AN INITIATIVE OF THE NETHERLANDS RED CROSS

Text Mining of Loss Data

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OUTLINE

WHY TEXT MINING

HOW IT WORKS

HOW WELL IT WORKS

WHO WORKS ON IT

CONCLUSIONS & OUTLOOK

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WHY TEXT MINING

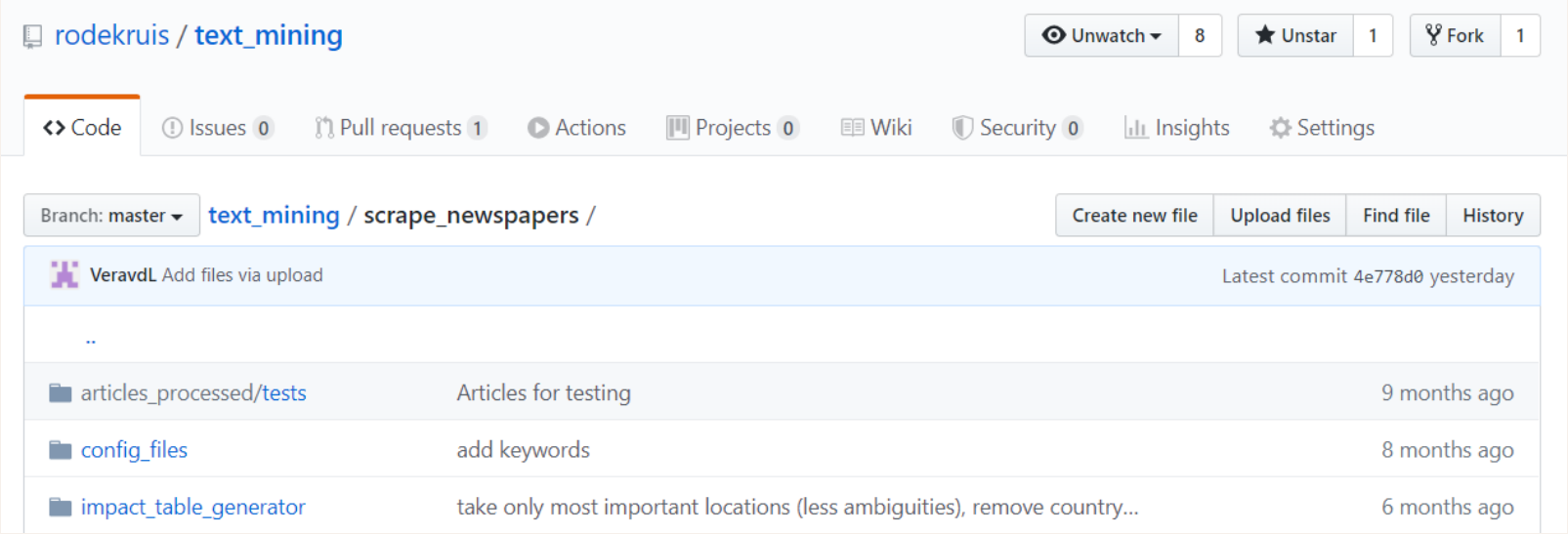
- **Loss and damage data**, i.e. data on the impact of natural disaster, is key information for **disaster preparedness programs** and **risk assessments.**
- Data mostly collected **manually** by agencies and governments
  - Governments: data often not accessible (e.g. only in paper format)
  - Humanitarian organizations: often only about intervention areas, no standard format
  - Private sector (e.g. insurance companies): proprietary data, possible biases
- Lots of information available in **local** and national **newspapers**, but highly **unstructured**

→ **TEXT MINING: extract structured loss data from news articles**

THE NEWS SCRAPER

510, the data team of the Netherlands Red Cross, has been developing an **open-source text mining framework** for loss data: the "***news scraper***"

https://github.com/rodekruis/text_mining/tree/master/scrape_newspapers



WHAT IS THE NEWS SCRAPER

The news scraper:

- input: disaster type and country
- output: loss data in tabular format, from local and national newspapers
- multilingual support (using spaCy's NLP models)
- mostly automated

Search:
"floods in Uganda"

type	where	when	...
flood	West Pokot	12 Aug 2002	...
drought	Karamoja	Sept 2005	...

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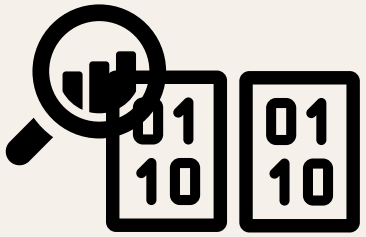
HOW IT WORKS

Three steps:

1) SCRAPE ARTICLES

2) ASSESS ARTICLE RELEVANCE

3) EXTRACT LOSS DATA



SCRAPE ARTICLES

1) SCRAPE ARTICLES:

- get a list of local and national news agencies (source: ABYZ)
- access all news agencies' websites and
  - search for articles about disasters
  - download results

