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Discussions

Interactive comment on "Road assessment after flood events using non-authoritative data" *by* E. Schnebele et al.

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article

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Road assessment after flood events using non-authoritative data
Author responses to Dr. Traverso (reviewer)

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Our responses are reported below, along with the unabridged comments from Dr. Traverso.

> The manuscript represents a good contribution to the study of consequences due to natural hazards, and it deals with new concepts of great interest for the geospatial global community.

We appreciate Dr. Traverso's positive comment.

> The scientific approach seems valid, but formulas and results have to be described in detail.

Please see the following sections for revisions to our methodology and results sections.

> Scientific assumptions related to: 3.2 Non-authoritative damage assessment; 3.3 Integration with authoritative data; 3.4 Generation of road damage map; are not clearly outlined with specifications of the methodology that was applied. Please describe in depth each step of flowchart Fig.3.

In order to describe our methods in more detail as requested, we have included revisions to all of Section 3: Methodology.

Section 3.1: Overview

This work is based on the fusion of non-authoritative data and its integration with traditional authoritative sources. Figure 3 illustrates the general methodology where non-authoritative data from multiple sources are combined to produce a spatial and temporal assessment of the disaster. While the precise definition of data fusion will vary by discipline, for example, in computer science the process of data integration is considered to be the "data fusion"; in this work data fusion refers to the model in its entirety. The methodology consists of a three step process:

1. Non-authoritative damage assessment.
2. Integration with authoritative data for damage assessment.
3. Generation of road damage map.

The model begins with the integration of non-authoritative data (i.e. crowdsourcing and VGI) to create a damage assessment. The step is method-independent and can be performed using any method best suited for a particular combination of data and location. Because this step is not limited to a specific data type, it can easily be extended to integrate additional or different sources. After a damage assessment is created from non-authoritative data, it is integrated with available authoritative data to enhance the damage assessment. This step can be in the form of validation, if "ground truth" data are available, or can consist of an additional integration step whereby authoritative and non-authoritative data are incorporated to fill in gaps in the spatial or temporal data infrastructure. The final step is the classification of roads which may be compromised as a result of flooding. This is accomplished by applying a road network to the damage

assessment. Depending on data availability and flood event characteristics, a temporal assessment of the flood event may be generated in addition to the spatial assessment. The specifics for each step as they apply in this paper are discussed Sections 3.2-3.4.

The novelty of this approach is the utilization of non-authoritative data to produce flood and road damage assessments. Although in this work specific crowdsourced data (Civil Air Patrol photos) and volunteered data (YouTube videos, Tweets) are utilized, this methodology can be extended to other sources. The goal of this paper is to illustrate how non-authoritative data can augment existing data and methods as well as optimize response initiatives by identifying areas of severe damage.

Section 3.2: Non-authoritative damage assessment

We integrate non-authoritative data by interpolating to create a damage assessment surface. The geostatistical technique of kriging creates an interpolated surface from the spatial arrangement and variance of the nearby measured values (Stein, 1999). Kriging allows for spatial correlation between values (i.e. locations/severity of flooding) to be considered and is often used with Earth science data (Oliver and Webster, 1990; Olea and Olea, 1999; Waters, 2008). Kriging utilizes the distance between points, similar to an inverse weighted distance method, but also considers the spatial arrangement of the nearby measured values. In addition, a kriging interpolator is capable of providing some measure of error associated with the predicted values (Stein, 1999). A variogram is created to estimate spatial autocorrelation between observed values $Z(x_i)$ at points $x_1, \ldots, x_n$. The variogram determines a weight w_i at each point x_i, and the value at a new position x_0 is interpolated as

$$\hat{Z}(x_0) = \sum_{i=1}^{n} w_i Z(x_i). \tag{1}$$

Section 3.3: Integration with authoritative data

For this research, authoritative data in the form of a storm surge map created by FEMA MOTF is utilized to (1) illustrate how non-authoritative data can provide a range of damage estimations enhancing traditional storm surge products and (2) as a comparison of authoritative estimated flood extent. The damage assessment surface created from the non-authoritative data is first limited to the FEMA estimated flood boundary to illustrate how non-authoritative data provide a range of damage values in contrast to the binary assessment (flooded/not flooded) provided by the FEMA MOTF map. Second, the area (m^2) classified as flooded by FEMA is used as a baseline by which the flooded area (m^2) estimated from non-authoritative sources can be measured against.

