Validation of the Visionmaker NYC Hydrological Model

Jacob Peacock Katie Smith Maya Kutz
New York City Engineers for a Sustainable World

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Abstract

Visionmaker NYC is a web-based, user-friendly environmental modeling system for New York City (NYC) created by the Wildlife Conservation Society (WCS). We empirically evaluate the floodwater component of the hydrological model contained within Visionmaker against observed flooding using reports from the NYC 311 help phone line and historical precipitation data. Of the 26 flood events identified from 2015, we tested 10 in Visionmaker and found that in no cases did Visonmaker NYC predict flooding correctly. The simplified "bucket model" for precipitation and drainage used by Visionmaker is the likely cause of this disparity and the hydrological model should be adjusted to include time dependence. We also critically evaluate the storm models used by Visionmaker and find significant disparities with other climatic data that should be addressed.

Contents

Introduction

Visionmaker NYC[1] is a web-based, user-friendly environmental modeling system for New York City (NYC) created by the Wildlife Conservation Society (WCS). To build a model, the user chooses parameters like climate scenario, precipitation events, and land-use types, collectively referred to as a “Vision” for the city. The model then predicts water usage, biodiversity, greenhouse gas emission, sustainable population, and other outputs for a selected area of NYC. Using this simplistic model, the user can gain a better understanding and appreciation for the dynamics and environment of the city.

Visionmaker is still in development, and many of the models which predict metrics of sustainability have not been validated. Starting in the Spring of 2016, we volunteered through Engineers for a Sustainable World NYC (ESW-NYC) to assess Visionmaker’s hydrological model. The model and the variables it relates are shown in Figure 1.[2]

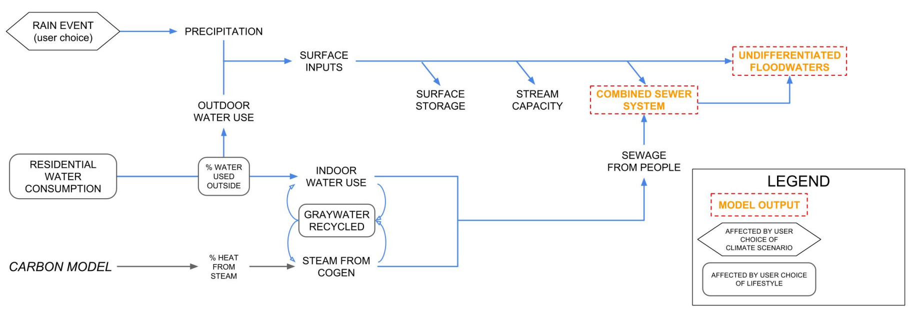

Figure 1: Visionmaker models hydrology in NYC as a simple flow-through bucket model: different components contribute to water input into the city’s geography (“ecosystem type” in Visionmaker), which ultimately determines the amount of runoff.

In a “black box” approach to validation, we evaluated the models prediction of street flooding (“Undifferentiated Floodwaters” in Visionmaker) against actual resident reports of flooding during rain storms. We also evaluated the modeling of rain storms within Visionmaker and compared this model with observed and projected rainfalls published by the Northeast Regional Climate Center (NRCC).

Throughout this report, file names will be referenced as `file/name/here.txt` and the corresponding files can be found hosted on Github.[3]

[1] https://visionmaker.us/nyc/
[2] https://visionmaker.us/resources/models/water/
[3] https://github.com/jpeacock29/Visionmaker-hydrological-validation

Testing Flood Predictions

Here, we empirically evaluate the floodwater component of the hydrological model contained within Visionmaker against observed flooding. Using reports from the NYC 311 help phone line, where residents frequently call to report hazardous or bothersome conditions and request services from the city, we generate a conservative estimate of when and where in NYC flooding occurred in 2015. Daily historical weather data was used to estimate the quantity of precipitation ostensibly causing each flood. This precipitation was then modeled in Visionmaker, producing a predicted volume of flood water. Comparing whether Visionmaker predictions of flooding coincide with known incidences of flooding allows us to test the efficacy of the model.

Methods

Mining 311 data for flooding events

Data on 311 reports from 2015 was obtained from the NYC Open Data portal.[4] Using the python programming language, the reports were filtered for those with (1) the word "flood" in the "Descriptor" field, (2) a "Complaint Type" of "Sewer" and (3) a provided longitude and latitude. Of the ~2.3 million reports, 9189 fitting this criteria were found.

