HHS Public Access
Author manuscript
Nat Hazards (Dordr). Author manuscript; available in PMC 2021 September 15.

Published in final edited form as:
Nat Hazards (Dordr). 2021 September 15; 105(1): 277–292. doi:10.1007/s11069-020-04309-w.

Using search-constrained inverse distance weight modeling for near real-time riverine flood modeling: Harris County, Texas, USA before, during, and after Hurricane Harvey

Andrew S. Berens[1], **Tess Palmer**[1], **Nina D. Dutton**[1], **Amy Lavery**[1], **Mark Moore**[2]

[1]Geospatial Research, Analysis, and Services Program (GRASP), Agency for Toxic Substances and Disease Registry, Centers for Disease Control and Prevention, 4770 Buford Hwy NE, Chamblee, GA 30341, USA

[2]Harris County Flood Control District, Houston, TX, USA

Abstract

Flooding poses a serious public health hazard throughout the world. Flood modeling is an important tool for emergency preparedness and response, but some common methods require a high degree of expertise or may be unworkable due to poor data quality or data availability issues. The conceptually simple method of inverse distance weight modeling offers an alternative. Using stream gauges as inputs, this study interpolated stream elevation via inverse distance weight modeling under 15 different model input parameter scenarios for Harris County, Texas, USA, from August 25th to September 15th, 2017 (before, during, and after Hurricane Harvey inundated the county). A digital elevation model was used to identify areas where modeled stream elevation exceeded ground elevation, indicating flooding. Imagery and observed high water marks were used to validate the models' outputs. There was a high degree of agreement (between 79 and 88%) between imagery and model outputs of parameterizations visually validated. Quantitative validations based on high water marks were also positive, with a Nash–Sutcliffe efficiency of in excess of .6 for all parameterizations relative to a Nash–Sutcliffe efficiency of the benchmark of 0.56. Inverse distance weight modeling offers a simple, accurate method for first-order estimations of riverine flooding in near real-time using readily available data, and outputs are robust to some alterations to input parameters.

Tess Palmer, LLE0@cdc.gov.

Author contributions Andrew Berens was the project leader and lead author. Tess Palmer, Nina Dutton, and Amy Lavery contributed to the data acquisition, analysis, validation of models, and writing of the paper. Mark Moore accessed and prepared the stream gauge data for analysis and offered a county-level perspective to the manuscript development. All authors read and approved the final manuscript.

Conflict of interest The authors declare that they have no conflict of interest.

Human and animal rights Not applicable.

Informed consent Not applicable.

The findings and conclusions in this study are those of the authors and do not necessarily represent the official position of the Centers for Disease Control and Prevention or the Agency for Toxic Substances and Disease Registry.

Keywords

Inverse distance weighting; Flood modeling; Hurricane harvey; Harris County; United states

1 Introduction

1.1 Background

Flood events represent a serious public health risk and remain the world's most common type of natural disaster (Center for Research on the Epidemiology of Disasters 2016). In addition to the direct risk of drowning, flood waters may directly influence the spread of disease by transporting pathogens, pests, and dangerous environmental contaminants (Ahern et al. 2005; Jonkman and Kelman 2005; ten Veldhuis et al. 2010; Yard et al. 2011). The risk of water-borne infection is also exacerbated when drinking water sources are flooded or a disruption occurs in sewage and other wastewater services (Jonkman and Kelman 2005; Cann et al. 2013). When waters recede, additional risk of illness occurs from pathogens persisting on formerly flooded surfaces or from mold growth inside of water-damaged buildings (Chew et al. 2006; Ivers and Ryan 2006; Centers for Disease Control and Prevention 2006; Rao et al. 2007; Riggs et al. 2008; Taylor et al. 2013).

Flood modeling can help mitigate these effects by providing emergency personnel with estimations of affected areas and identifying areas to target for public health response. Traditional methods for assessing flooding and flood risk include hydrologic modeling and observational methods, such as satellite and radar imagery. These methods, however, are complex, and accuracy can vary due to limited or low quality data (Al-Sabhan et al. 2003; Gallien et al. 2013). Hydrologic modeling requires a thorough understanding of how factors such as infiltration rate, rainfall, and urbanization interact (Chen et al. 2009; Kia et al. 2012) and may not be realistic for local authorities without hydrology expertise. Observational methods of obtaining real-time flooding information are also problematic. Obtaining visible band aerial imagery taken from high altitude will likely be impossible during the worst of the flooding event when clouds obstruct views. Obtaining up-to-date flooding information requires lower-altitude aerial imaging, which will cover less area than high-altitude imaging (Lillesand et al. 2008), may only be available in certain areas (Schumann et al. 2011), and is likely to miss peak inundation levels. Space-based alternatives, such as synthetic-aperture radar (SAR) that could penetrate clouds, require access to and availability of a limited number of capable satellites (Horritt and Bates 2002). Even when available, aerial and satellite products are unlikely to provide the needed temporal resolution for adequate situational awareness.

If available, real-time data paired with easily implemented geographic information science (GIS) techniques could serve to fill in gaps left by hydrologic modeling and image/satellite products. Rabie et al. (2017) concluded that as few as 4 stream gages paired with a relatively high-resolution digital elevation model (DEM) could be used to estimate flooding extent with reasonably high accuracy via the conceptually simple method of inverse distance weight (IDW) modeling (see Sect. 2.2 for an explanation of IDW). Similar techniques used by Longenecker et al. (2019) show that streamline elevation can be accurately interpolated between gauges, allowing for an estimation of input points all along the stream channel, augmenting a limited number of gauges. DEMs, which are continuous, allow for the estimation of flooding beyond the stream's floodplain and thus for modeling of severe, out of bank flood events that may impact homes. In the USA, United States Geological Survey (USGS) stream gauges, which are spread throughout the country, often measure stream height or elevation at 15-min intervals, providing the temporal resolution needed for proper situational awareness. Other local systems, using ALERT, ALERT2, or other systems may report with similar or better temporal resolution.

The efficacy of stream gauge and DEM data as IDW model inputs for riverine flood modeling does remain somewhat uncertain. Questions remain as to the accuracy of the method when applied to an area with data derived from multiple converging stream channels and barriers to flow (e.g., dams). The ease of running IDW analyses in modern GIS software also calls into question how altering input parameters of the tool affects output accuracy, as such alterations can be made easily and without understanding their function. Further, it is not known how well this method assesses flooding depth, which could be critical to assessing exposure risk as water recedes (e.g., mold growth in formerly flooded buildings (Riggs et al. 2008)). Evaluating this technique under circumstances different from Rabie et al. (2017) using multiple sources of validation data can help to address some of the above-mentioned uncertainty.