Section 3.4: Generation of road damage map

The identification of affected roads is accomplished by pairing a road network with the damage assessment surface. A layer comprising a high resolution road network is added to the damage assessment surface layer. Roads are then identified as potentially compromised or impassable based on the underlying damage assessment. The classification of roads is accomplished in ArcGIS 10 using the clip tool to select roads which are located within each damage class. Depending on the range of damage values as well as the scale of the domain, the classes can then be aggregated to facilitate a reduction in complexity and present a clearer representation. Potentially affected roads could also be classified as a function of distance from the flood source (i.e. river or coastline) or distance from the flood boundary.

> The length of the paper is a bit too short for a complete description of the process, please describe better chapter 4 and underline classes that were assumed for values of road damage map.

Please see revised sections 4.1.1 and 4.2:

Section 4.1.1 Spatial assessment:

Civil Air Patrol damage assessments for the area from 33N to 26N latitude and 90W to 84W longitude were downloaded directly from MapMill. The photographs were collected by the Civil Air Patrol between October 31-November 11, 2013 (within days of Hurricane Sandy impacting the New York City area). The photos were aggregated into a 500m grid structure. The value for each grid point is a function of the number of images present in each grid and their average crowdsourced damage assessment. As a result, each grid has a value from 1 to 10, with 1 representing no damage and 10 severe damage/flooding.

The videos were provided with geolocated information, and were visually assessed by the author. The small number of videos (n=15) did not require any crowdsourcing or automated assessment. Furthermore, it is shown in Schnebele and Cervone (2013) that even a small number of properly located VGI data can help improve flood assessment. Each video point was assigned a value of 10 (severe damage/flooding).

The Civil Air Patrol and YouTube data were fused together using a kriging interpolation as described in section 3.2, resulting in a damage assessment surface generated solely from non-authoritative data. Ordinary kriging generated a strong interpolation model. Cross-validation statistics yielded a standardized mean prediction error of 0.0008 and a standardized root-mean-squared prediction error of 0.9967. Figure 2c illustrates the damage assessment within the boundaries of the FEMA surge extent. A histogram (Figure 4) shows the ranges in these damage assessment values. The peak in medium/severe damage values (7-8) illustrates how non-authoritative data can provide damage information not conveyed in the FEMA map.

Ground information in the form of geolocated videos (Figure 5) enhances the non-authoritative data set by providing flood information not conveyed in the Civil Air Patrol photos. As illustrated in (Figure 6), the locations of the videos (green triangles) did not coincide with locations of photos rated as medium/severe damage (larger orange circles, values 7-10). Reasons for this disparity may include the fact that flooding captured on video had receded before the Civil Air Patrol flights or because the images were captured at night, or because flooding may have occurred in areas which were not in a flight path or were unable to be seen from aerial platforms (ie. flooding in tunnels, under overpasses). By using multiple data sources, flood or damage details not captured by one source can be provided by another.

A comparison of flood surface area between the two maps was also conducted. The storm surge area on the FEMA map is approximately 121 km^2. Using the higher rated areas of damage (regions with values from 7-10) from the non-authoritative assessment yielded an approximate surface area of flooding and damage of 157 km^2 (Figure 7). Using only the areas classified as medium-severely damaged, the surface area generated from non-authoritative sources is within 23% of FEMA's surge extent for New York City.

Overall, there is a very good agreement between the flood extent from FEMA and the assessment generated with the proposed methodology. Figure 9 shows examples of agreement between photos identifying flooding/damage and the FEMA generated flood extent while Figure 10 includes examples where the locations of flooding or damage did not agree between the Civil Air Patrol and the FEMA data. These areas were located along coastal edges and therefore precision is most likely the cause of the discrepancies.