From these 9189 reports of flooding, we identified "storm periods" as consecutive days of the year with more than 50 reports of flooding. This threshold was chosen heuristically to include most of the peaks observed in Figure 2. For each of these 19 storm periods, we identified geospatial clusters of flooding reports where several reports of flooding were made in close geographic proximity. We applied the DBSCAN algorithm to perform the clustering using the longitudes and latitudes given in the flood reports. We represent each cluster as a single "flood event" occurring at the average time and location of the flood reports composing the cluster.

This analysis can be reproduced by running `make.sh`. Note that the DBSCAN algorithm is non-deterministic and may not produce exactly the same results in each run.

Details of the DBSCAN algorithm

The DBSCAN algorithm requires two parameters: n, the number of reports required to form a cluster, and ϵ which, roughly, indicates the maximum distance allowed between reports in the same cluster. We choose these parameters conservatively, erring on the side of caution in order to select only the most

[4] https://data.cityofnewyork.us/dataset/311-Service-Requests-From-2015/57g5-etyj

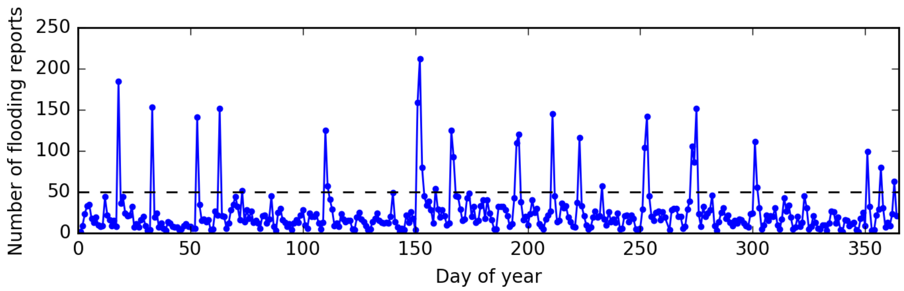

Figure 2: The number of reports of flooding on each day of the year. The dashed horizontal line indicates our cut-off threshold for a "storm period".

likely flooding events. Thus, we required $n = 3$ reports of flooding to form a cluster and ϵ corresponding to approximately 0.25 miles as the maximum distance between reports in a cluster. The clusters include only those reports that appeared close together; many others are classified as "outlier" points by the DBSCAN algorithm and ignored in further analysis.

Lastly, we note that the clustering algorithm applied Euclidean distance to the longitudes and latitudes of the reports and imparts a slight distortion. (Specifically, while 1 degree of latitude is 69 statutory miles, 1 degree of longitude is ~53 statutory miles at the latitude of NYC. Thus reports separated by 1 degree of longitude are actually closer together than those separated by 1 degree of latitude; however, the algorithm would treat the points as the same distance apart.) Since we are dealing with a relatively small area far from the poles, this distortion likely negligibly affects the results of the clustering and our later analysis. To correct this, we might use the Vincenty distance during clustering.

Cross-referencing daily precipitation

Daily precipitation data was obtained from the Northeast Regional Climate Center using the Central Park weather station.[5] Precipitation is given in inches of rainfall and liquid equivalent of snowfall. For each of the flooding events identified in the 311 data, we summed the reported precipitation for each day spanned by the flood event (column `central_park_daily_precipitation_inches` of `Visionmaker_modelling_results/Visionmaker_flood_predictions.csv`).

Modeling in Visionmaker

For each flooding event, the aggregated precipitation was used to model the flooded area in Visionmaker as follows, making reference to the columns of the

[5] http://climodtest.nrcc.cornell.edu/

spreadsheet `Visionmaker_modelling_results/Visionmaker_flood_predictions.csv`:

1. After opening Visionmaker and logging in, follow the menus and buttons: `Manage > Visions > Create New Vision`. Visions were named as `test_` followed by the identifier from column `flood_id`. No additional parameters were set and the default "Base on" value of "New York City (2014)" was retained.

