Measuring Recovery to Build up Metrics of Resilience to Flash Floods Based on Pollutant Discharge Data: A Case Study in East China

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1 | Introduction:
Motivations & Challenges & Highlights
I Introduction

Increasing Attentions on Disaster Resilience, especially area vulnerable to natural hazards.

Motivations

Challenges

Highlights
Introduction

Increasing Attentions on Disaster Resilience, especially area vulnerable to natural hazards.

Motivations

- Frequent flash floods in China
- Call for resilience development
- Antecedent resilience condition affects the post-disaster recovery process
- Use recovery measurement as an external term to validate the resilience metrics and identify the dominant factors of local resilience

→ How to measure recovery capability ?!
Introduction

Increasing Attentions on Disaster Resilience, especially area vulnerable to natural hazards.

Challenges

- Short-term recovery after flash floods
- Long-term: population increase
- Weather condition: Optical RS images
- Cost-efficiency: Radar data

- Proper recovery indicators: refuinctioning of people’s lives and livelihoods more than receding of floodwater
Introduction

Increasing Attentions on Disaster Resilience, especially area vulnerable to natural hazards.

**Highlights**

- A new approach to measure recovery capability based on pollutant discharge data
- Enterprises with heavy pollutant discharges are required to disclose the records of pollutant discharge per hour online
- A chance to detect the disturbance caused by flash floods → monitor recovery process
Methodology:
Study Area & Framework & Procedures
I Methodology

Record-breaking
✓ Worst flood in 600 years;
✓ Affect over 65,000 people; Cause 410 million RMB loss;
✓ New national precipitation record of 247 millimeters in 24 hours

Data availability
✓ Records from rain gauge stations
✓ Hourly waste water and gas emission data published online
← Ministry of Environmental Protection of China

Study Area: Changzhou City, Jiangsu Province of China
I Methodology

The Whole Framework

• Measure Recovery Capability
  ✓ Data Preprocessing
  ✓ Change Detection
  ✓ Optimize Detection Results

• Validate Metrics of Resilience
  ✓ Select Potential Indicators
  ✓ Logistic regression:

\[
\log \left( \frac{P(Y = k_i)}{P(Y = K)} \right) = a_i + b_{i1}x_1 + b_{i2}x_2 + \cdots + b_{ij}x_j
\]
I Methodology

Preprocessing of Pollutant Discharge Data

✓ Eliminate the tendency and periodicity of time series: (the first difference with 1-cycle lags)

✓ Achieve a stationary and independent series over time

Pollutant Discharge Data is Very Sensitive to Flood Disturbance!
I Methodology

**Detect Change Points in Pollutant Discharge Time Series Data**

- **DOWNPOUR**: the degree of rainfall reaches downpour level if over 24 h precipitation accumulation exceeds **50 mm** and tends to continue (the Chinese precipitation classification system).

- **Assumption**: if the sample enterprise or its surrounding areas are inundated, its pollutant discharge records will be disturbed (changes **START**) during the downpour and recover (changes **END**) after it.

- **START POINT**: the first immediately after the time of the **FIRST** downpour record of its **NEAREST** rain gauge station.

- **END POINT**: the first of the alternatives immediately after the time of the **LAST** downpour record, as observed by its nearest rain gauge station.

- \[ D_{Return}(i) = T_{End \ of \ Change \ detected}(i) - T_{End \ of \ Downpour}(i) \]
I Methodology

Compare and Optimize the Detection Results

- As the sample monitoring point demonstrates change ONLY when the sample area or the surrounding area is affected by the flood, we examined the final change detection results of sample enterprises with respect to the flood-damaged area.

- For this purpose 100 m buffers for each sample monitoring point were created and used to examine whether they INTERSECT with the damaged area.

- The detection accuracy is calculated following Equations (1) and (2), based on real situations (damage or non-damage) and detection results (change or non-change), as shown in Table 1.

\[
 r_{correct} = \frac{a+d}{a+b+c+d} \quad (1) \quad r_{misdetect} = \frac{b+c}{a+b+c+d} \quad (2)
\]

- ![Sample results of three different methods: Multiple Changes in Variance of Cumulative Sums of Squares (Mvc, Killick and Eckley, 2014); Change Point Model (Cpm, Hawkin et al, 2003); Energy statistic-based Change Point Model (ecp, Szekely and Rizzo, 2005&2010).](image)

| Table 1. Comparison of Detection Results |
|-------------------------------|----|----|
| Samples          | Change | Non-Change |
| Damage           | a     | b     |
| Non-Damage       | c     | d     |
Methodology