ASSESS ARTICLE RELEVANCE

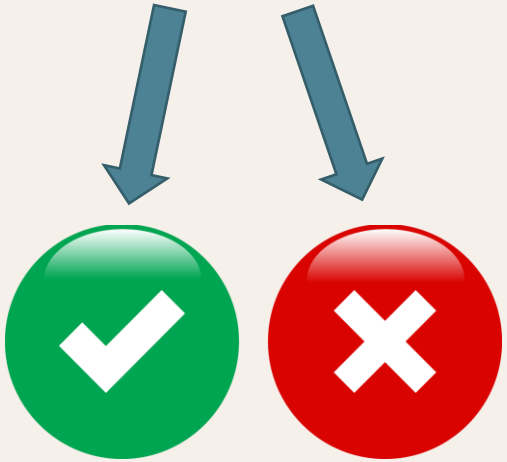
2) ASSESS ARTICLE RELEVANCE:

- to determine if an article is relevant or not
- two possible approaches:
  1. automated classification based on keywords
  2. manual tagging with an interactive prompt

```
Article #1/295: CANIVEAUX BOUCHES : Des risques d'inondations dans la capitale
Is it topical? t (True), f (False), i (Inspect text), q (Quit)  i
CANIVEAUX BOUCHES : Des risques d'inondations dans la capitale

La ville de Bamako reçoit ces jours-ci de fortes pluies alors que presque tous
 ses caniveaux sont obstrués. Un risque d'inondations pointe à l'horizon avec
le mois d'août ou « thio-thio kalo« (mois de grandes précipitations) qui s'ann
once. Il y a urgence.

L'obstruction des caniveaux est un problème sérieux à Bamako surtout en cette
période hivernale. Le peu de caniveaux dans la ville sont bouchés par des ordu
res de toutes sortes. La ville est plus que jamais exposée à un risque d'inond
ations.
```



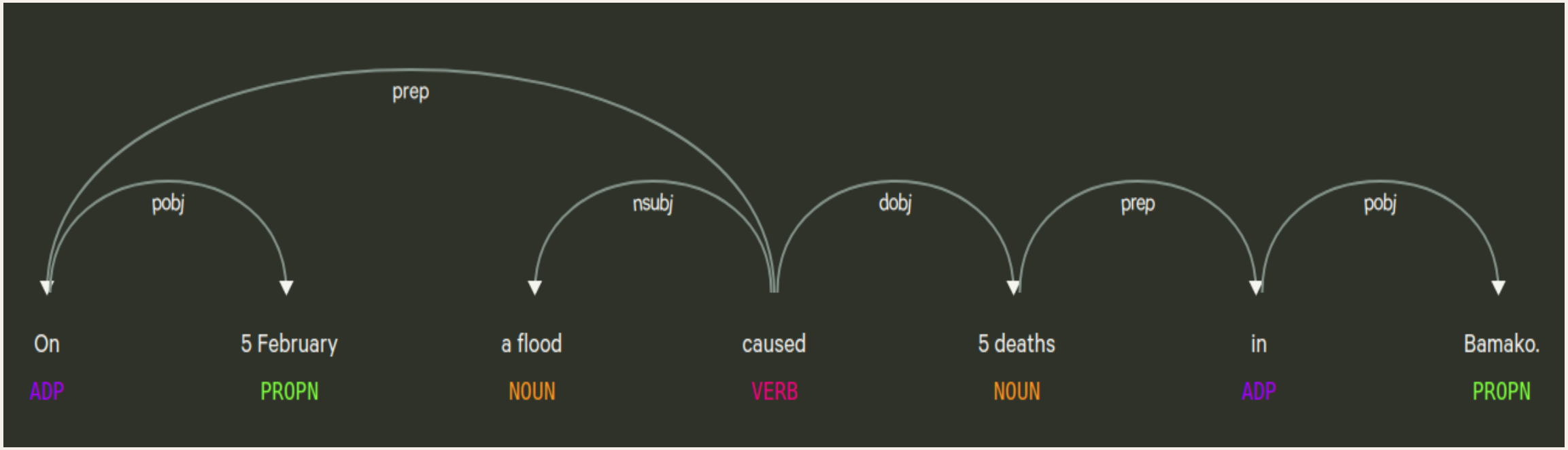
EXTRACT LOSS DATA

3) EXTRACT LOSS DATA

- based on **Natural Language Processing** (NLP) algorithms and models
- Built in python on top of the Spacy framework spaCy
- Step-wise approach:
  1. Tokenize text (divide in words)
  2. Create **syntax trees** (a.k.a. *parse trees*)
  3. Navigate syntax trees and extract loss data

SYNTAX TREE: EXAMPLE

"On 5 February a flood caused 5 deaths in Bamako"



EXTRACT LOSS DATA: EXAMPLE

EXAMPLE ARTICLE

Title: Floods in Bamako, Date: 12/04/2001

Last week, floods in the capital affected 500 people and killed 7.

There were also 3 victims in Sirakoro and 4 in Kotuba.

EXTRACT LOSS DATA: EXAMPLE

STEP 3.1: Assign article location

Title: Floods in **Bamako**, Date: 12/04/2001

Last week, floods in the capital affected 500 people and killed 7.

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EXTRACT LOSS DATA: EXAMPLE

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There were also 3 victims in **Sirakoro** and 4 in **Kotuba**.