Sources of error in non-authoritative data, such as incorrect information (false positive/negative) or improper geolocation needed to be considered. Incorrect information can be mitigated by including visually verified photos/videos and the application of multiple sources. Crowdsourcing, in particular, can increase accuracy and enhance information reliability compared to single source observations (Giles, 2005). Geolocation errors can be reduced with automation.

Sparse data or data skewed in favor of densely populated or landmark areas makes

the use of non-authoritative data sources especially challenging. Increasing data volume and integrating authoritative data into the methodology can yield increased confidence and include underrepresented areas. Although non-authoritative data can provide timely, local information, they are often viewed with uncertainty. Conversely, the verification and authentication of authoritative data can be slower to ascertain and collect but yield trusted results.

Section 4.2: Road damage map

The non-authoritative damage assessment was also utilized to identify areas of potential road damage. Although, for the sake of comparison, the damage assessment was limited to within the authoritative FEMA surge extent area (Figure 2c), for the classification of road damage, the area was not limited to the authoritative extent. The fusion of the non-authoritative data predicted flooding and damage outside the FEMA flood extent boundaries, so the full damage assessment was utilized for the road classification.

The road network from the TIGER/line® shapefile was layered over the damage assessment map. Roads were then classified based on the underlying damage assessment layer by clipping and then segregating roads from the original road network layer (Figure 2d). This yielded 10 individual road classes, with values from 1-10, representing the original 10 damage classes from the gridded Civil Air Patrol crowdsoured photos and YouTube videos. Roads classified with values between 1-3 were considered to have no damage and were not included in Figure 2d. The remaining classes were aggregated into slight (values 4-6), medium (value 7), and severe (values 8-10) damage. The selection of class assignment was based on how the gridded values from the crowdsourced Civil Air Patrol data set were ascertained. The gridded values were a function of number of photos and their averaged values which originally consisted of three classes ranging from 1-3. Therefore, the final road classifications were also represented as three damage classes.

By using the damage assessment layer along with a high resolution road network layer, roads which may have severe damage can be identified at the street level. This is critically important during disasters when evacuations and response initiatives are paramount. For example, following the Colorado floods of September 2013 over 1000 bridges required inspection and approximately 200 miles of highway and 50 bridges were destroyed [1]. Rapid and directed identification of affected areas can aid authorities in prioritizing site visits and response initiatives as well as task additional aerial data collection.

> Please consider the word "damage" as uncountable name with the exception of legal contexts or claims for money.

We have changed the incorrect ‘damages’ to ‘damage’ throughout the revised version of the manuscript.

> In conclusion, I recommend to accept this paper after minor improvements focused to an in-depth comprehension of the work.

We thank Dr. Traverso for his recommendation.

References

Giles, J., 2005. Internet encyclopaedias go head to head. Nature 438 (7070), 900–901.

Olea, R. A., Olea, R. A., 1999. Geostatistics for Engineers and Earth Scientists. Kluwer Academic Boston.

Oliver, M. A., Webster, R., 1990. Kriging: A method of interpolation for geographical information systems. International Journal of Geographical Information System 4 (3), 313–332.

[1] http://www.denverpost.com/breakingnews, http://www.thedenverchannel.com/news/local-news/

Schnebele, E., Cervone, G., 2013. Improving remote sensing flood assessment using volunteered geographical data. Nat. Hazards Earth Syst. Sci 13, 669–677.

Stein, M. L., 1999. Interpolation of Spatial Data: Some Theory for Kriging. Springer Verlag.

Waters, N., 2008. Representing surfaces in the natural environment: Implications for research and geographical education. In: Representing, Modeling and Visualizing the Natural Environment: Innovations in GIS 13. Mount, N.J., Harvey, G.L., Aplin, P. and Priestnall, G., Eds. CRC Press, pp. 21–39.