1.2 Study purpose

The purpose of this study was to assess the efficacy and accuracy of a spatial interpolation-based model of riverine flooding that could be used in near real time for emergency response and recovery by nonsubject-matter experts with only intermediate GIS skill. We aimed to determine whether the conceptually simple method of IDW modeling, with minimal data and computing requirements, could accurately assess riverine inundation extent and depth in an environment with multiple, converging stream channels throughout the duration of a flooding event. This study aims to deepen our knowledge about the utility of IDW modeling in providing accurate approximations of flooding extent and depth in an easy to use, repeatable way to provide awareness of riverine inundation conditions throughout a flooding event, even if users are not subject-matter experts.

2 Methods

2.1 Study area

This study focused on Harris County, Texas, USA (Fig. 1) immediately before, during, and after the county was inundated by Hurricane Harvey in August 2017. Starting after Harvey made landfall in Texas on August 25th, Harris County, the core of the Houston metropolitan area, experienced a historic single point rainfall maximum of 47.40 inches (1.203 m) (Clear Creek at I-45). This rainfall led to massive flooding throughout the county. Buildup of water in two United States Army Corps of Engineers reservoirs in the county necessitated controlled dam releases, which kept some county streams in flood stage several days after the rain stopped.

Harris County, which sits adjacent to Galveston Bay, contains almost all of Houston proper and has a population of more than four million people (United States Census Bureau, census.gov/quickfacts). The bulk of the county's 4600 km^2 is land with only about 192 km^2 covered by water. The county's elevation ranges from about 97 m in the northwest to sea level in the southwest, on Galveston Bay. Two reservoirs (Barker and Addicks) and a lake (Lake Houston) (Fig. 1) have dams that are used to manage water flow.

2.2 GIS data

GIS data for this project were collected from online and local sources. DEMs (3 m resolution) were obtained online from the United States Department of Agriculture's National Geospatial Center of Excellence. In total, 50 DEMs were downloaded and then merged using ERDAS IMAGINE 2016 (Hexagon Geospatial, Norcross, GA, USA) to create a single, continuous DEM for all of Harris County (Fig. 2). Stream gauge readings were provided by the Harris County Flood Control District (HCFCD), and these data were supplemented with USGS stream gauge data. This left the project with 140 stream gauge sites (Fig. 2) in and around Harris County and a total of 3,080 stream gauge elevation readings (1 per day per gauge from August 25th through September 15th). All spatial layers were projected into universal transverse Mercator (zone 15 north). The projection and all GIS analyses were done using ArcGIS Pro 2.1, and visual validation was done using ArcMap 10.6 (Esri, Redlands, CA, USA).

2.3 Riverine flood modeling

A series of GIS operations were completed using the 3D and spatial analyst extensions of ArcGIS to create a modeled flood extent and depth at noon for each day during the duration of the flooding event (August 25th through September 15th). August 25th, which experienced minimal rain, represents a baseline, while September 15th represents the end of the flood event, with all stream gauges in Harris falling out of flood stage by the following day. An IDW model was used to create a continuous raster of modeled stream elevation (a raster is a data model that stores information for a given area as a matrix of pixels). An IDW model determines the value of an unknown raster location through a weighted combination of values at known points within the unknown location's "search radius" (points within this "search radius" are termed neighbors). IDW assumes that any similarities between two points decrease as the distance between them increases (termed distance decay) (Watson and Philip 1985). Weighting in our model was based on the inverse of the squared distance of the known locations (i.e., stream gauges) from the unknown location, so influence of input points decreased with the square of distance from the unknown point (the number distance is raised to in the IDW equation is termed the power function). A polyline shapefile of the three primary dams in Harris County (Fig. 1) was used as an input barrier that constrained the IDW's search radius. These dams represent real-world discontinuities in stream elevation. Inclusion of the dam polyline in the IDW as a barrier ensured that stream gauges from the opposite side of the dam were not used to determine flood elevation inside the dam's retention area, thus constraining the neighborhood searched used in the IDW. This search constraining is intended to limit post-model manual adjustments, which other work done using easy-to-implement techniques have needed to address areas with flood mitigation barriers that were erroneously marked as flooded (e.g., Longenecker et al. 2019). These barrier files can be included as an input in the ArcMap IDW tool, but the same concept could be applied in other GIS software by processing areas on opposite sides of the barriers separately.

Given the large number of stream gauges in Harris County, the IDW model initially used a variable search radius to give weight to only the five closest (not crossing a barrier) stream gauges (i.e., each point was calculated using 5 neighbors). This ensured that cells were calculated using local data, which is more likely to be indicative of a given cell's starting elevation. The use of the inverse squared distance (rather than the simple inverse) ensured that if one of the five points was very far away, its weight would be much lower, again ensuring that local information was the most influential. For computational efficiency, the output of the IDW was set to 10 m resolution.

The raster resulting from the IDW model was processed to produce an output displaying just the modeled depth and extent. First, the IDW model output was clipped to the extent of Harris County (IDW outputs are, by default, the minimum size required to reach all input points). Next, the *greater than* and *raster reclassify* tools were used to identify the portion of the IDW output that had modeled elevations higher than the underlying DEM. This identified area was used to clip the IDW output, leaving only modeled elevation values greater than the DEM. Finally, the DEM was subtracted from the IDW output to produce a raster displaying flood depth above ground (or depth above normal water level over preexisting water features).

Given the ease of running an IDW analysis in modern GIS software, the process described above was repeated with altered parameters to evaluate how output performance changed. Permutations of this study's method changed both the number of neighboring points considered and the power function used to weight points based on their distance from the unknown point being calculated. Ultimately, 15 alternative parameterizations were tested using either 3, 5, or 7 neighbors to calculate the value of unknown points and a power function of either 1, 1.5, 2, 2.5, or 3 to weight the relevance of those neighbors by their distance from the unknown point.

