Mitiga

Hitting the mark: Using AI in hail and windstorm identification

Dr. Alejandro Martí
Sam Macintyre

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Convective Storms

50%

of all-weather event insured losses globally (x2 from the 90’s)

Hail

$8-14B

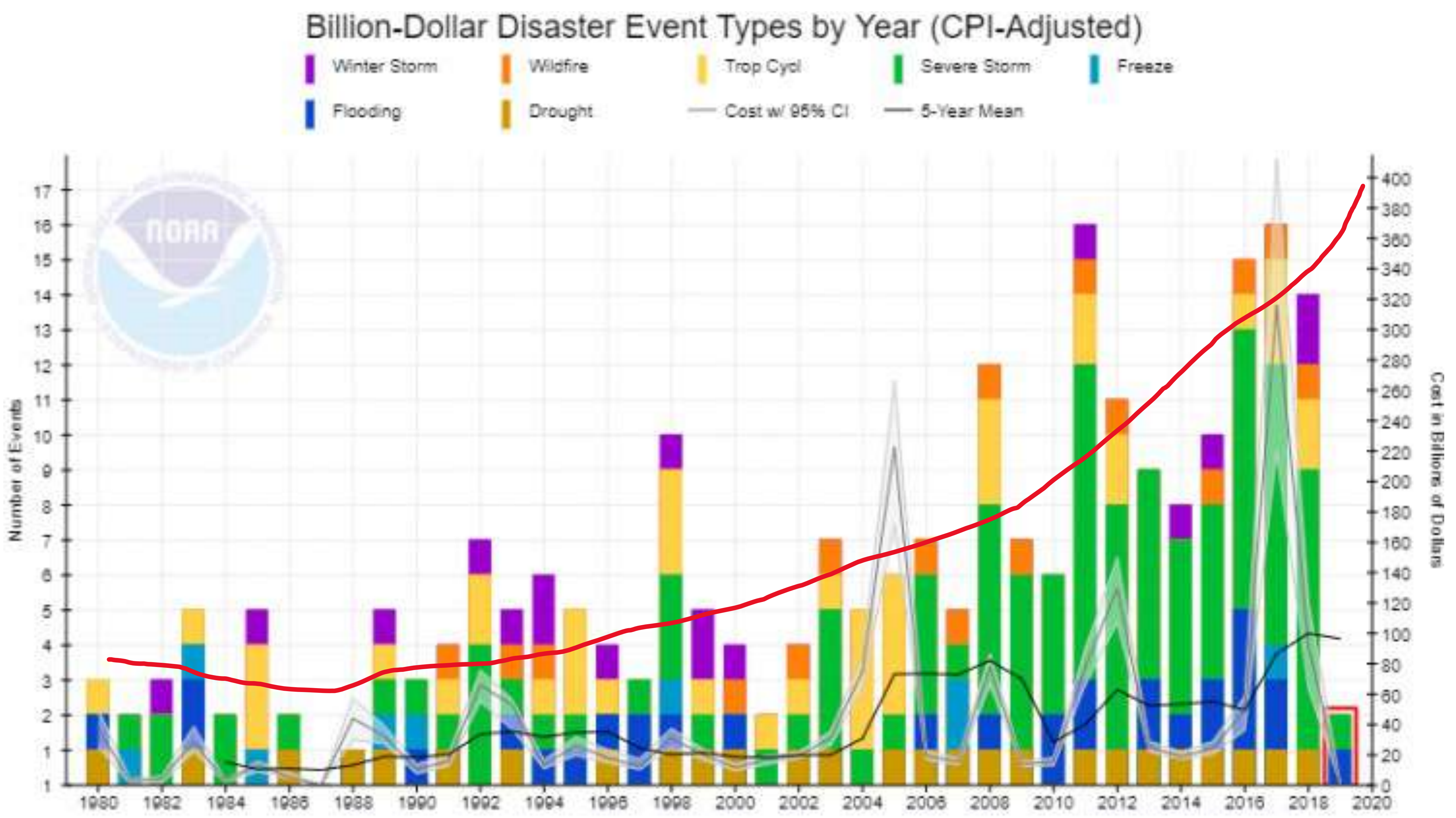
Average losses in the US alone
2020, Aon