EXTRACT LOSS DATA: EXAMPLE

STEP 3.2: Look for numbers

Title: Floods in **Bamako**, Date: 12/04/2001

Last week, floods in the capital affected **500** people and killed **7**.

There were also **3** victims in **Sirakoro** and **4** in **Kotuba**.

EXTRACT LOSS DATA: EXAMPLE

STEP 3.3: Assign impact and location

Title: Floods in **Bamako**, Date: 12/04/2001

Last week, floods in the capital **affected 500** people and **killed 7**.

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EXTRACT LOSS DATA: EXAMPLE

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EXTRACT LOSS DATA: EXAMPLE

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EXTRACT LOSS DATA: EXAMPLE

STEP 3.4: Output

type	where	when	affected people	casualties
flood	Bamako	12 Apr 2001	500	7
flood	Sirakoro	12 Apr 2001		3
Flood	Kotuba	12 Apr 2001		4

Loss data categories: **people affected, casualties, houses affected, infrastructures affected**

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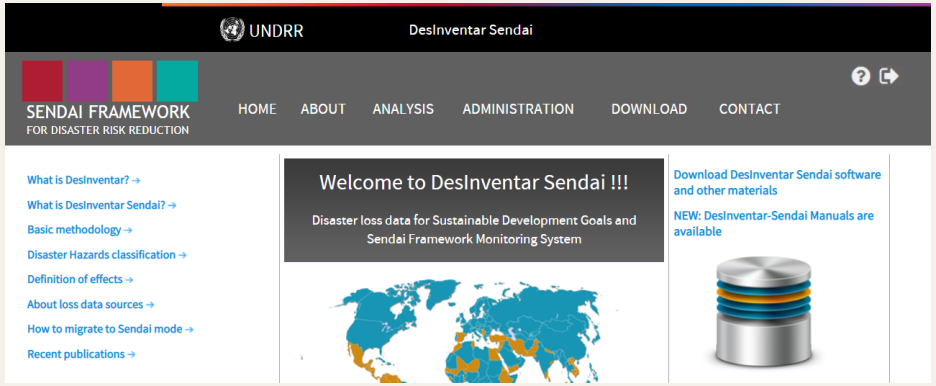
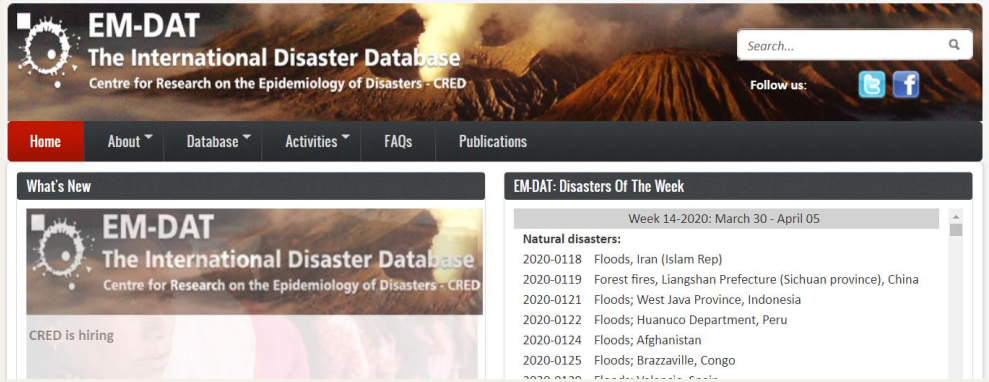
MODEL VALIDATION

Model validation:

- Using as reference two loss databases: DesInventar (UN) and EM-DAT (CRED / UCLouvain)