2. Since the flooding events are marked by longitude and latitude, but Visionmaker does not provide a search functionality for longitude and latitude, Google Maps was used to assist in locating flooding events. Once zoomed to the appropriate level (ie, 17), the geographic area of the Vision is defined as the blocks surrounding the specified longitude and latitude and the Vision is saved.[6]

3. The aggregated precipitation of the flooding event is next converted to the appropriate Visionmaker parameters. Internally, the Visionmaker model uses the product of two parameters, storm duration and storm intensity, to determine the total precipitation of a storm. Since Visionmaker uses a "bucket model" in determining floodwater output, only this total precipitation affects the results.[7] Externally, these two parameters are determined by two broader parameters, "Climate" and "Rain Event". The Visionmaker NYC parameters used for each flood event and the total precipitation are found in columns `visionmaker_precipitation_event`, `visionmaker_climate` and `visionmaker_total_precipitation`, respectively. These values were selected with the aide of a table relating each combination of "Climate" and "Rain Event" to the corresponding total precipitation[8] and chosen to follow the observed precipitation as closely as possible.

4. After inputting the appropriate values for the "Climate" and "Rain Event", looking in "Environmental Performance" section "Water", the value "Floodwater" is selected from the drop-down menu. The displayed value is reported in column `visionmaker_floodwater`.

Results & Discussion

Using the 311 data, 26 flood events were identified.[9] As a sanity check, we observe that almost all flood events identified occurred during periods of significant precipitation in the historical weather record. Furthermore, flood events often overlap geographically (Figure 3), having flooded during multiple storm events,

[6] Access to the "ESW-NYC" account, which contains the exact regions used for each model, is available upon request.

[7] https://visionmaker.us/resources/models/water/' and https://visionmaker.us/info/metric/27/

[8] `inputs/storm_modelling.csv`

[9] `outputs/311_2015_floods.csv`

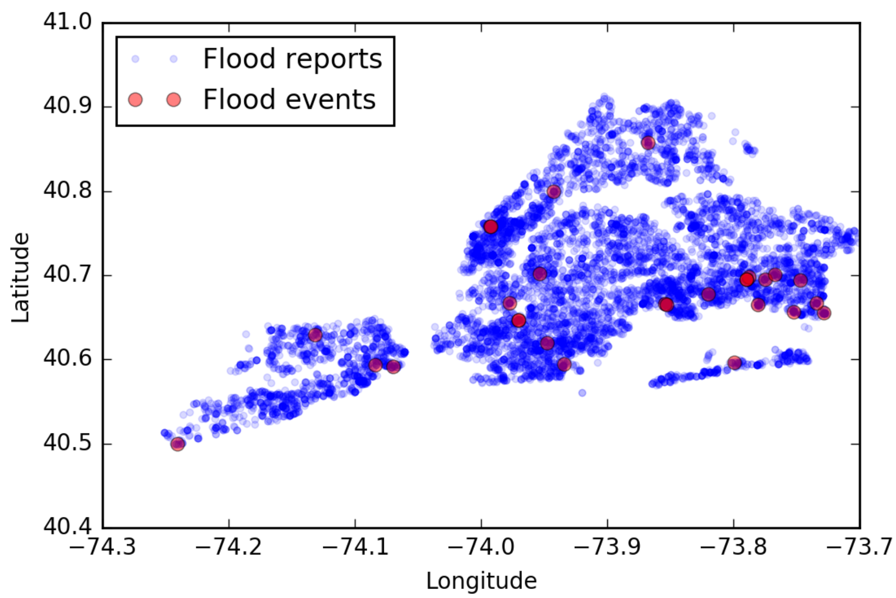

Figure 3: The 26 flood events, red, plotted over all flood reports, blue. Note the outline of New York City formed by the flood reports as well as the darker red points where two flood events coincide.

as might be expected of a low-lying area prone to flooding. To further validate our flood events, future work might also consider elevation data, that may confirm flooding occurs in low-lying areas. These checks give us some assurance that our identified flood events are plausible.

Of the 26 flood events, we modeled a sample of 10 in Visionmaker. The Visionmaker model did not predict flooding at any of the flood events under the observed precipitation conditions.[10] It is possible that some floods occur through mechanisms outside the Visionmaker model, like trash clogging a drainway, a pipe burst or storm surge. However, we would expect these first two effects to account for only a fraction of floods and storm surge would be limited to those flood events near the coasts. The data does not substantiate any of these hypotheses and we would nonetheless expect at least some of the flood events to correspond to genuine precipitation-induced flooding.