Windstorms

$5B

Average losses in Europe alone

2015, JRC technical report



Adapted from NOAA, 2020

Need for a unified risk modeling

Need for a unified risk modeling

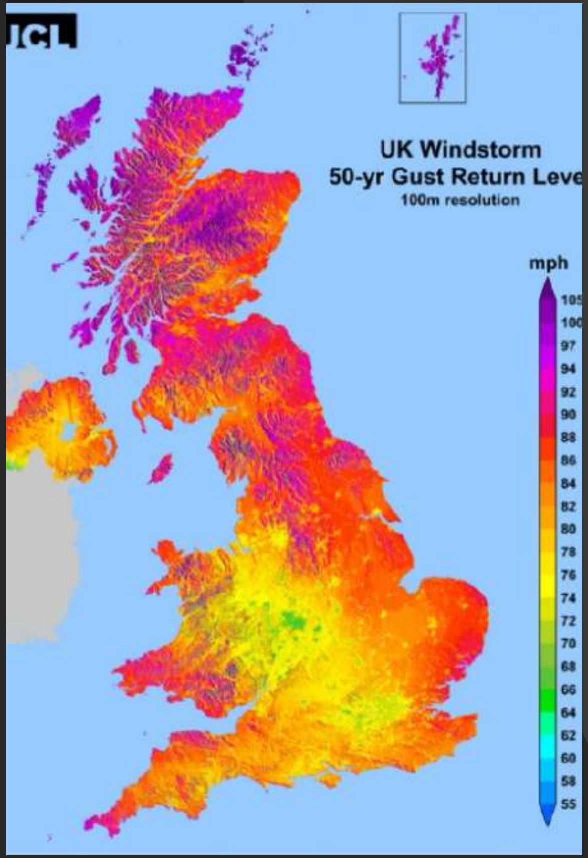
No standard guidelines for hail and windstorms hazard mapping

Current references dependent on well-established on-site observation SCS networks

Not the case in most countries (specially in LMIC)

Hazard mapping: rationale

Hazard maps display the location, frequency and severity of the respective hazard and are an essential part of hazard assessment and mitigation strategies.

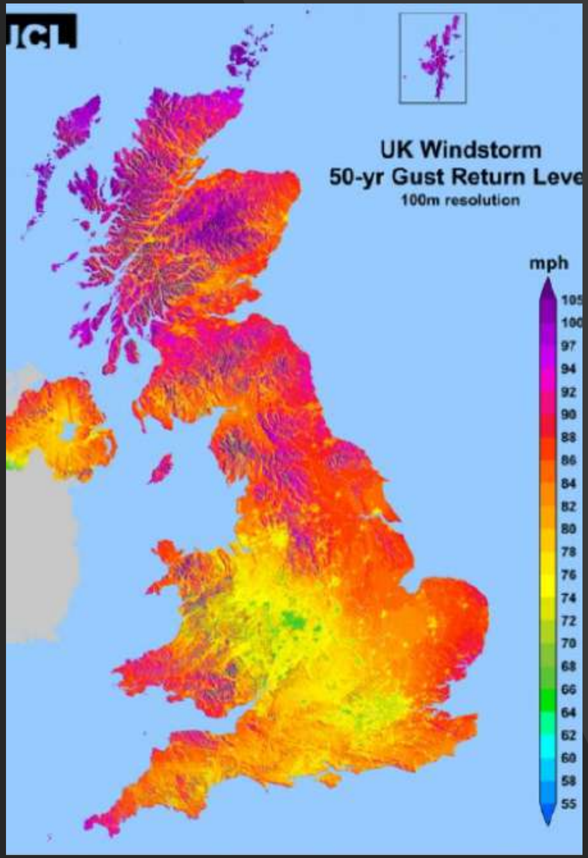


Windstorm Hazard Map – UK (UCL)

Hazard mapping: rationale

Accurate and reliable hazard mapping plays a key role in informing many operations and sectors:

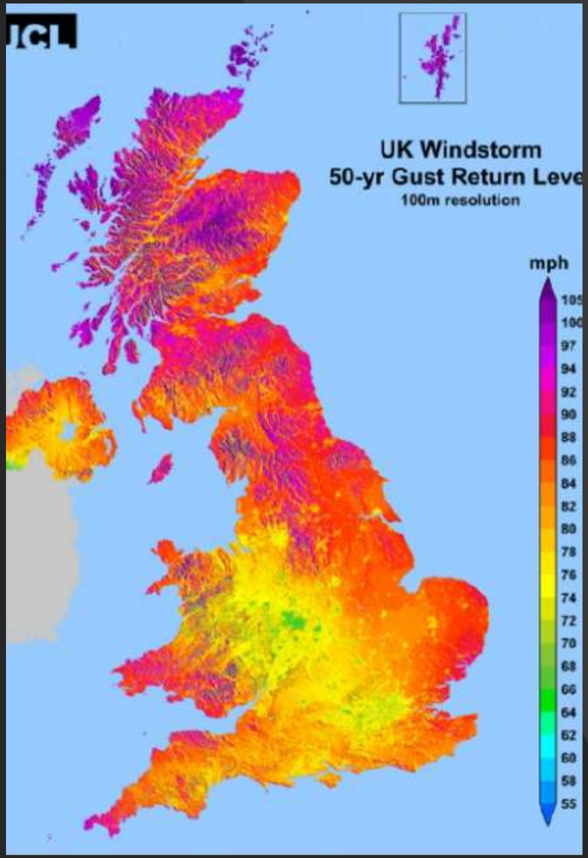
- **Operations**
  - Disaster management and planning
  - Infrastructure planning and resource allocation
- **Sectors**
  - Insurance (premiums)
  - Communities vulnerable to high impact hazards



Windstorm Hazard Map – UK (UCL)

Hazard mapping: challenges

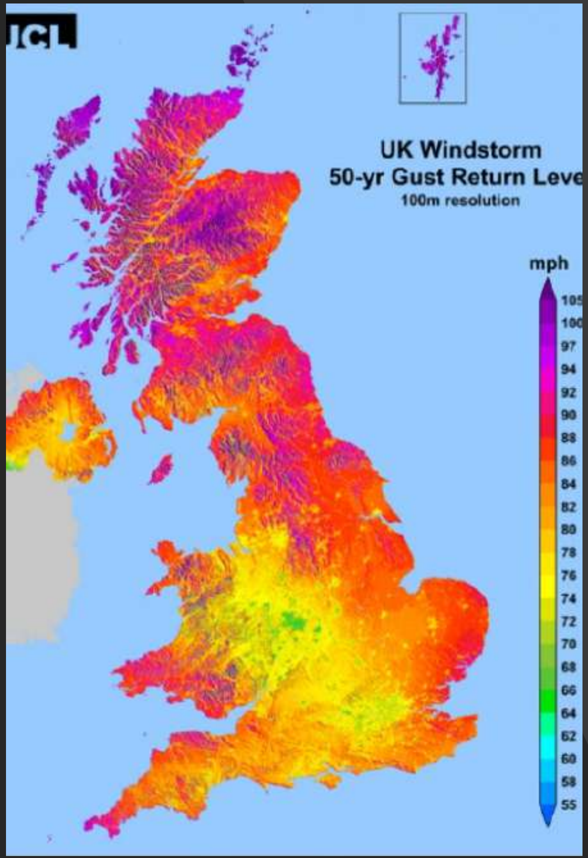
Hazard mapping requires estimates of event severity and frequency (recurrence) = initial **Severe Weather Event Dataset (iSWED)**



Windstorm Hazard Map – UK (UCL)

Hazard mapping: challenges

- **Historical data availability**
  - Lack of monitoring systems and infrastructure
  - Not distributed covered (geographically)
- **Severity not recorded**
  - Event data may exist without intensity
- **Data consistency**
  - Data must be consistent in scales, format and have sufficient geographical distribution



Windstorm Hazard Map – UK (UCL)

Hazard mapping: challenges

Full iSWED (rare)

Partial iSWED (few locations)

Insufficient iSWED (most common)