2.4 Model validation

Quantitative validation of the initial model (i.e., the initial parameterization—5 neighbors, power function of 2) output was done using bridge high water mark (HWM) data collected by HCFCD. HCFCD measured the elevation of observed HWMs at 442 bridges throughout Harris County. The modeled depth for each day of flooding was extracted to the HWM points, and the maximum value was kept as a modeled HWM depth. The same DEM used in the modeling method was subtracted from observed HWM elevations to obtain observed HWM depths. Next, to ensure the independence of the validation dataset, any HWM depth within 1 km of a stream gauge used in the model was removed, leaving 243 points for validation. Descriptive statistics relating modeled versus observed values, as well as the index of agreement (d), were calculated per Willmott (1982) and Diem's (2003) suggestion for evaluating spatial models (the index of agreement is a statistic used to assess the accuracy of spatial models). We also calculated the Nash–Sutcliffe model efficiency coefficient (NSE) for the modeled depths (NSE is a statistic used to assess model accuracy, see Sect. 3.3 for more information). To place our NSE in context, per Schaefli and Gupta's (2007) recommendation, we calculated the benchmark efficiency (BE) and the NSE of the benchmark (NSEB), using the average of all previous HWM depths recorded at each HWM site used in validation as the benchmark. HCFCD provided historic HWM data from 1948 to 2016 (HCFCD measures the HWM of bridges that experienced flooding whenever a flood occurs), which were used to calculate these averages.

Validation of the initial model outputs continued with a visual validation of modeled flood extent against available aerial imagery. After Hurricane Harvey moved away from Harris County, the United States' National Oceanic and Atmospheric Administration's (NOAA) Ocean Service, National Geodetic Survey (NGS) imaged a large portion of the county, focusing especially on stream channels. The resulting dataset (Hurricane Harvey: Emergency Response Imagery of the Surrounding Regions, see https://storms.ngs.noaa.gov/storms/harvey/index.html) was used to compare observed flood extent for portions of five days to the modeled outputs from those days (August 30th to September 3rd). A fishnet of 1 km^2 grid cells was created for the county. From all the resulting cells, 500 that had imagery were randomly selected for evaluation. Two cells were not fully covered by a single day and were excluded, leaving 498 cells for assessment. Each of these 498 grid cells was visually evaluated, and it was recorded if the modeled extent and observed extent agreed or disagreed. In the case of disagreement, it was further noted whether the model over- or underestimated the flooding extent.

Each cell was evaluated by 3 different analysts. If a majority of those analysts could not agree if a cell agreed or disagreed (or whether a disagreement was an over or under prediction), a fourth analyst made a final evaluation. Because the outputs were naturally pixelated, errors in extent of less than 30 m were disregarded (a 30 m^2 grid was overlaid on the imagery to assist in evaluation). Disagreements occurring over preexisting (i.e., not the result of flooding) water features (e.g., streams or lakes) evident in baseline imagery available from ESRI basemaps were disregarded because that extent information would already be contained within the underlying elevation data.

To assess how altering the number of neighbors and the power function of the IDW model would affect output accuracy, HWM data were used to assess the NSE and BE of the 14 alternate parameterizations run. HWM were extracted the same way in all fifteen cases. The 7 alternate parameterizations with the highest NSE values were then visually validated in the same way as the initial parameterization. The same imagery and 498 1 km^2 grid cells were used in all 8 visual assessments.

3 Results

3.1 Model outputs

The initial search-constrained IDW model outputs to give a sense of how the flood event evolved as Hurricane Harvey progressed. Modeled extents show no flooding outside of normal flood areas at noon on August 25th (before any stream in the county entered flood stage), which functions as the area's baseline (Fig. 3a). Modeled extents peak on August 27th and 28th (n.b. only noon gauge readings were used in the modeling), with streams in central Harris County and the south/southeast of the county flooding severely on the 27th, and stream channels in the east and north/northwest of the county flooding severely on the 28th (Fig. 3b, c). By August 31st, the model indicates that the bulk of flooding began to recede or had already receded, with the exception of Buffalo Bayou (downstream of the reservoir outflows), which remained flooded as the result of a controlled release of Addicks and Barker Reservoirs in the central east of the county (Fig. 3d).

3.2 Validation using imagery

Validation of the initial parameterization (5 neighbors, power function of 2) using available NOAA aerial imagery indicated a reasonable degree of agreement between modeled and observed extent. Of the 498 1 km^2 assessed, 409 were determined to have a modeled and observed flooding extent with a percent agreement of 82.1. Of the 89 cells that showed disagreement between model and observed flooding, 75.3% (67) were underestimates, with most underestimates occurring west-northwest of the county's center (Fig. 4).

3.3 Validation using high water marks

Based on quantitative validation comparing modeled and observed HWM depths, our initial model outputs (from the initial parameterization: 5 neighbors, power function of 2) can be considered valid. Diem (2003) proposes that modeled surfaces should fulfill five criteria to be considered valid: (1) the modeled mean ($\bar{p}$) and (2) standard deviation (s_p) should approximate the observed mean ($\bar{o}$) and standard deviation (s_p), (3) the relative error should approach 0, (4) the unsystematic root mean squared error ($RMSE_u$) should approach the root mean squared error ($RMSE$), and (5) d should approach 1. Our $\bar{p}$ and s_p were 14.6 ft (4.45 m) and 11.4 ft (3.47 m) respectively, compared to an $\bar{o}$ and s_o of 17.2 ft (5.24 m) and 10.2 ft (3.11 m) respectively (n = 243 for all quantitative validation). Our modeled HWM depths had a relative error of 0.33 and a $RMSE_u$ of 5.2 compared to a $RMSE$ of 5.8, while d was 0.92.

Further evaluation of the modeled HWM depths derived from the model's initial parameterization using the NSE also indicates satisfactory model performance. Using modeled HWM depths, we calculated a NSE of 0.67, which is indicative of a model performing markedly better than simply substituting the mean for all observations (Moriasi et al. 2007; Nash and Sutcliffe 1970). To more fully evaluate model performance, the NSE should be compared to a NSEB (Schaefli and Gupta 2007). Using the average of all previously measured HWM depths at each bridge as a benchmark, we calculated a NSEB of 0.56 (with a BE of 0.26), meaning our modeled depths are an improvement over the benchmark of slightly more than 20%. It should be noted that the accuracy of HWM data is generally ± 1 foot.

3.4 Comparison of alternate parameterizations of the IDW model

In addition to the initial IDW model, parameterization using five neighbors and a power function of 2, 14 other parameterizations were run. The NSE and BE of all fifteen parameterizations indicate similar levels of output accuracy. Table 1 shows the NSE and BE values for all fifteen parameterizations. The seven alternate parameterizations with the highest NSE values were also validated visually in the same way as the initial parameterization. Table 2 shows the results of visual validation for all 8 parameterizations evaluated. While there were minor differences in NSE values and percent agreement of visual validation against imagery, all the fifteen model parameterizations performed well. Each of the fifteen alternatives had an NSE value over 0.6 with the worst NSE value still out-performing the NSEB by 16.3%. Similarly, the eight parameterizations that had extents compared to observed flooding in the NOAA imagery all showed agreement in over 79% of 1 km^2 cells assessed, with the highest agreement in excess of 88% (5 neighbors, power function of 1.5). Parameterizations using 5 neighbors consistently had higher NSE values than the three or seven neighbor parameterizations using the same power function, though all values are very similar, ranging from 0.613 to 0.669.