Select and Validate Resilience Metrics

- **Potential Resilience Indicators:**
  - Social
  - Economic
  - Infrastructural
  - Environmental

- **Validate the Selected Indicators:**
  - Calculate and Reclassify recovery capability based on the recovery duration
  - Logistic Regression

\[
\log \left( \frac{P(Y = k_i)}{P(Y = K)} \right) = a_i + b_{i1}x_1 + b_{i2}x_2 + \cdots + b_{ij}x_j
\]
3

Results & Analysis
Recovery Measurement & Identification of Significant Resilience Indicators
I Results & Analysis

Table 3. Detection results of the three methods.

<table>
<thead>
<tr>
<th></th>
<th>MVC</th>
<th>Change</th>
<th>Non-Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Damage</td>
<td>28</td>
<td>18</td>
<td></td>
</tr>
<tr>
<td>Non-Damage</td>
<td>3</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>CPM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Damage</td>
<td>35</td>
<td>12</td>
<td></td>
</tr>
<tr>
<td>Non-Damage</td>
<td>8</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>ECP</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Damage</td>
<td>35</td>
<td>11</td>
<td></td>
</tr>
<tr>
<td>Non-Damage</td>
<td>5</td>
<td>6</td>
<td></td>
</tr>
</tbody>
</table>

Table 4. Accuracy of detection.

<table>
<thead>
<tr>
<th>Measure</th>
<th>MVC</th>
<th>CPM</th>
<th>ECP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct Detection Rate</td>
<td>0.63</td>
<td>0.65</td>
<td>0.72</td>
</tr>
<tr>
<td>Misdetection Rate</td>
<td>0.37</td>
<td>0.35</td>
<td>0.28</td>
</tr>
</tbody>
</table>
I Results & Analysis
I Results & Analysis

Table 5. Regression results of potential variables.

<table>
<thead>
<tr>
<th>Component</th>
<th>Variable</th>
<th>Estimate</th>
<th>Significance (Two-Tailed)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social</td>
<td>Sex Ratio</td>
<td>1.074</td>
<td>0.050 *</td>
</tr>
<tr>
<td></td>
<td>Health Service</td>
<td>1.219</td>
<td>0.043 *</td>
</tr>
<tr>
<td>Economic</td>
<td>Ratio of Urban to Rural</td>
<td>1.393</td>
<td>0.044 *</td>
</tr>
<tr>
<td></td>
<td>Share of CBD</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Infrastructural</td>
<td>Road Density</td>
<td>3.009</td>
<td>0.003 **</td>
</tr>
<tr>
<td></td>
<td>Access to Open Space</td>
<td>2.537</td>
<td>0.002 **</td>
</tr>
<tr>
<td>Environmental</td>
<td>Slope</td>
<td>1.176</td>
<td>0.014 *</td>
</tr>
<tr>
<td></td>
<td>River Density</td>
<td>0.934</td>
<td>0.092</td>
</tr>
<tr>
<td></td>
<td>Urban Green Area</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Control</td>
<td>Return Speed of Water Level</td>
<td>1.053</td>
<td>0.010 **</td>
</tr>
</tbody>
</table>

Note: All data were standardized using “Z-score” conversion before regression; for the whole model, significance = 0.001, pseudo $R^2$ (Nagelkerke) = 0.614; Significance of the test of parallel = 0.804 > 0.005, which means the ordinal model is acceptable; * Significant at 0.05; ** Significant at 0.01.

Figure 5. Average Return Speed of Water Level at Sub-district (or lower) Level.
Conclusion

Improvements & Limitations
Conclusion

**IMPROVEMENTs**

- Propose a new method to measure recovery capability, using change detection analysis based on the time series of waste-water and waster gas discharge/emission data;
- Build a linkage between recovery and disaster resilience, using recovery measurement as external validation to identify metrics of resilience;
- Make it possible for government and urban planners to detect dominant factors in building up community resilience based on the results of logistic regression analysis.

**LIMITATIONs**

- Consider kinds of data sources for a more comprehensive recovery measurement given the arrival of the “Age of Big Data” (i.e. radar data, traffic flow data, social media, etc.);
- Collect more potential resilience indicators if possible;
- Incorporate developed change detection models
Recent Publication:

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