The role of AI in hazard mapping: hail and windstorms

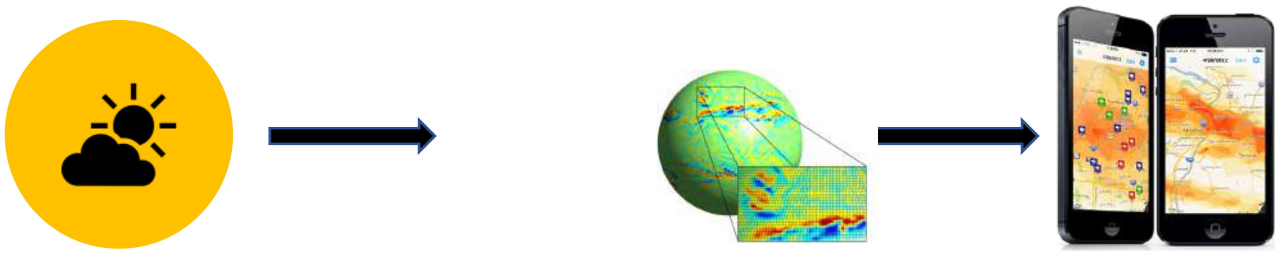

Full iSWED
Hazard Map

Full iSWED

Hazard Map

Full iSWED

Hazard Map



Partial iSWED

NWP + AI

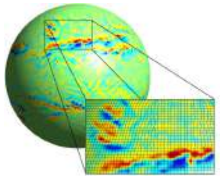
Hazard Map

- **NWP Simulations + Statistical theory** can be used to create event-frequency-intensity datasets that can be used for hazard mapping

Full iSWED

Hazard Map

Partial iSWED

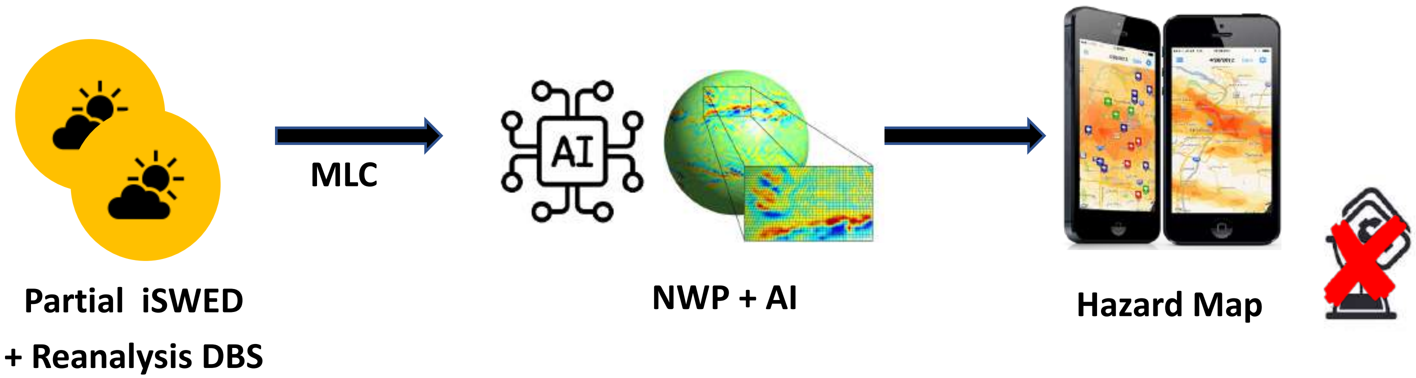


NWP + AI

Hazard Map

- **Costly** (HPC, data size, expertise)
- **Time consuming**

Inefficient as most "event-days" do not have meteorological conditions to produce desired hazard



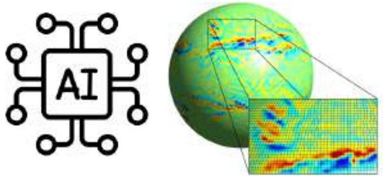
- **The Role of AI:** Machine Learning Classifiers (**MLC**) can identify the conditions that most likely lead to convective events, reducing the number of simulations and time required dramatically

Full iSWED

Hazard Map

Partial iSWED
+ Reanalysis DBS

Class
imbalance



NWP + AI

Hazard Map

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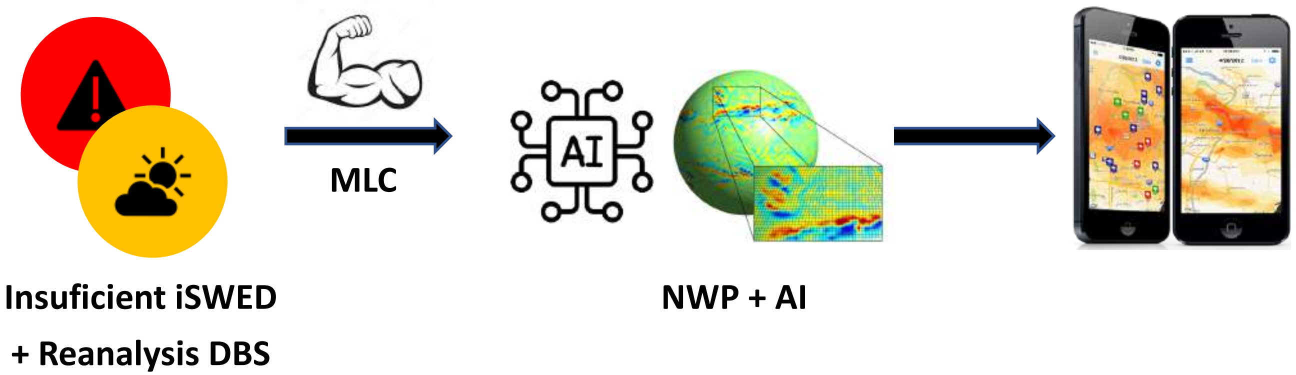