4 Discussion

This study tested the accuracy of a relatively easy-to-implement, near real-time flood modeling technique that has emergency response applications. During a flooding event, situational awareness is important for distributing resources and responding to changing conditions. A key part of that situational awareness is knowledge of current flood extents and depths (Al-Sabhan et al. 2003). While other observational methods of determining flood extents exist (e.g., SAR and aerial imagery), our method provides a higher temporal resolution and is less likely to be subject to data availability constraints. Even along streams with few stream gauges, IDW can provide a reasonably accurate picture of flood extent (Rabie et al. 2017).

4.1 Comparison of model parameterizations

There was no consistently preferred number of neighbors or power function when comparing among the fifteen parameterizations on the basis of NSE and BE or eight parameterizations subjected to the visual validation on the basis of that validation. Taken together, it appears that the accuracy of outputs is reasonably robust to alterations in the initial IDW model parameters. In terms of applications, this could imply that this methodology may be a preferable first approximation of flooding even if carried out by someone with less expertise in spatial modeling than would be needed for other methods.

4.2 Model validation

While all eight model parameterizations validated against imagery showed reasonable agreement with observation, visual examination of the imagery validation across all parameterizations (Fig. 5) highlights two circumstances that may generate increased error. An area of disagreement apparent in most or all parameterizations in the county’s northwest appears to correlate with agricultural fields. This is possibly because of small topographic features, such as a raised berm surrounding a field, for which the method fails to account. Such features may keep water from entering areas that would flood if the feature were not there or vis-versa. Possible solution may be to include these small topographic features as search barriers when creating the initial IDW model output or including land-use as a parameter to adjust model outputs after the fact.

Another broader area of error is visually apparent around the two reservoirs in the county (west of county center). The error is potentially the result of minimally relevant stream gauges being weighted too heavily. Since all estimated depth values are calculated based on a set number of neighbors (3, 5, or 7), areas between two streams will likely be calculated based on gauges from both streams. In addition to having multiple streams in close proximity, the reservoirs had IDW search barriers on one side (the two dams retaining them). To find the set number of neighbors, unknown points may be searching further away as a result of not being able to search across the barriers. In these cases, the distance alone may not be a sufficient indicator of input relevance, leading to the overweighting of gauges that are less indicative of the situation on the ground. In these cases, including stream catchment areas as search barriers and including a max distance for neighbors may help attenuate these errors.

4.3 Limitations

Visual validation using the NOAA imagery has some limitations. The NOAA images only cover a small portion of time, August 30th to September 3rd. Additionally, each day's imagery only covers a part of the county. Without better spatial and temporal coverage we were unable to ensure that the levels of agreement observed hold for the entire flood event. In the earlier days of the flooding event, collecting imagery was impractical, given meteorological conditions. The positive results from the HWM validation indicate that the model performed well on the days before the imagery, as most HWMs were likely reached during the peak flooding on August 27th and 28th, before imagery was available.

While the model validated well against observed HWM depths, that method of validation also presents limitations. The primary limitation is related to the location of HWM depth measurements. While the county is well covered by HWM depth readings, all these readings are restricted to stream channels. Without imagery to confirm extent when the HWM depths occurred, or depth readings from outside of stream channels, we were unable to confirm whether depth estimates worsened the further they were from a stream channel. However, the positive results of the visual validation based on NOAA imagery imply that extent estimates were fairly accurate, at least over the time and area covered by the imagery.

The applicability of this method outside the USA could also not be evaluated by this paper. While global digital elevation raster products exist (e.g., asterweb.jpl.nasa.gov/gdem.asp), the spatial resolution of these products is smaller than what was used for this project. The availability of stream gauge data will also vary greatly country to country, as it can within the USA. That said, where data are available this technique could be implemented. Given the utility of this technique as a tool to augment situational awareness of local response efforts, pairing the processes defined in our effort with local knowledge of data availability and limitations could aid response efforts outside the US.

A final limitation of our search-constrained IDW modeling method for riverine flooding has to do with a limited case study. Without conducting analyses of our method in other flood events, we cannot confirm that this method is equally effective in other geographic areas. Harris County does have more stream gauges than most other places in the country. Perhaps applying our method to an area of the country with fewer stream gauges would yield different results. It should be noted, however, that the use of IDW for river flood modeling in another study validated well despite having far fewer gauges with which to work (Rabie et al. 2017). Additionally, this method is only able to estimate flooding originating from streams. This accounts for most of the flooding in Harris County during Hurricane Harvey, but other locations could experience coastal or low-point flooding, which our model cannot account for. In summary, our model has been validated for areas with a sufficiently large and dense network of stream gauges and for instances of flooding caused by stream overflow. Areas of study differing on these two criteria necessitate further validation.

Low point flooding in areas disconnected from the stream channel is worthy of special note. This project's method may erroneously miss flooding that occurs in topographic "bowls" that collect runoff but are above the interpolated stream elevation. Other "bowls" that fall below the elevation may be marked as flooded, even if high surrounding areas would keep such flooding from occurring. These areas may require manual correction, as has been done in similar projects (e.g., Longenecker et al. 2019). Alternatively, if low point "bowls" that have flood mitigating structures in place, such as levees, are identified beforehand, the mitigating structures can be added as a search-constraining feature, as the dams of Harris County were in this project. The inclusion of these structures as part of the input would reduce errors and help limit the need manual corrections.

4.4 Applications

Our method of flood modeling may help public health officials identify locations in need of public health action, specifically related to mold prevention, infection control, and injuries. This is especially true for response activities that occur during or immediately after the flooding event, when other methods of assessing flooding are not feasible. Disease surveillance efforts can focus on areas most affected by the flooding to provide guidance to local health practitioners about illnesses that may occur. For rapid needs assessments in a community, which are needed to coordinate relief efforts (Waring et al. 2005), the temporal resolution of our method also identifies areas that may be inaccessible for the time frame of the modeled inundation. Furthermore, these inaccessible areas may need additional resources if people are unable to evacuate but have medical needs. Knowing the depth and duration of flooding in areas may also help responders determine which areas to target for remediation when waters recede. Near real-time, high temporal resolution flood models, such as our method, may also be helpful in responding to secondary disasters resulting from flooding. In the case of Hurricane Harvey and the Harris County area, the explosion at the flooded Arkema Chemical Plant in Crosby, Texas, would represent one such emergency (see csb.gov/arkema-inc-chemical-plant-fire-). Other flood-related incidents might include contaminant releases from former industrial facilities, landfills, and other hazardous waste sites. Knowing the flooding conditions of these locations and the surrounding area can be essential in responding and minimizing potentially deleterious effects.