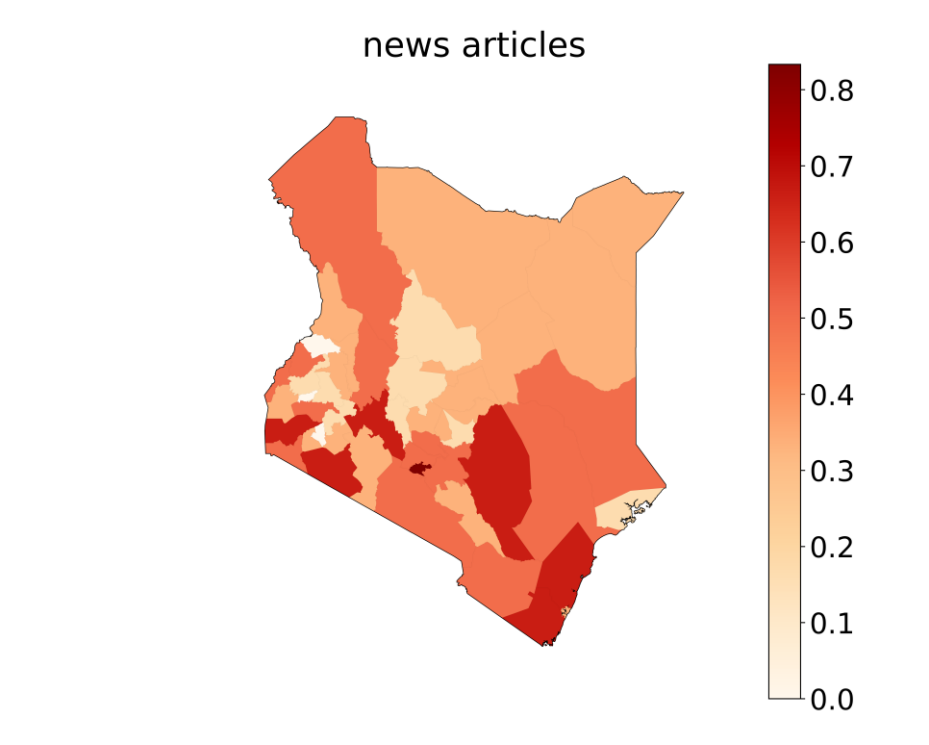


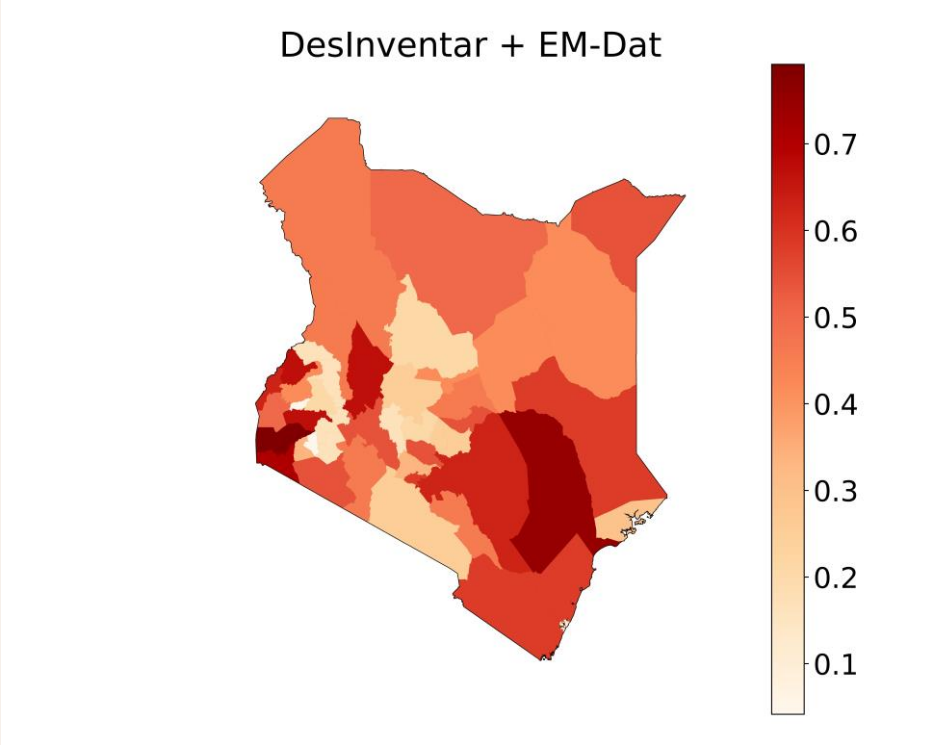


- Performance indicator: annual incidence rate of disaster at sub-national level
  - Annual incidence is defined as 1 or more occurence(s) of disaster per year
  - first administrative level considered
- Metric: root mean squared error (RMSE) on annual incidence rate