- **Transfer learning** involves leveraging problem contexts which are well-defined and data rich
- It can be used in regions where data is too sparse/incomplete to train **Machine Learning models (MLC)**

Full iSWED

Hazard Map

Partial iSWED
+ Reanalysis DBS

Class
imbalance

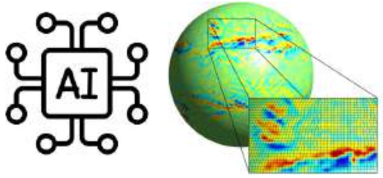
NWP + AI

Hazard Map

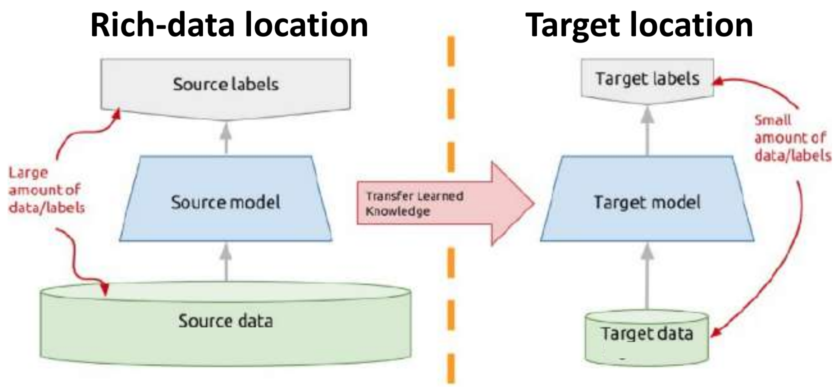
- **The Role of AI:** Machine Learning Classifiers can identify the conditions that most likely lead to convective events, reducing the number of simulations and time required dramatically