Beyond emergency response, using stream gauge data in the way described by this study could help with retrospective studies that look at the effect of flood events on health outcomes. Health data that include a temporal component could be more accurately paired with the flooding conditions of the specifically relevant time by using the temporally closest stream gauge data. This methodology could also allow public health researchers to more easily characterize flooding throughout an entire event when looking at health outcomes in a given area. Further, this method could allow public health officials to rapidly identify at-risk populations that may be exposed to flooding during an event.

Outside of public health, this method could function as a preliminary flooding prediction tool. While the method requires stream gauge inputs, those inputs could be estimated for future flooding events. Even crude estimations could identify areas at risk of flooding, helping planners and flood managers assess areas most at risk for flooding. With limited time or resources, our method could help prioritize more intensive data collection and modeling efforts. Further, areas that show persistent error when using our method could highlight locations where additional gauges could be most useful. While larger events like Hurricane Harvey will often have support from many stakeholders, such as the National Weather Service, that can provide subject-matter experts and resources needed for more complex flood modeling, the IDW modeling method laid out here could help smaller, local agencies that lack stakeholder support. The ability to implement IDW modeling in off-the-shelf GIS software would allow low-resource agencies to respond to and prepare for flood events that are unlikely to garner outside support. This method could also allow for more immediate response at the local level while waiting for larger stakeholders to muster in response to serve events.

4.5 Future work

Future studies could improve on this methodology in a variety of ways. First, this application could be used to model historical flooding events in other topographic environments. Doing so would help determine if this method has broad geographic applicability. Second, future studies could focus on altering the modeling parameters as was done in this study to determine if a specific parameterization is preferable or if results are robust to changes in initial IDW model parameters. Additional work could try to identify which if any study area characteristic should be considered when selecting model parameters. Such future studies could evaluate how different sources or resolutions of DEMs impact results. Input data features, such as DEM resolution, could be a factor in what model parameters are preferable. Finally, our method could be compared to others. Testing search-constrained IDW against other flood model methods (e.g., hydrologic modeling) and other interpolation techniques (e.g., kriging) would help determine if IDW is the preferable method for riverine flood modeling.

Additional work on this topic could also focus on applying this methodology outside the USA. While the concept employed here is theoretically applicable anywhere stream flooding is at risk, differences in the availability of elevation data or the structure and density of stream gauge networks outside the USA may affect the accuracy of IDW modeling. In addition to determining how the model is impacted by various topographies, as suggested above, seeing how the data variations across different countries affect model results will further inform the geographic applicability of our method.

5 Conclusion

Our study presented a relatively simple method for near real-time riverine flooding estimation. Consistent with previous work on the topic, we showed that stream gauge measurements and DEMs were sufficient to create accurate depth and extent estimations. This study went further, showing that IDW modeling produced accurate results even in an area with many streams and multiple barriers intended to control flooding and that outputs are accurate even if IDW model parameters are altered somewhat. While our method will need to be tested against other cases to confirm broader applicability, search-constrained IDW modeling could help emergency managers maintain situational awareness during flood events and help inform response and recovery decisions after the event ends. As floods continue to pose a consistent and serious hazard, our method could add a helpful tool to mitigate the public health risks posed by flooding.

6 Availability of data

Digital elevation models and stream gauge data used in this work are publicly available. Modeled inundation heights derived from these inputs are available by request to the authors.

Acknowledgments

Funding Not applicable.

References

Ahern M, Kovats RS, Wilkinson P, Few R, Matthies F (2005) Global health impacts of floods: epidemiologic evidence. Epidemiol Rev 27:36–46. 10.1093/epirev/mxi004 [PubMed: 15958425]

Al-Sabhan W, Mulligan M, Blackburn GA (2003) A real-time hydrological model for flood prediction using GIS and the WWW. Comput Environ Urban Syst 27(1):9–32. 10.1016/S0198-9715(01)00010-2

Cann KF, Thomas DR, Salmon RL, Wyn-Jones AP, Kay D (2013) Extreme water-related weather events and waterborne disease. Epidemiol Infect 141(4):671–686. 10.1017/S0950268812001653 [PubMed: 22877498]

Center for Research on the Epidemiology of Disasters (2016) Poverty & Death: Disaster Mortality 1996–2015. United Nations Office for Disaster Risk Reduction. https://www.unisdr.org/we/inform/publications/50589. Accessed 16 Sept 2019

Centers for Disease Control and Prevention (2006) Health concerns associated with mold in water-damaged homes after Hurricanes Katrina and Rita-New Orleans area, Louisiana, October 2005. MMWR Morb Mortal Wkly Rep 55(2):41–44 [PubMed: 16424858]

Chen J, Hill AA, Urbano LD (2009) A GIS-based model for urban flood inundation. J Hydrol 373(1–2):184–192. 10.1016/j.jhydrol.2009.04.021

Chew GL, Wilson J, Rabito FA, Grimsley F, Iqbal S, Reponen T, Muilenberg ML, Thorne PS, Dearborn DG, Morley RL (2006) Mold and endotoxin levels in the aftermath of Hurricane Katrina: a pilot project of homes in New Orleans undergoing renovation. Environ Health Perspect 114(12):1883–1889. 10.1289/ehp.9258 [PubMed: 17185280]

Diem JE (2003) A critical examination of ozone mapping from a spatial-scale perspective. Environ Pollut 125(3):369–383. 10.1016/s0269-7491(03)00110-6 [PubMed: 12826415]

Gallien TW, Barnard PL, van Ormondt M, Foxgrover AC, Sanders BF (2013) A parcel-scale coastal flood forecasting prototype for a southern California urbanized embayment. J Coast Res 29(3):642–656. 10.2112/JCOASTRES-D-12-00114.1

Horritt MS, Bates PD (2002) Evaluation of 1D and 2D numerical models for predicting river flood inundation. J Hydrol 268:87–99. 10.1016/S0022-1694(02)00121-X

