2000 to 4500), moderate claim watersheds (500 to 2000), and low claim watersheds (500 or less), with low claim watersheds being the omitted category. Given the spatial clustering of the high to low claim watershed types (Figure 4), as well as similar realizations of observable variables such as housing units, population density, and NFIP market penetration over the sample period, it is likely these watershed types may have similar values of unobservables and therefore we utilized the group effect control. We did however also run models (not reported here) with individual watershed fixed effects as well as no watershed fixed effects at all (either individual or grouped) with the results from these models on our groundwater variables of interest overall similar to the results described below.

Six models utilizing both standardized groundwater levels in each watershed (Table 2) and depth to groundwater from the mean watershed elevation (Table 3) were generated for this analysis. Model
In the data, or lack of variation. For example, the percentage of effective average value and model results are provided for both standardized groundwater levels in each watershed flood claims increases by a factor of 1.6 when including watershed land-use and flood vulnerability variables. There was little to no variation in areas of forestry, private conservation, public lands, ranching, semi-natural private, and water, so these were excluded.

IV. Flood Claim Regression Analysis Results

Regression model results are provided for both standardized groundwater levels in each watershed (Table 2) and depth to groundwater from the mean watershed elevation (Table 3). As shown in Tables 2 and 3, the likelihood ratio chi-squared test indicates that each of the models estimated is statistically significant at the 1 percent level. Additionally, for all models, the log-transformed over-dispersion parameter is statistically significant at the 1 percent level, indicating the appropriateness of the negative binomial estimation. Watershed and year fixed effects are also consistently statistically significant and positive for all models provided in Tables 2 and 3. From the McFadden’s adjusted r-squared value, all models in both Tables 2 and 3 capture approximately 17 percent of the overall count of claim variation in the data (or 46 percent based on the Cox-Snell/Maximum Likelihood r-squared).

Most notably, in 10 out of 12 models, both the standardized groundwater levels (Table 2) and the depth to groundwater from the mean elevation (Table 3) are statistically significant predictors of flood claim counts at the p<0.01 level. This result is robust across all model specifications where we have also controlled for rainfall amounts, as well as a number of key watershed exposure and vulnerability factors. Moreover, the coefficient signs meet our expectations that higher standardized groundwater levels have a positive relationship with the count of residential flood claims, whereas greater depths to groundwater have a negative relationship with the count of residential flood claims.

The magnitude of the impact of groundwater levels of flood claims is apparent from the model coefficients. For example, for model (1) in Table 2 the estimated standardized groundwater coefficient has a value of 1.37, indicating that if all other variables are held constant, the expected count of monthly watershed flood claims increases by a factor of 3.9 (290 percent increase) for each unit increase in standardized groundwater levels. For models (2) to (6) in Table 2, which include monthly rainfall values, an average standardized groundwater coefficient value of approximately 0.48 is estimated across these five models. Given this average value and holding all other variables constant, as standardized groundwater levels increase by one unit the expected count of monthly watershed flood claims increases by a factor of 1.6 (a 60 percent increase). From Table 3 the average groundwater depth coefficient is approximately -0.71 across all 6 models. Thus, from this average value and holding all other variables constant, as the depth to groundwater from the mean watershed elevation increases by one unit (i.e.,
groundwater levels go down) the expected count of monthly flood claims decreases by a factor of 0.49 (a 51 percent decrease).

Across all models in Tables 2 and 3, the monthly rainfall amounts, as well as the number of NFIP policies in force (represented by the NFIP market penetration rate) are statistically significant at p<0.01. These variables are positively correlated with flood claim counts for an average Miami-Dade watershed. Our models also indicate that although monthly rainfall amount is a statistically significant driver of flood claim counts, the impact of this variable is relatively small per unit. We expect the impact of rainfall would be much larger if groundwater levels were not actively managed in this region. Similarly, the impacts of many of the watershed land use variables on flood claim counts is relatively small, although they are generally statistically significant at p<0.05. This could be due to the lack of monthly variation inherent in the data. On the other hand, watershed areas of new rural residential or new suburban land use are positively correlated with flood claim counts across all models. However, the watershed vulnerability variables have a statistically significant effect only when the standardized groundwater levels are used as the independent variable. This is shown in models (4) to (6) in Table 2, in which the flood claim count increases with the percentage of the watershed area that is not wetland but is also characterized as poor drainage or lying within the 100-year floodplain. As the percentage of wetlands increases in each watershed, the count of flood claims decreases, implying an ecosystem value of reduced flood damages from the presence of wetlands.