CASE STUDY #1

Country: Kenya, disaster: flood, language: English



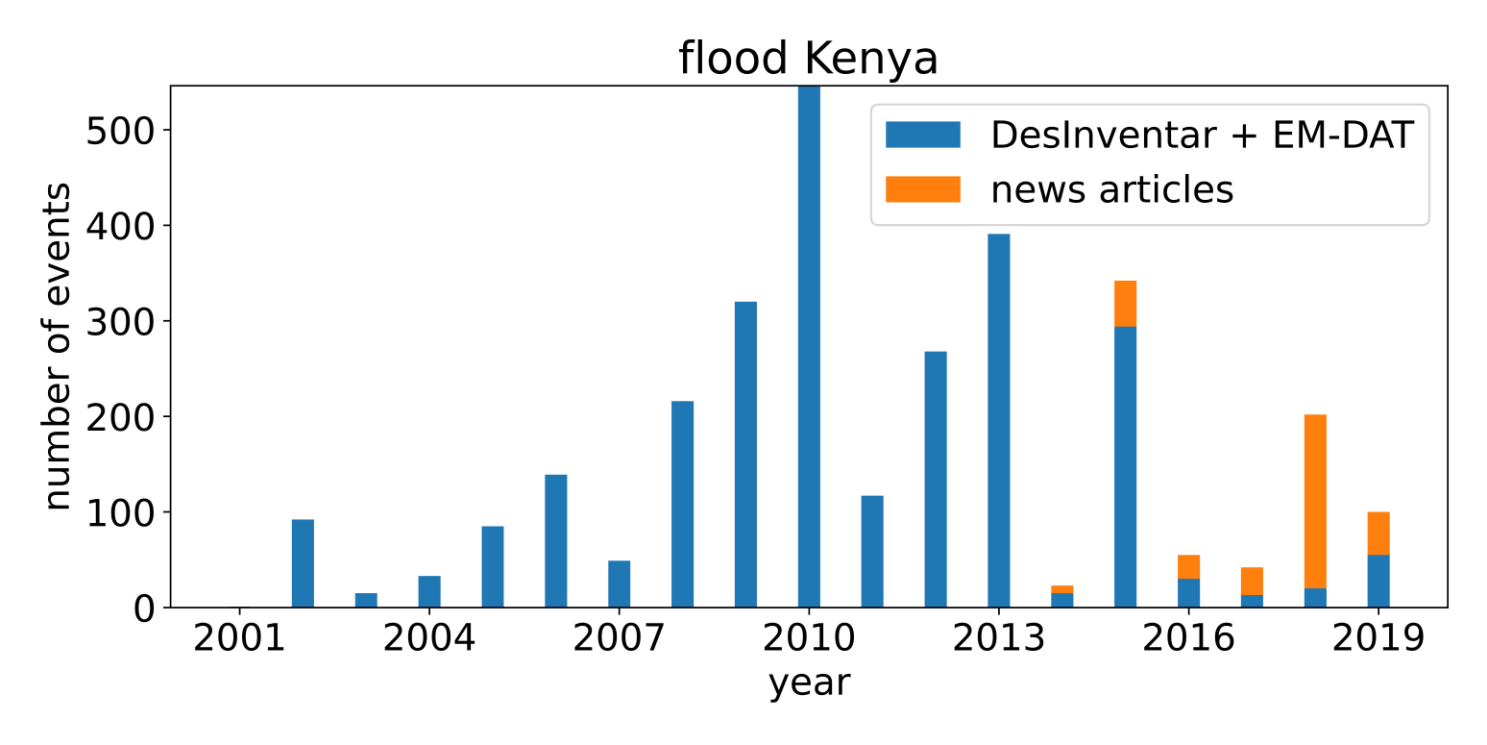


annual incidence rate

- 145 news articles, 337 unique loss data entries
- News articles vs DesInv.+EM-DAT: RMSE 0.14

CASE STUDY #1

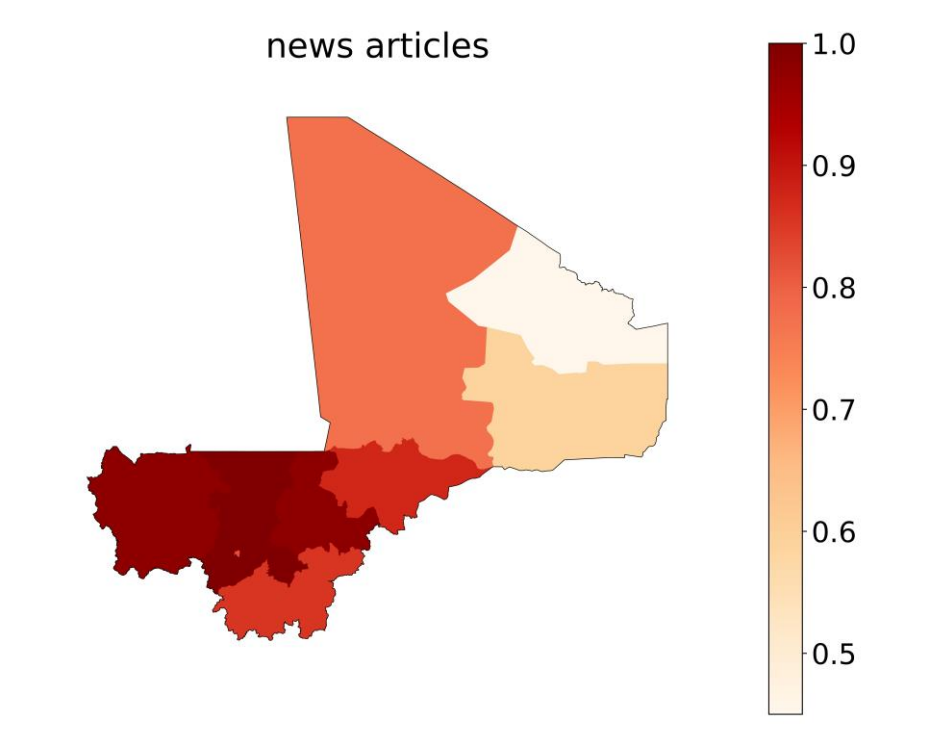
Country: Kenya, disaster: flood, language: English