Ivers LC, Ryan ET (2006) Infectious diseases of severe weather-related and flood-related natural disasters. Curr Opin Infect Dis 19(5):408–414. 10.1097/01.qco.0000244044.85393.9e [PubMed: 16940862]

Jonkman SN, Kelman I (2005) An analysis of the causes and circumstances of flood disaster deaths. Disasters 29(1):75–97. 10.1111/j.0361-3666.2005.00275.x [PubMed: 15720382]

Kia MB, Pirasteh S, Pradhan B, Mahmud AR, Sulaiman WNA, Moradi A (2012) An artificial neural network model for flood simulation using GIS: Johor River Basin, Malaysia. Environ Earth Sci 67:251–264. 10.1007/s12665-011-1504-z

Lillesand TM, Kiefer RW, Chipman JW (2008) Remote sensing and image interpretation, 6th edn. Wiley, Hoboken

Longenecker HE, Graeden E, Kluskiewicz D, Zuzak C, Rozelle J, Aziz AL (2019) A rapid flood risk assessment method for response operations and nonsubject-matter-expert community planning. J Flood Risk Manag 13(1):1–20. 10.1111/jfr3.12579

Moriasi DN, Arnold JG, van Liew MW, Bingner RL, Harmel RD, Veith TL (2007) Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans Am Soc Agric Biol Eng 50(3):885–900. 10.13031/2013.23153

Nash JE, Sutcliffe JV (1970) River flow forecasting through conceptual models part—a discussion of principles. J Hydrol 10(3):282–290

Rabie A, Peterson EW, Kostelnick J, Rowley RJ (2017) Optimizing digital elevation model resolution inputs and number of stream gauges in geographic information system predictions of flood inundation: a case study along the Illinois River, USA. Environ Eng Geosci 23(4):345–357. 10.2113/gseegeosci.23.4.345

Rao CY, Riggs MA, Chew GL, Muilenberg ML, Thorne PS, Van Sickle D, Dunn KH, Brown C (2007) Characterization of airborne molds, endotoxins, and glucans in homes in New Orleans after Hurricanes Katrina and Rita. Appl Environ Microbiol 73(5):1630–1634. 10.1128/AEM.01973-06 [PubMed: 17209066]

Riggs MA, Rao CY, Brown CM, Van Sickle D, Cummings KJ, Dunn KH, Deddens JA, Ferdinands J, Callahan D, Moolenaar RL, Pinkerton LE (2008) Resident cleanup activities, characteristics of flood-damaged homes and airborne microbial concentrations in New Orleans, Louisiana, October 2005. Environ Res 106(3):401–409. 10.1016/j.envres.2007.11.004 [PubMed: 18199434]

Schaefli B, Gupta HV (2007) Do Nash values have value? Hydrol Process 21:2075–2080. 10.1002/hyp.6825

Schumann GJP, Neal JC, Mason DC, Bates PD (2011) The accuracy of sequential aerial photography and SAR data for observing urban flood dynamics, a case study of the UK summer 2007 floods. Remote Sens Environ 115(10):2536–2546. 10.1016/j.rse.2011.04.039

Taylor J, Biddulph P, Davies M, Lai KM (2013) Predicting the microbial exposure risks in urban floods using GIS, building simulation, and microbial models. Environ Int 51:182–195. 10.1016/j.envint.2012.10.006 [PubMed: 23266909]

ten Veldhuis JAE, Clemens FHLR, Sterk G, Berends BR (2010) Microbial risks associated with exposure to pathogens in contaminated urban flood water. Water Res 44(9):2910–2918. 10.1016/j.watres.2010.02.009 [PubMed: 20227742]

Waring S, Zakos-Feliberti A, Wood R, Stone M, Padgett P, Arafat R (2005) The utility of geographic information systems (GIS) in rapid epidemiological assessments following weather-related disasters: methodological issues based on the Tropical Storm Allison Experience. Int J Hyg Environ Health 208(1–2):109–116. 10.1016/j.ijheh.2005.01.020 [PubMed: 15881984]

Watson DF, Philip GM (1985) A refinement of inverse distance weighted interpolation. Geoprocessing 2:315–327

Willmott CJ (1982) Some comments on the evaluation of model performance. Bull Am Meteorol Soc 63(11):1309–1313. 10.1175/1520-0477(1982)063<1309:SCOTEO>2.0.CO;2

Yard EE, Murphy MW, Schneeberger C, Narayanan J, Hoo E, Freiman A, Lewis LS (2011) Hill VR (2014) Microbial and chemical contamination during and after flooding in the Ohio River—

Kentucky. J Environ Sci Health A Tox Hazard Subst Environ Eng 49(11):1236–1243. 10.1080/10934529.2014.910036

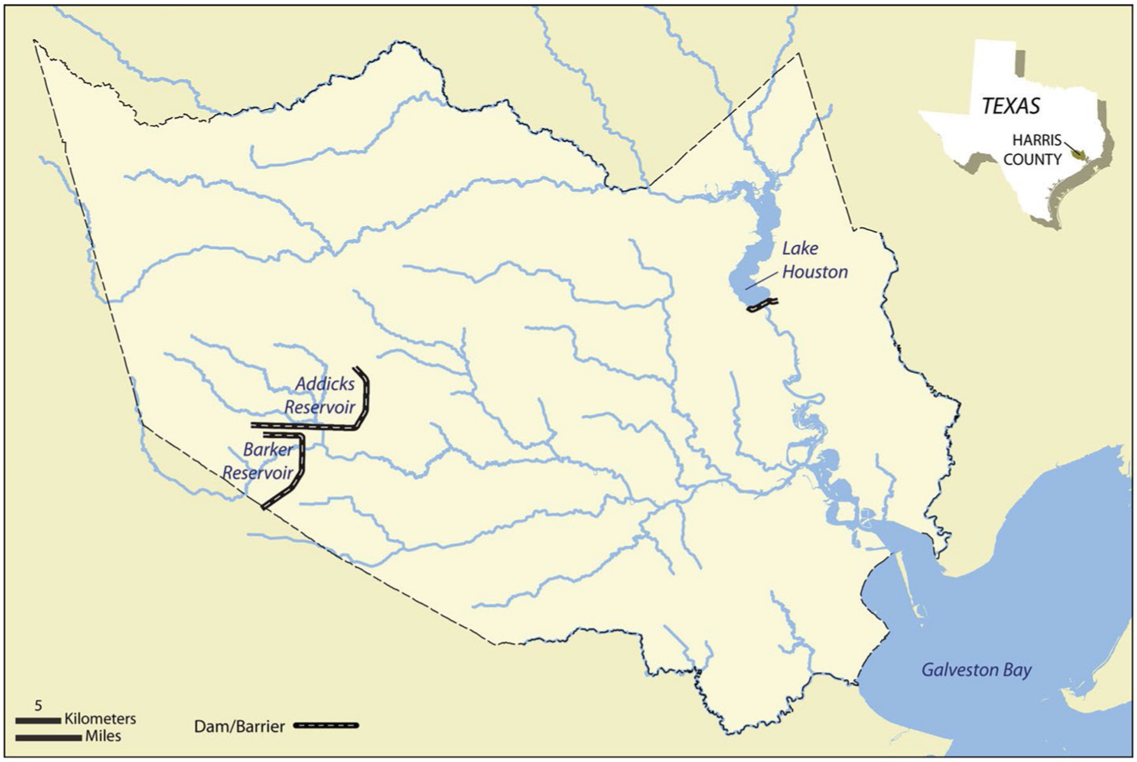

Fig. 1.