V. Potential HEO Application

Regression results from Section IV have established a robust and statistically significant relationship between groundwater levels and the number of monthly flood claims incurred in Miami-Dade watersheds. These results can be used to construct a representative urban residential flood penalty function for the Miami-Dade study area for use in a HEO framework. A HEO model is often developed as a constrained optimization model to determine efficient water allocation schemes that maximize economic gains or minimize losses (i.e., system penalties), subject to bio-physical and operational constraints (Brouwer and Hofkes, 2008; Harou et al., 2009). In these models, economic-based penalty functions represent the total economic costs of too little or too much water, calculated by integrating under the marginal value (demand) curve in the case of water scarcity, or the marginal cost curve in case of flood damage, as shown conceptually in Figure 6. These models have been applied in various settings (Mirchi et al. 2010; Booker et al., 2012) to quantify the impact of water management decisions on key economic sectors such as the impact of water shortages on urban residential (Draper et al., 2003; Jenkins et al., 2003; Harou et al., 2009; Booker et al., 2012) or agricultural users (e.g., Rosegrant et al., 1998; Ward and Pulido-Velázquez, 2008; Maneta et al., 2009) and the impacts of flooding on urban areas (Brouwer and Hofkes, 2008; Harou et al., 2009; Booker et al., 2012). Mirichi et al. (2017, this issue) have developed a HEO model of the South Florida Water Resources System.

Our methodology of relating urban residential flood claim losses to managed groundwater levels enables the proof-of-concept development of an economic-based urban flood penalty function. We specifically utilize the model (6) results from Table 2 for this illustrative exercise. Model (6) is the most comprehensive model estimated of the six alternative models provided in Table 2, with the lowest AIC value as well as the highest pseudo r-squared results. We use the prgen command from the Stata SPost package of programs for post-estimation analysis (Long and Freese, 2006) on the model (6) coefficient.
estimates in Table 2 to predict expected counts of flood claims for specific levels of standardized groundwater levels for a high-claim watershed, while holding all other unspecified explanatory variables at their mean values. Mean values for all other variables are: monthly rainfall = 121.1 mm, gw level previous month = .010, rainfall previous month = 121.05 mm, rainfall two previous months = 120.80 mm, population per single-family acre = 24.3, housing units = 34,197; NFIP market penetration rate = 31.2 percent; acres agriculture = 3165; acres high intensity urban = 756; acres low intensity urban = 3552; acres new rural residential = 432; acres new suburban = 3731; canal miles = 34.2; poor drainage percentage = 26.1 percent; wetland percentage = 6.7 percent; and 100 year floodplain percentage = 43.6 percent.

Figure 7a illustrates the expected count of flood claims for 0.5-unit increments of standardized groundwater levels for a high-claim watershed, along with the 95 percent confidence interval for these predictions. Confidence intervals for this and all further specifications listed were generated through the STATA 12.1 .prgen command specifying the bootstrap option with 100 replications (Long and Freese, 2006). The expected count of monthly flood claims for a high-claim watershed in Miami Dade ranges from 1.8 to 120.5, depending on groundwater levels relative to the long-term mean (Figure 7a). For example, for a high-claim watershed that has a groundwater level 1.0 standard deviation above its long-term mean value for any particular month, the expected count of claims is 11.3, with a confidence interval of 3.3 to 30.7 claims. Assuming a straightforward average claim loss amount of $7,515 as per Section III, these expected claim counts can be translated into a representative economic-based flood penalty function based on monthly groundwater levels (Figure 7b). The penalty function indicates that depending on the groundwater level, in an average month, the expected monthly flood claim losses for a high-claim watershed in Miami Dade range from $13,346 to $905,482. For example, for an average high-claim watershed that has a standardized groundwater level 1.0 unit above its long-term mean value for any particular month, the expected flood claim loss is $85,025 within a confidence interval of $24,932 to $230,553.