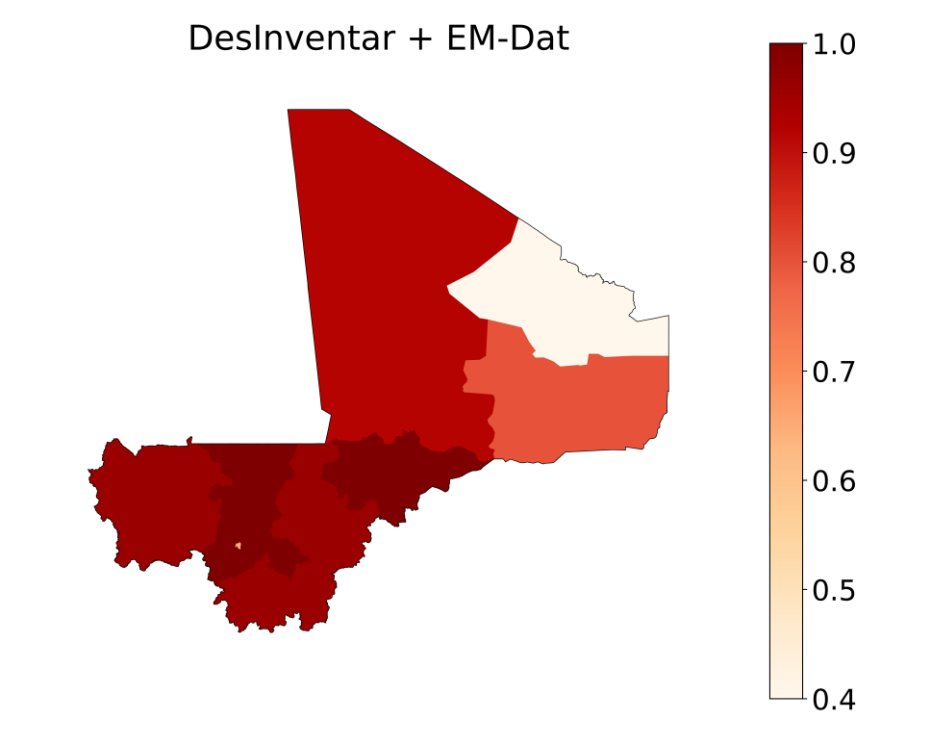


- News articles **only from 2014**
- From 2016, **more data from** news articles than from DesInv.+EM-DAT

CASE STUDY #2

Country: Mali, disaster: flood, language: French



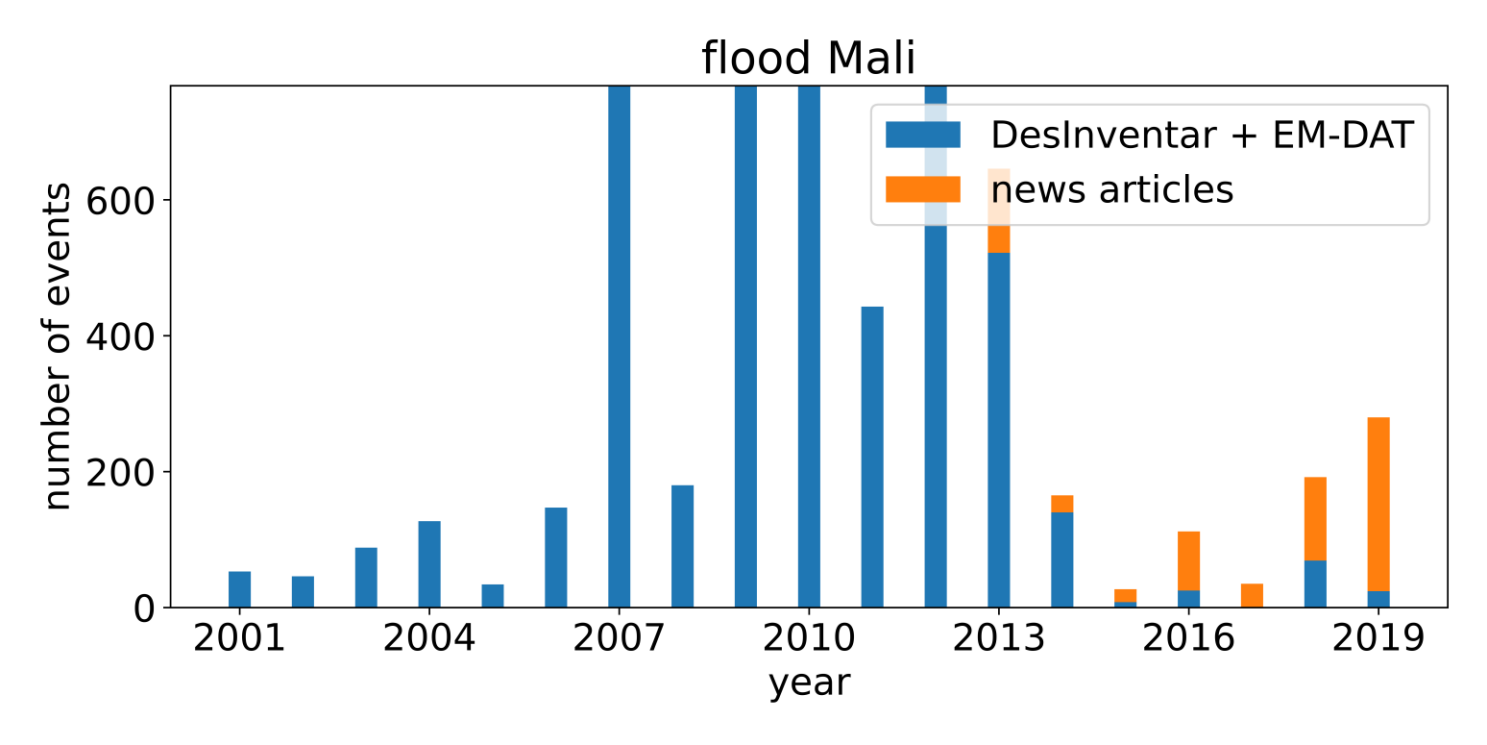


annual incidence rate

- 520 news articles, 682 unique loss data entries
- News articles vs DesInv.+EM-DAT: RMSE 0.13