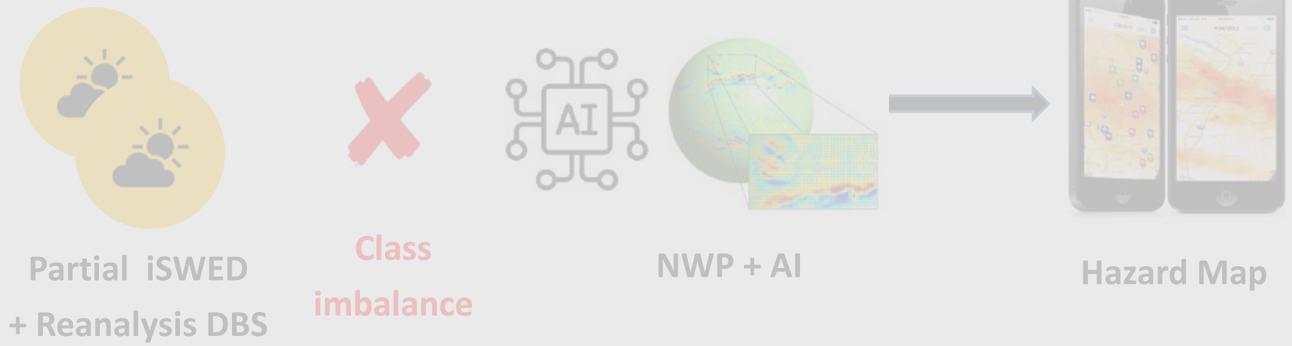
Insuficient iSWED
+ Reanalysis DBS

MLC



NWP + AI





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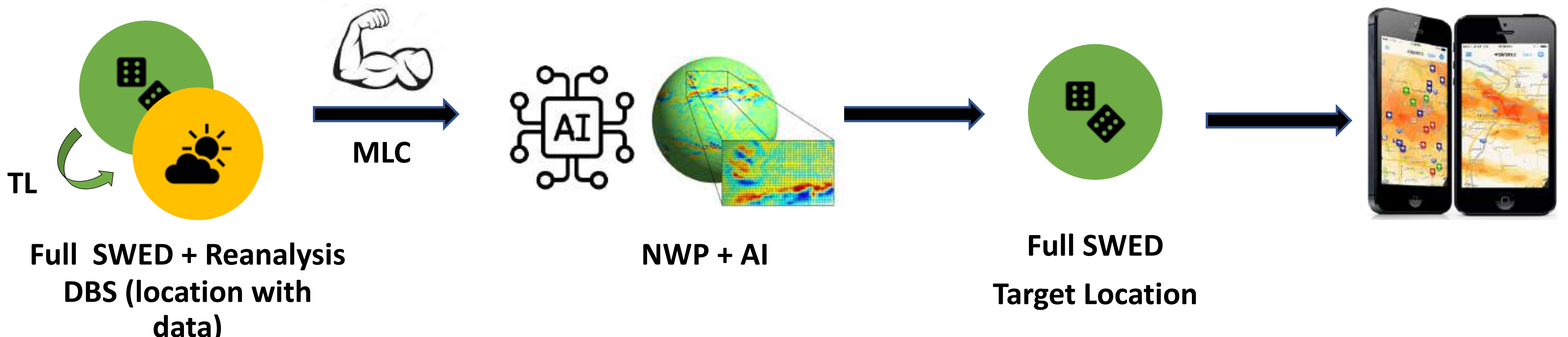
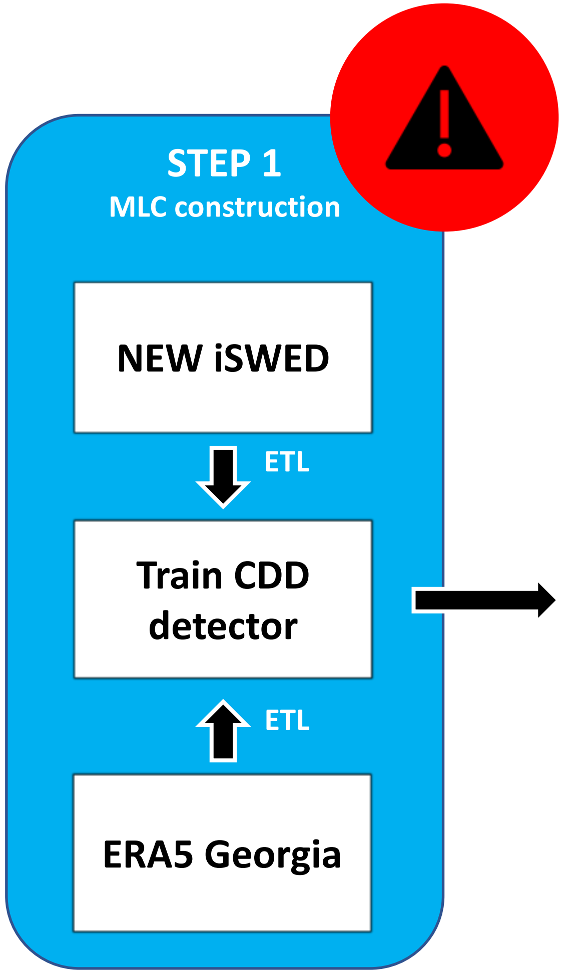


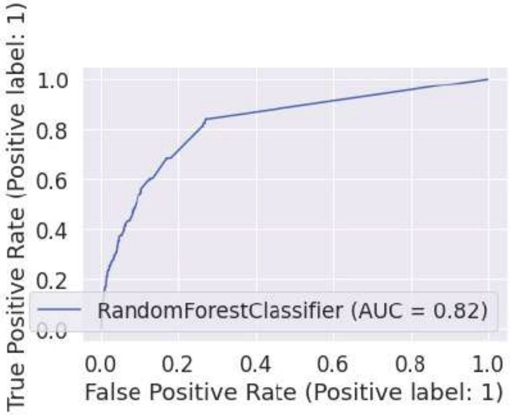
Unified methodology for hail and windstorm hazard mapping