The model itself seems the most likely source of failure. In particular, Visionmaker uses a “bucket model” to calculate floodwaters: whatever volume of the total precipitation does not runoff into streams or stormwater drainage is accounted for as floodwaters. Under this model, flooding only occurs when the total precipitation exceeds the volume of stormwater and stream drainage. However, actual flooding is observed as a transient phenomena, occurring only during brief periods of intense precipitation. (The generally brief durations of reported floods support this notion.) While the total volume of an intense rain event may not be enough to overwhelm the total volume of drainage available, the *rate* of precipitation may exceed the rate of drainage, thus producing flooding. Since the rates of precipitation are not considered in the bucket model, this effect may account for the disagreement between prediction and observation.

Suggestions

- Adjust the hydrological model to include time dependence, for example, by considering a precipitation rate exceeding the drainage rate as a cause of temporary flooding.
- Use the data generated in this report as calibration when adjusting parameters and evaluating model choices.
- Consider renaming “floodwaters” to “other runoff”, since it does not correspond to the common understanding of a flood.

Minor:

- Allow more precise or direct manipulation of total rainfall in storm events. The actual total rainfall has significant discontinuities; see[11].
- Allow search of Visionmaker by longitude and latitude.

[10] `Visionmaker_flood_predictions.csv`
[11] `inputs/storm_modelling.csv`

Comparing Rainfall Data

In this section, we compare the storm parameters used in Visionmaker's storm events with those independently produced by the Northeast Regional Climate Center (NRCC). In particular, we compare empirical storm intensity models as well as predicted increases in storm intensity due to climate change given by both sources.

Methods

Visionmaker uses six storm types parameterized by intensity, duration, and return period (equivalent to storm frequency; see Table 1). Intensity is the rate of precipitation during a storm event in inches per hour. Duration is how long the storm event lasts in hours. Return period is a measure of how likely a storm is to occur. For example, a storm with a 5-year return period has a $1/5 = 20\%$ chance of occurring in any given year and occurs on average once every five years.

Table 1: Six Visionmaker storm types and the baseline intensity used to determine future intensities.[12]

Rain Event	**Duration** (hour)	**Baseline Intensity** (inch/hour)	**Return Period** (year)
Clear Day	0	NA	NA
Rainy Day	6	0.65	2
Severe Storm	24	1.1	100
Showers	2	0.4	NA
Soaking Storm	12	0.6	10
Thunderstorm	1	1.75	5

The parameters of four of the six Visionmaker storm types are derived from the intensity-duration-frequency (IDF) curve shown in Figure 4. As for the other two storm types, "Clear Day" has zero rainfall and does not require analysis, and "Showers" was not derived empirically but as an *ad hoc* estimation.

To forecast rain intensities for future climate scenarios, the same baseline data is used, but scaled up by fixed percentages published by the NYC Panel on Climate Change (NPCC). These percentage scaling factors describe increases in total annual rainfall and generally result in increasing intensity over time. The report cited for the 2100–2109 projections has a lower scaling factor than those used for earlier projections.[15]

[12] `inputs/storm_modelling.csv`

[14] *The NYC DEP Climate Change Program Assessment and Action Plan.* A Report Based on the Ongoing Work of the DEP Climate Change Task Force; May 2008. http://www.nyc.gov/html/dep/html/news/climate_change_report_05-08.shtml

[15] Visionmaker uses the following sources for different time periods ("Climate Scenarios"):