Reference map of Harris County, Texas, USA, displaying stream channels and identifying the locations of Lake Houston, Galveston Bay, and the dams at Addicks Reservoir, Barker Reservoir, and Lake Houston

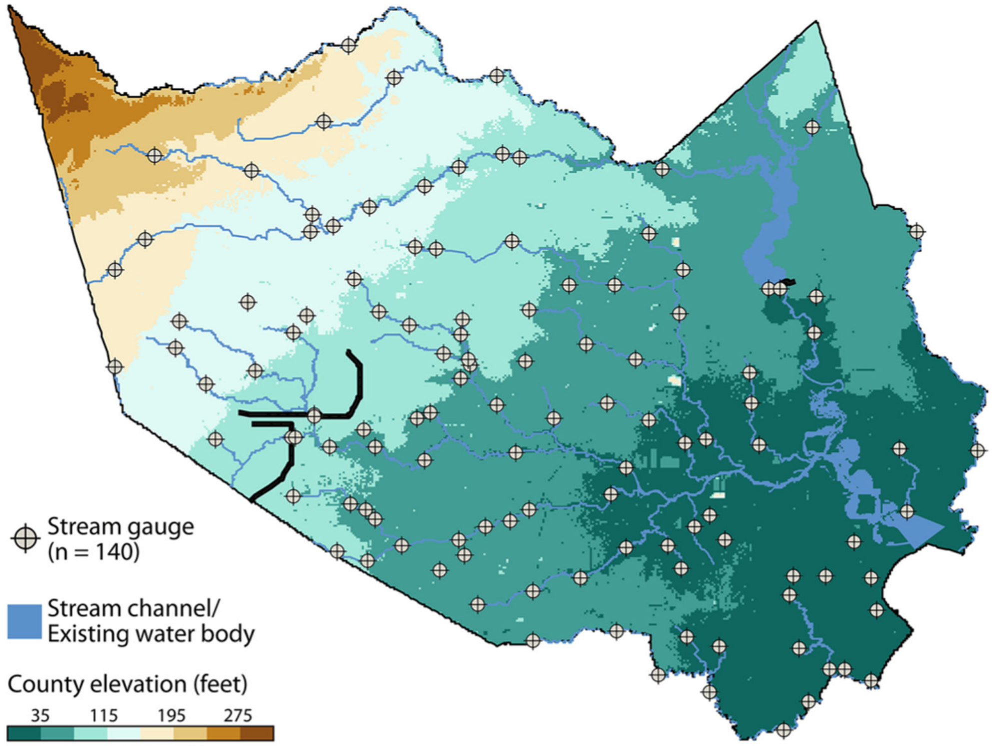

Fig. 2.
Harris County stream gauge locations and elevation

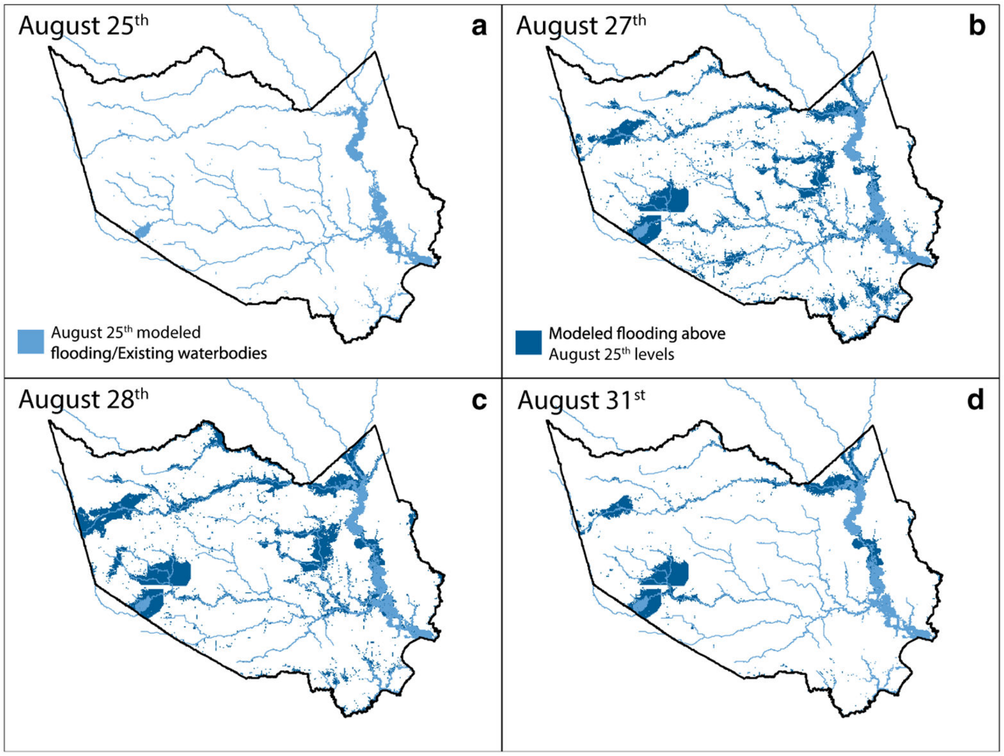

Fig. 3.