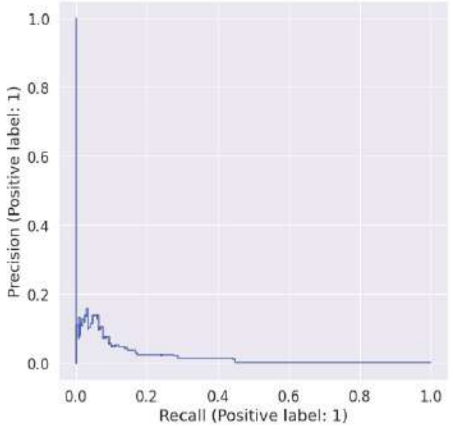
Georg-AI

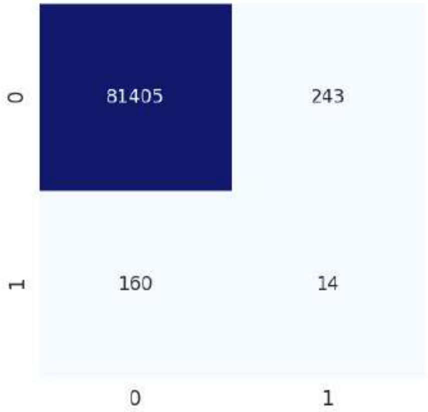
AI: Data Availability

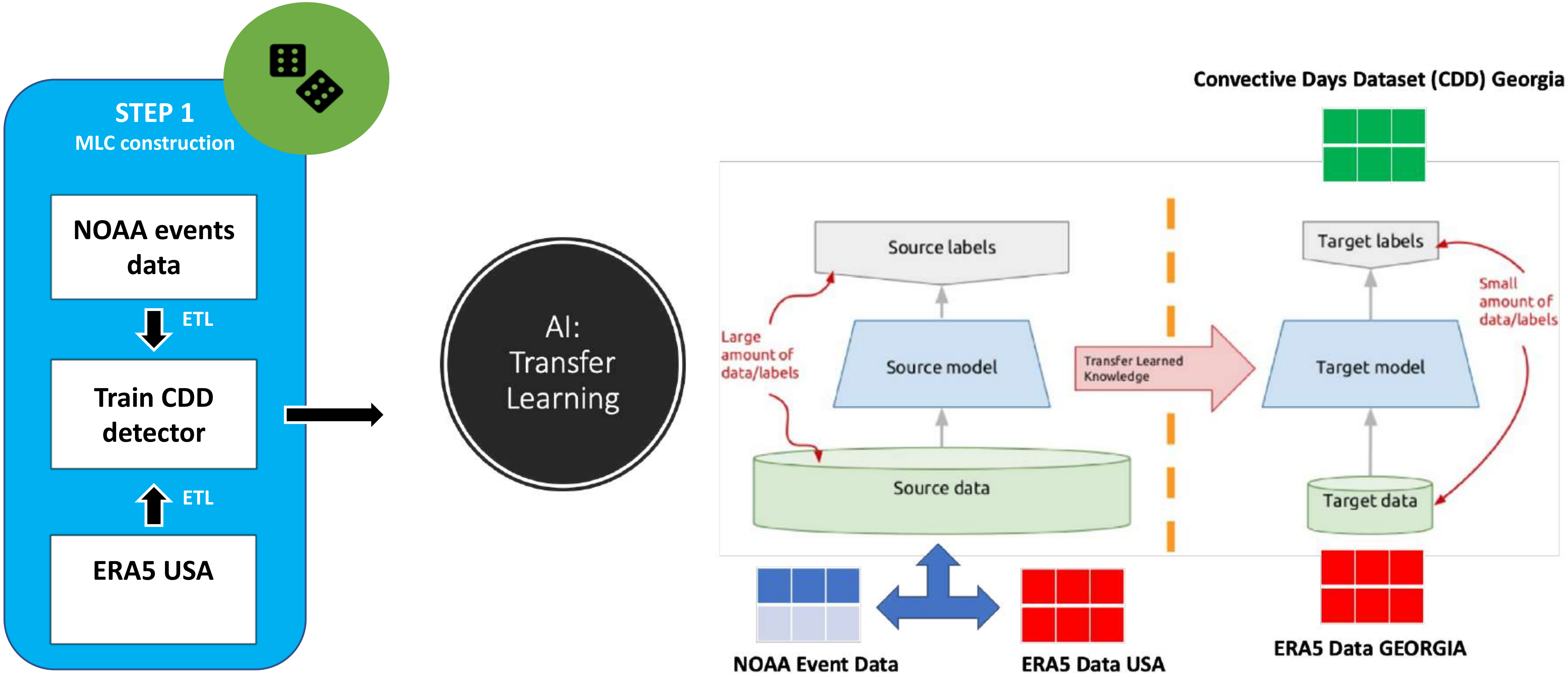
- Georgian National Environmental Agency's iSWED proved insufficient (~800 records)
  - Incomplete geographically and temporally
  - No or limited intensity information
  - Advanced monitoring network in its infancy