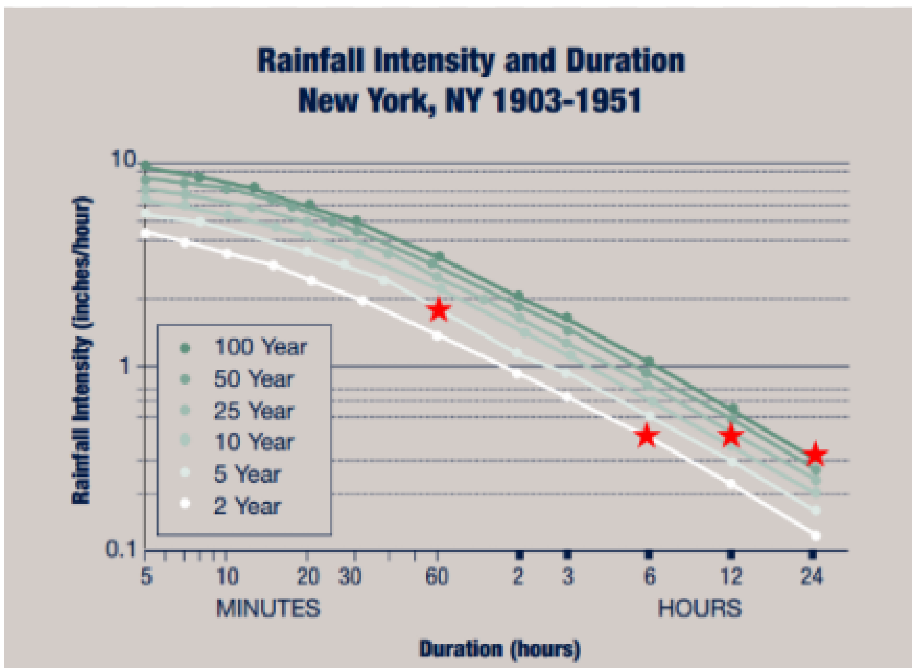

Figure 4: This IDF curve was published in a climate change impact report by the DEP of NYC in 2008. From left to right, the red stars correspond to "Thunderstorm," "Rainy Day," "Soaking Storm," and "Severe Storm" rain events.[14]

To collect the NRCC data, each Visionmaker storm type was matched by duration and return period with the interactive IDF curve published by the NRCC for the Central Park weather station (“CNTRL PK TWR”).[16] This IDF curve provides projected mean rainfall intensities for 2010–2039, 2040–2069, and 2070–2099. We selected the “High RCP 8.5” emission scenario, rather than the “Low RCP 4.5,”[17] as it more closely matched the Visionmaker data.

For both the Visionmaker and NRCC data, total rainfall was calculated as the product of intensity and duration. Plots of intensity and total rainfall were produced in R.

Results & Discussion

The NRCC and Visionmaker datasets broadly correlate, with short storms modeled as more intense and longer storms as less intense. However, the magnitudes of rainfall intensities are generally much higher in Visionmaker than in the NRCC data, except for “Thunderstorms” (Figure 5). The implausibly high rainfalls of the Severe Storm far exceed reasonable maximums and would account for most of New York City’s average annual rainfall. The reason for this discrepancy is obscure, but the cited IDF curve uses very old data, outdated IDF models, and the log scale appears erroneous.[18]

As noted in the methods, Visionmaker calculates future and past climate scenarios using fixed percentages of the baseline intensities from the Figure 4 IDF curve.

1609: Stahle et al. 1998 The Lost Colony and Jamestown droughts. *Science*, New Series, Vol 280. http://www.uark.edu/misc/dendro/PUBS/1998_Science.pdf (March 11, 2017).

1970-2010: City of New York Department of Environmental Protection. 2008. *The NYC DEP Climate Change Program Assessment and Action Plan.* New York: Department of Environmental Protection. http://www.nyc.gov/html/dep/pdf/climate/climate_chapter2.pdf (November 11, 2013).

2020-2029 & 2050-2059: New York City Panel on Climate Change. 2013. Climate Risk Information 2013: *Observations, Climate Change, Projections, and Maps.* New York: City of New York Special Initiative on Rebuilding and Resiliancy. http://www.nyc.gov/html/planyc2030/downloads/pdf/npcc_climate_risk_information_2013_report.pdf (September 25, 2013).

2080-2089: Horton, R., O’Grady, M., & New York City Panel on Climate Change. (2009). *Climate Risk Information: New York City Panel on Climate Change.* New York: New York City Panel on Climate Change.

2100-2109: Rosenzweig, C., Solecki, W., Blake, R. A., Bowman, M. J., Gornitz, V., Jacob, K. H., . . . , Yohe, G. W. (2015). Appendix I: Climate Risk and Projections NPCC 2015 Infographics. *Annals of the New York Academy of Sciences*, 1336(1), 109–115. https://doi.org/10.1111/nyas.12715

[16] http://ny-idf-projections.nrcc.cornell.edu/index.html

[17] This emission scenario corresponds to the higher model of greenhouse gas concentration given by the Intergovernmental Panel on Climate Change: 1200 ppm of CO_2 equivalent by 2100, or four times the current concentration.