CASE STUDY #2

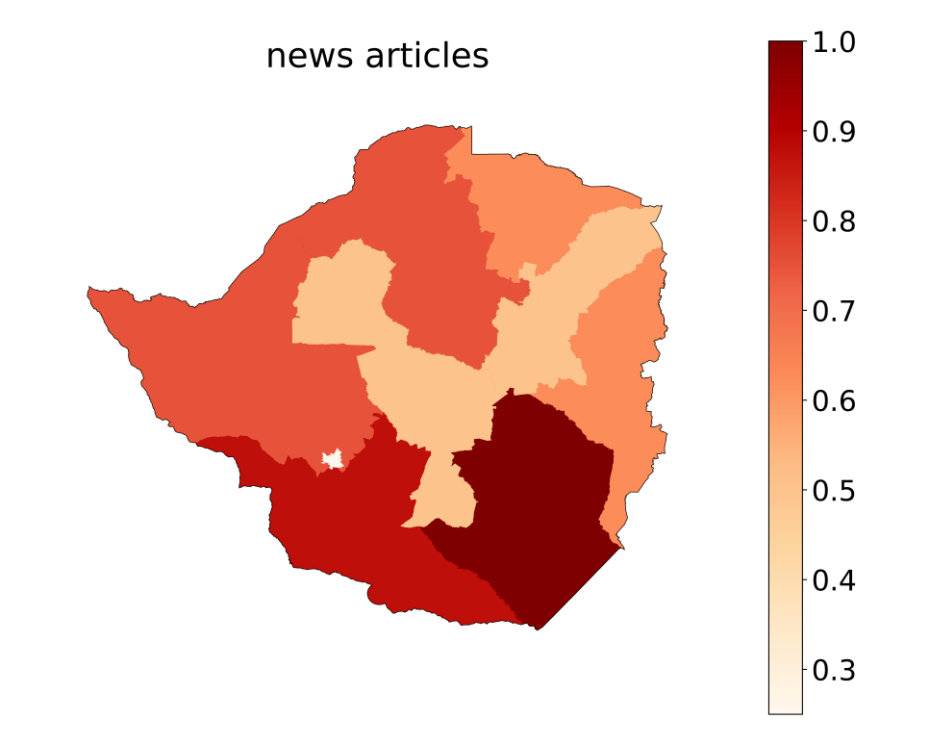
Country: Mali, disaster: flood, language: French

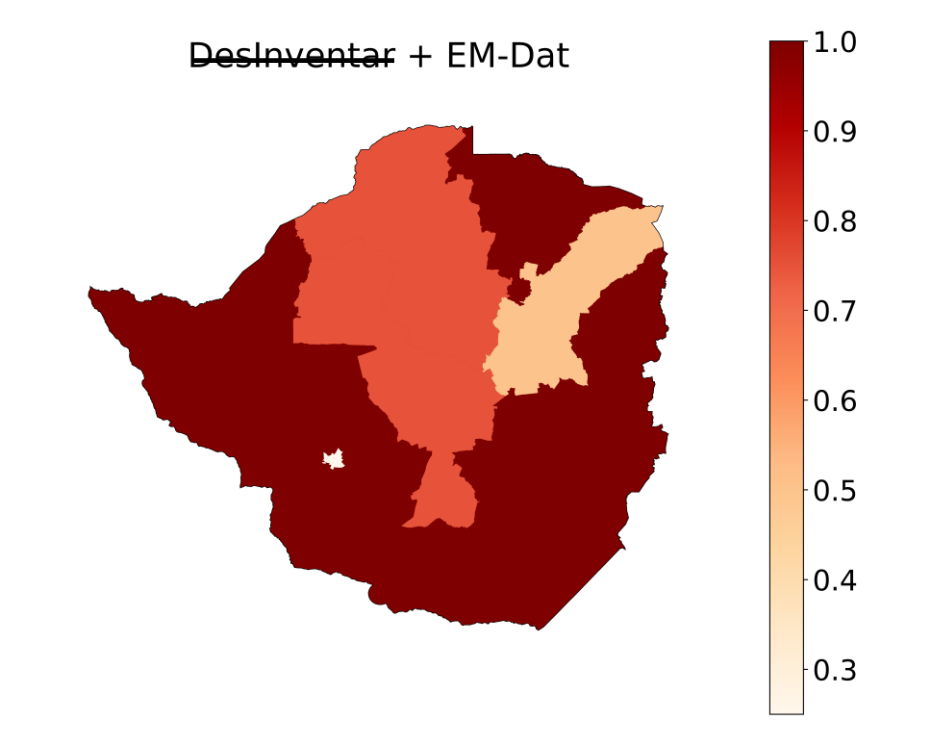


- News articles **only from 2012**
- From 2014, **more data from** news articles than from DesInv.+EM-DAT