In the representative penalty function of Fig. 7b, all explanatory variables other than standardized groundwater levels were set at their mean values to predict the expected number of claims, regardless of and whether or not the watershed is a high-claim watershed. However, these other explanatory variables could be modified to values expected under various scenarios of interest. As an example, we predict the claim counts for a watershed scenario having 2500 to 10000 acres of new suburban land use in a heavy rainfall month (using September average rainfall, 231 mm), with a corresponding standardized groundwater level at 2.0 units above its long term mean, and a 50 percent NFIP market penetration rate. All other variables were set at their mean values, including the high-claim watershed fixed effect variable. Figures 8a and 8b illustrate the predicted count of claims and corresponding representative economic losses (assuming each claim = $7515) for this scenario but here excluding the confidence bounds. Residential monthly flood penalties range from approximately $40,000, with minimal increases in suburban land-use, up to nearly $8 million in flood losses for high levels of new suburban development. In this scenario, we have again set the standardized groundwater level at 2.0 units above its long term mean. Under a SLR scenario with higher standardized groundwater levels achieved/maintained in relation to the long term mean, this curve would shift to represent larger economic penalties.

While we have utilized a straightforward simple average of our average dollar loss ($7,515) for the results presented in Figures 7b and 8b, the relationship between groundwater levels, the number of claims, and ultimately the dollar losses realized is more complex than this. For a full HEO model
application a more detailed development of such a relationship would be appropriate. To provide some
more context to this here, we provide a further analysis of the dollar losses of claims in our study area.
Firstly, while our statistical model is based upon the number of all residential claims where “residential”
equates to single-family, two- to four-family, and other residential structures, here we limit our dollar loss
analysis to single-family claims only as coverage limits, and importantly, building exposure and
vulnerability drivers of dollar losses would be different for the different types of residential structures.
Also, the NFIP data indicate whether claims were closed with or without payment. As only dollar losses
are provided for claims that are closed with an associated insurance payment, we also limit our dollar loss
analysis to closed claims with a realized dollar loss greater than zero. Note however that even though
claims might have been closed without payment, this does not indicate that flood damage did not occur
to the insured, but rather that this damage was not covered by the NFIP. Given our primary focus on
whether a flood loss occurred or not due to higher groundwater levels, we therefore included both closed
claims with and without payment in our count models estimated in Section IV. Accounting for the data in
this way allows for an analysis of 17,440 single-family residential closed claims with a total of roughly $273
million of losses; a significant majority (83 percent) of the total $327 million in losses from all claims used
in the count models.

Figure 9 presents the distribution of the dollar losses by overall losses (top left), year (top right),
loss type (bottom left), and water depth (bottom right). The mean overall dollar loss amount is $15,667
with a median value of $7,688. For Figure 7b if we instead use this average dollar loss value as opposed
to $7,515, in an average month we now find that the expected monthly flood claim losses for a high-claim
watershed in Miami Dade range from $27,823 to $1.887 million depending on the groundwater level.
While there clearly is a relatively wide distribution of loss amounts as would be expected, the 75th
percentile of the overall claim dollar losses are $18,182 dollars or less. We see similar loss distribution
ranges for dollar loss amounts over time and even by loss type. For thirteen of the fifteen years’ worth of
claim loss data that we have modeled, the 75th percentile of dollars losses per year is $20,000 or less with
only 2005 and 2010 having loss distributions more extensive than this. The mean of the average claim
dollar losses per year is $11,665. The NFIP also identifies in the claim data significant flood events by a
catastrophe number. Here we see again that the 75th percentile of dollar losses is $20,000 or less for all
but Hurricane Katrina in 2005 (even after excluding storm surge losses). The average loss for significant
flood events is $13,551 vs. $11,049 for the non-significantly identified flood events in the claims data.