[18] Typically, log scales are divided into five or ten minor increments. This IDF curve divides into six and seven minor increments for the 0.1–1 and 1–10 major increments, respectively.

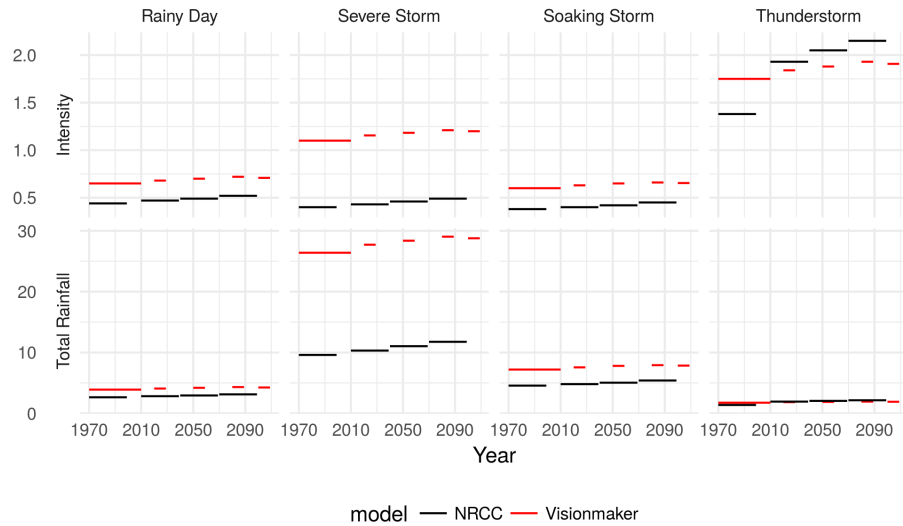

Figure 5: Plots of storm intensity and rainfall across different time periods and storm types. NRCC data is shown in black; Visionmaker in red.

For example, 2080–2089 storm intensities are modeled as 110% of the 1903–1950 baseline.[19] These percentages are derived from the total annual precipitation predictions published in various NPCC reports. The projected future rainfall in Visionmaker roughly match the increases in the NRCC data: both show an increase in storm intensity of between 0.05 and 0.1 inches/hour over the 21st century for all storm types. However, the fixed percentages in the NPCC reports are meant to represent changes to average total annual precipitation, rather than the intensity of an individual storm. Furthermore, Visionmaker is currently set to model everything on June 1st, meaning that snow and other annual variations (eg, seasons) should not count towards Visionmaker's calculations.

We also noted that Visionmaker's 2100s projections have lower intensities and total rainfalls than the 2080s, due to a change in the NPCC report used for these predictions. This conclusion is inconsistent with trends of the NRCC data and likely attributable to the alternate model used.

Finally, Visionmaker uses 1609, the year the Dutch began exploring NYC for settlement, as a Past Climate Scenario. Based on evidence showing extreme drought in Jamestown, Virginia in 1609, Visionmaker decreased the 1903–1950 baseline intensity by 10%. As it is not obvious that a drought in Virginia would reach New York, this projection needs more substantial evidence. Further, an intensity decline of 10% may not be consistent with observed extreme drought

[19] Visionmaker refers to the baseline data as representing 1970–2000, but the cited IDF curve actually uses data from 1903–1950.

[20].

Suggestions

- Critically examine discrepancy between Visionmaker's storm event parameters and those of the NRCC.
- If the Figure 4 IDF curve is retained, update "baseline" time period from "1970–1999" to "1903–1950" to more accurately reflect source data.
- Choose a return period and data source for the 2-hour storm type "Shower."
- Provide a more nuanced view of storm events and effects of climate change.
- Use a single source to predict future climate scenarios.
- Produce a more rigorous estimate of 1600s precipitation.
- Consider showing flood map delineations, even as a simple layer added for different Climate Scenarios.

[20] "USGS WaterWatch – Streamflow Conditions." *USGS WaterWatch – Streamflow Conditions.* 28 Mar 2017. https://waterwatch.usgs.gov/?id=ww_drought