CASE STUDY #3

Country: Zimbabwe, disaster: drought, language: English



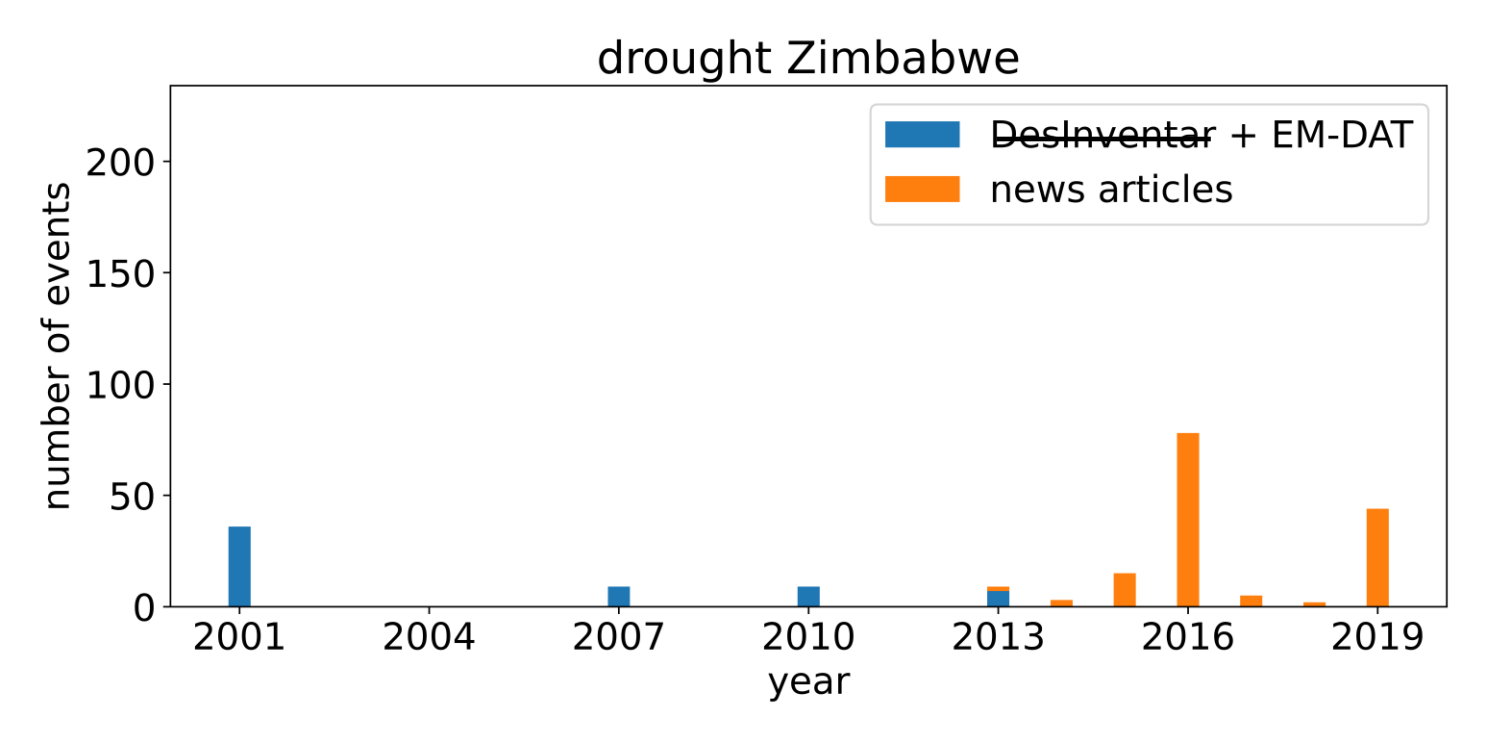


annual incidence rate

- 176 news articles, 171 unique loss data entries
- News articles vs EM-DAT (no data on DesInventar): RMSE 0.22

CASE STUDY #2

Country: Zimbabwe, disaster: drought, language: English



- News articles **only from 2013**
- From 2013, **more data from** news articles than from EM-DAT

DISCUSSION

Results:

- Reasonable **agreement** between loss data from news articles and other databases*
- **Large amount** of data available from news, but **only from the last 6-8 years**

Main **limitations**:

- Multiple articles about same event → possible double-counting
- Bias towards major cities: news agencies are more likely to report disasters in cities than rural areas
- Article date used as event date, not always accurate
- Location not always accurate in complex sentences

*measured as RMSE on annual incidence rate

CONCLUSIONS AND OUTLOOK

- We developed an **open-source framework** for **text mining** of loss data: the ***news scraper***
- Mostly automated, highly customizable, multilingual support
- **Valid complement** to existing loss data sources
- Next steps:
  - Extend validation
  - Automated classification of relevance
  - Improve loss data extraction: merge multiple events, date parsing, solve location ambiguities

CONTRIBUTORS

The *news scraper* is a **collaborative** work of professional **volunteers** and **students** at 510 Netherlands Red Cross!

Many thanks to

- Bonnie van Vuure
- Monica Turner
- Wessel de Jong