Finally, we illustrate the distribution of losses for various water depth amounts available in the
claim data where water depth in the claim information is indicated as the depth of the water relative to
the lowest floor of the building. As would be expected, as water depths rise, so do dollar losses on average
and overall distribution. This is important for a HEO application because dollar loss values would be
different for different groundwater level departures from their long-term means. As an example from
Figure 7b, if instead of using the $7515 average for a standardized groundwater level 1.0 unit above its
long-term mean value, we now assume that this is the same as a water depth of five feet and therefore
use the corresponding average dollar loss for five foot depth equal to $29,054. The expected flood claim
loss for the expected 11.3 number of claims from our count models is now $328,717 within a confidence
interval of $96,390 to $891,348. For our claim data however, 84 percent of the claims had a water depth
of four feet or less. Nonetheless, for a more detailed HEO application than what we have provided here,
VI. Concluding Remarks

South Florida water managers face potentially large economic trade-offs associated with simultaneously meeting both the flood control and freshwater demands of the urban, environmental and agricultural sectors. The difficulties in meeting these often conflicting demands result from the unique environmental setting of South Florida, characterized by seasonal rainfall patterns, extreme and often localized weather events, ground elevations near sea level, and a highly transmissive surficial aquifer upon which many of the residents rely on for drinking water and irrigation. Moreover, in South Florida, land use types with highly diverse targets for optimal groundwater levels are often adjacent, complicating efforts to simultaneously meet water management objectives, especially during high rainfall events. Planners and policymakers therefore need an improved understanding of the potential trade-offs associated with different water management strategies. For example, we illustrate that the average flood losses resulting from the incurred flood claims in a heavily developed urbanized watershed can be as high as $8 million per month under current groundwater level conditions. This is the first estimate of this kind in South Florida. Estimates from other land use types are also needed. Information on flooding costs in relation to water levels for all land-use types, when combined with information on the economic benefits of abundant water supplies (including the value of water-dependent ecosystem services; Richardson et al. 2014), will enable more precise calculations of the economic trade-offs associated with water management strategies. Significantly, the methodology we have developed enables the proof-of-concept development of an economically-based urban flood penalty function suitable for use in a HEO model. In regions such as South Florida, a HEO model incorporating penalty functions of this type for all sectors that rely on water supplies and flood control will provide managers with new insights into the economic dimensions of alternative water management strategies. Approaches of this type are expected to have applications in other coastal regions.

Accurately predicting the magnitude of future flooding costs associated with adaptive water management strategies under climate and land use change scenarios will require additional analyses utilizing both regional simulation models and HEO applications. For example, while rising sea levels will decrease the hydraulic efficiency of the C&SF system, the adoption of other management strategies such as actively pumping stormwater offshore or the development of new drinking water sources (e.g. reservoir construction, desalinization) may also result in changes in target groundwater levels and, therefore, changes in the potential economic trade-offs associated with use of the existing levee-canal system to provide both flood control and resistance to salt water intrusion. Representations of these types of strategic and infrastructure adjustments along with climate and land use changes in complementary simulation and optimization models will allow more accurate evaluations of the potential impacts of new management strategies across all water-reliant economic sectors in South Florida, including agriculture. Because South Florida has been identified as highly-vulnerable to climate change and sea level rise (see Aumen et al. 2015 and associated papers; Strauss et al. 2015), both of which may have significant impacts on water resources, and because relatively small changes in surface and groundwater levels can have a significant effect on water availability and flood risks, novel approaches such as these are needed to better inform policymakers and planners seeking to guide development in this region.
Acknowledgements:
This material is based upon work supported by the National Science Foundation under Grant No 1204780.
This is Florida International University Sea Level Solutions Center contribution #____.
Figure 1: South Florida Water Management Regional System