Riverine flood model outputs resulting from search-constrained IDW modeling in Harris County on four dates in 2017: before Hurricane Harvey flooding on August 25th (**a**), severe flooding on August 27th (**b**) and 28th (**c**), and after most flooding had receded on August 31st (**d**)

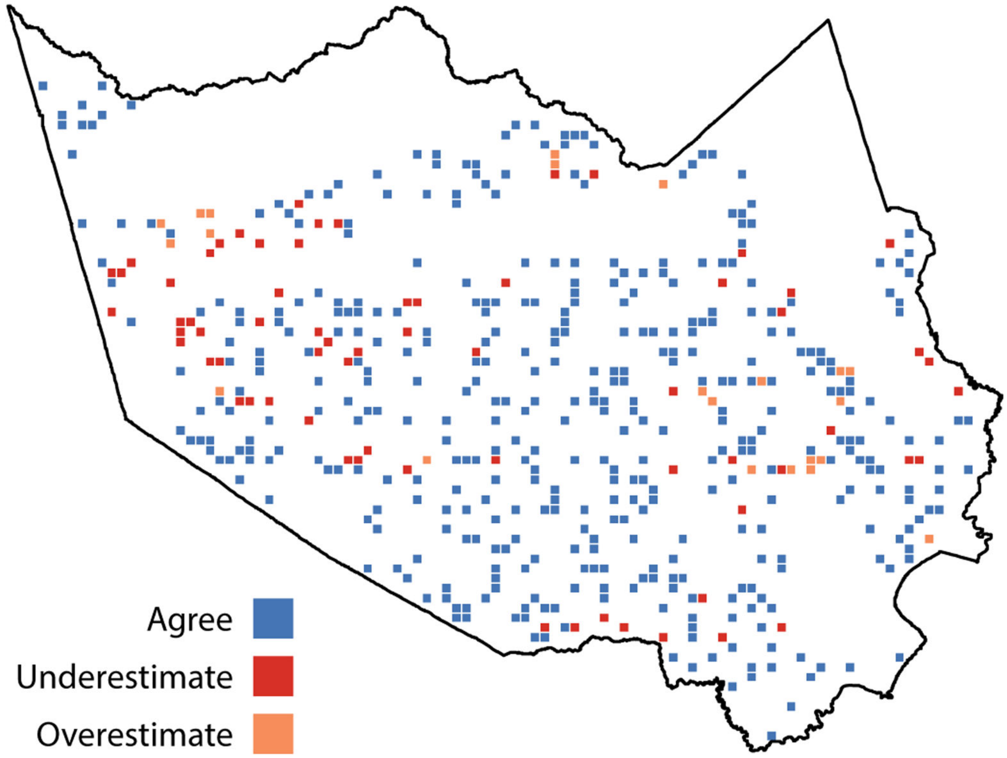

Fig. 4.

Results of visual validation of initial flood model outputs (5 neighbors, power function of 2) using available NOAA imagery. Each grid cell is color-coded by whether visual assessment of the cell indicated that the modeled flooding extent agreed with imagery (blue) was an underestimate when compared with imagery (red), or was an overestimate when compared with imagery (orange)

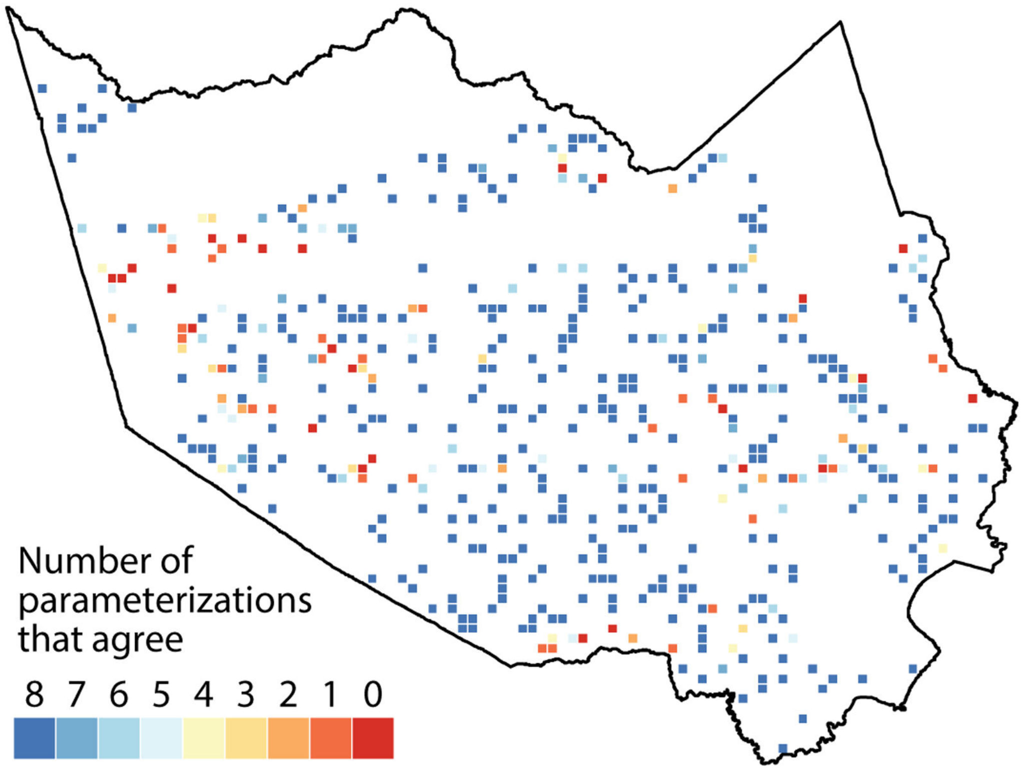

Fig. 5.
Number of model parameterizations in which a given cell is assessed as agreeing with NOAA imagery

Table 1

NSE (BE) of all 15 alternative parameterizations of IDM model evaluated

Power function	Neighbors used		
	3	**5***	**7**
1	0.613 (0.187)	0.660 (0.279)	0.625 (0.214)
1.5	0.623 (0.209)	0.669 (0.299)	0.644 (0.253)
2*	0.626 (0.215)	0.669 (0.300)	0.650 (0.267)
2.5	0.624 (0.211)	0.663 (0.290)	0.650 (0.267)
3	0.620 (0.203)	0.655 (0.273)	0.646 (0.259)

*Initial model parameters used

Table 2

Results of NOAA image validation for all 498 1 km2 cells evaluated for initial parametrization and 7 alternate parameterizations selected based on NSE values

	Agree	Underestimate	Overestimate
5 neighbors			
Power function of 1	413	65	20
Power function of 1.5	439	44	15
Power function of 2*	409	67	22
Power function of 2.5	408	74	16
Power function of 3	412	63	23
7 neighbors			
Power function of 2	396	70	32
Power function of 2.5	421	60	17
Power function of 3	408	84	6

*Initial model parameters used