Figure 2: Lower East Coast Flood Control System Constraints

Source: System Constraints to Moving Water South

Figure 3: Miami Dade County 16 SFWMD Watershed Study Area
Figure 4: High Flood Claim Watersheds
Figure 5: Distribution of Standardized Monthly Groundwater Levels
Figure 6: Hypothetical water delivery penalty function
Figure 7a: Predicted Count of Monthly Flood Claims for High-Claim Watershed

Figure 7b: Corresponding Representative Urban Flood Penalty Function for High-Claim Watershed
Figure 8a: Predicted Count of Monthly Flood Claims for Varying Levels of New Suburban Land-Use Acreage and Standardized GW Levels = 2.0, Rainfall = 231 mm, and NFIP Market penetration = 0.5

Figure 8b: Corresponding Economic Flood Loss Trade-off for Varying Levels of New Suburban Land-Use Acreage from Figure 8a.
Figure 9: Dollar Loss Distribution of Single-Family Residential Claims – Overall (top left), by year (top right), by event type (bottom left), and by water depth (bottom right)
Table 1: Miami Dade County 16 SFWMD Watershed Study Area Overview

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<td>274,671</td>
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<td>39,042</td>
<td>9</td>
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<td>123</td>
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<td>6,280</td>
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<td>90</td>
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<td>704</td>
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<td>Total</td>
<td>328</td>
<td>1,747,995</td>
<td>312</td>
<td>43,551</td>
<td>100%</td>
<td>181,680</td>
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<td>Model (6)</td>
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<td>Standardized monthly groundwater (GW) levels</td>
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<td>0.52***</td>
<td>0.55***</td>
<td>0.46***</td>
<td>0.44***</td>
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<td>GW levels in prior month</td>
<td>0.21*</td>
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<td>Rainfall in prior month</td>
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<td>Rainfall in prior two months</td>
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<td>Housing Units</td>
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<td>.00002***</td>
<td>-.00004*</td>
<td>-.0001***</td>
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* p<.1; ** p<.05; *** p<.01; standard errors are suppressed
Table 3: Watershed Groundwater Depth to the Mean watershed Elevation Regression Results

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<th>Model (4)</th>
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<td>Depth to GW from mean elevation</td>
<td>-0.38***</td>
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<td>Monthly rainfall in mm</td>
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<td>GW levels in prior month</td>
<td>0.98***</td>
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<td>Rainfall in prior month</td>
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<td>Rainfall in prior two months</td>
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<td>Population per single-family acre</td>
<td>-0.03*</td>
<td>-0.26</td>
<td>-0.25</td>
<td>0.029***</td>
<td>0.031**</td>
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<td>Housing Units</td>
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<td>NFIP Market Penetration Rate</td>
<td>0.52</td>
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<td>2.67***</td>
<td>5.05***</td>
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<td>Acres Agriculture</td>
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<td>Acres New Rural Residential</td>
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<td>Acres New Suburban</td>
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<td>Canal Miles</td>
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<td>Poor Drainage Percentage</td>
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<td>Wetland Percentage</td>
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<td>100 year floodplain percentage</td>
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<td>High-Claim watershed</td>
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* p<.1; ** p<.05; *** p<.01; standard errors are suppressed
References


Ali Mirchi; David W Watkins; Vic Engel; Michael C Sukop; Jeffrey Czajkowski ; Mahadev Bhat; Jennifer Rehage; David Letson; Yuki Takatsuka, A Hydro-economic Model of South Florida Water Resources System, *Science of the Total Environment* xxx (2017) xxx-xxx (This issue)


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Sukop, M.C., M. Rogers, G. Gaunnel, J.M. Infanti, K. Hagemann, High temporal resolution modeling of the impact of rain, tides, and sea level rise on water table flooding in the Arch Creek basin, Miami-Dade County Florida USA, Science of the Total Environment xxx (2017) xxx-xxx (This issue)