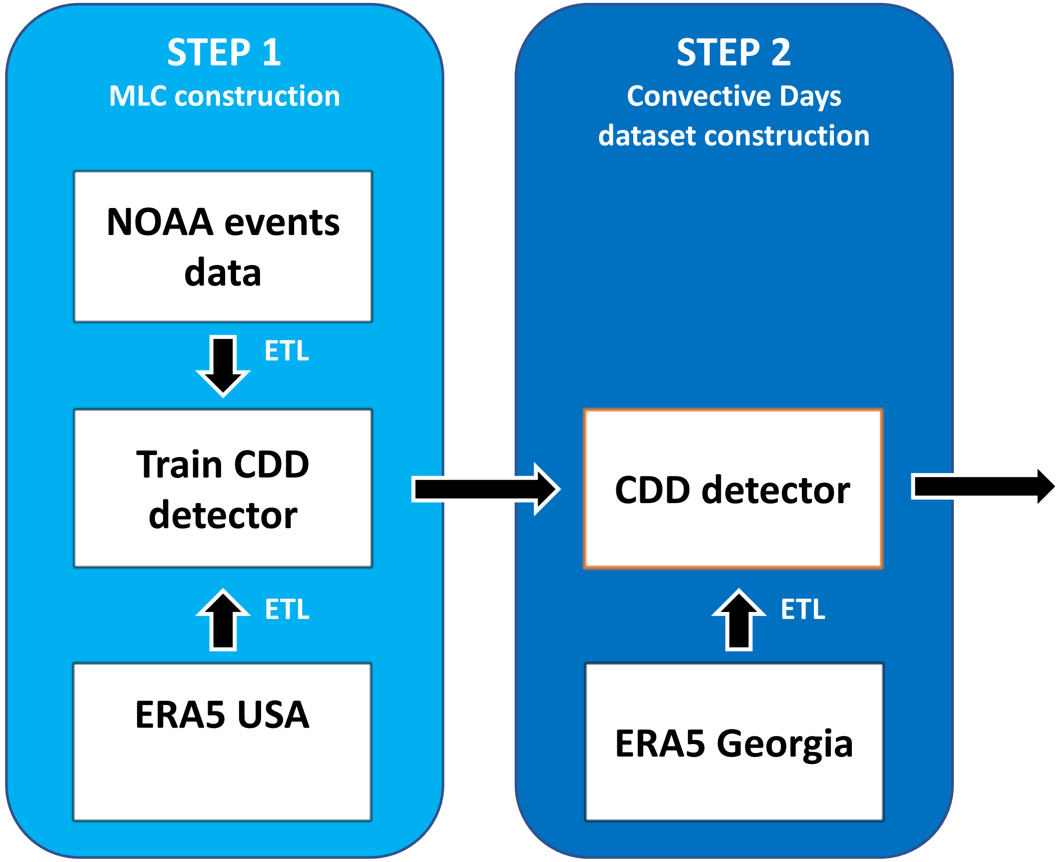

STEP 1
MLC construction
NEW iSWED
ETL
Train CDD detector
ETL
ERA5 Georgia


True Positive Rate (Positive label: 1)
1.0
0.8
0.6
0.4
0.2
0.0
RandomForestClassifier (AUC = 0.82)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (Positive label: 1)


Precision (Positive label: 1)
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Recall (Positive label: 1)


0
1
81405
243
160
14
0
1


STEP 1
MLC construction
NOAA events data
ETL
Train CDD detector
ETL
ERA5 USA
AI: Transfer Learning
Convective Days Dataset (CDD) Georgia
Source labels
Large amount of data/labels
Source model
Source data
Transfer Learned Knowledge
Target labels
Small amount of data/labels
Target model
Target data
NOAA Event Data
ERA5 Data USA
ERA5 Data GEORGIA


STEP 1
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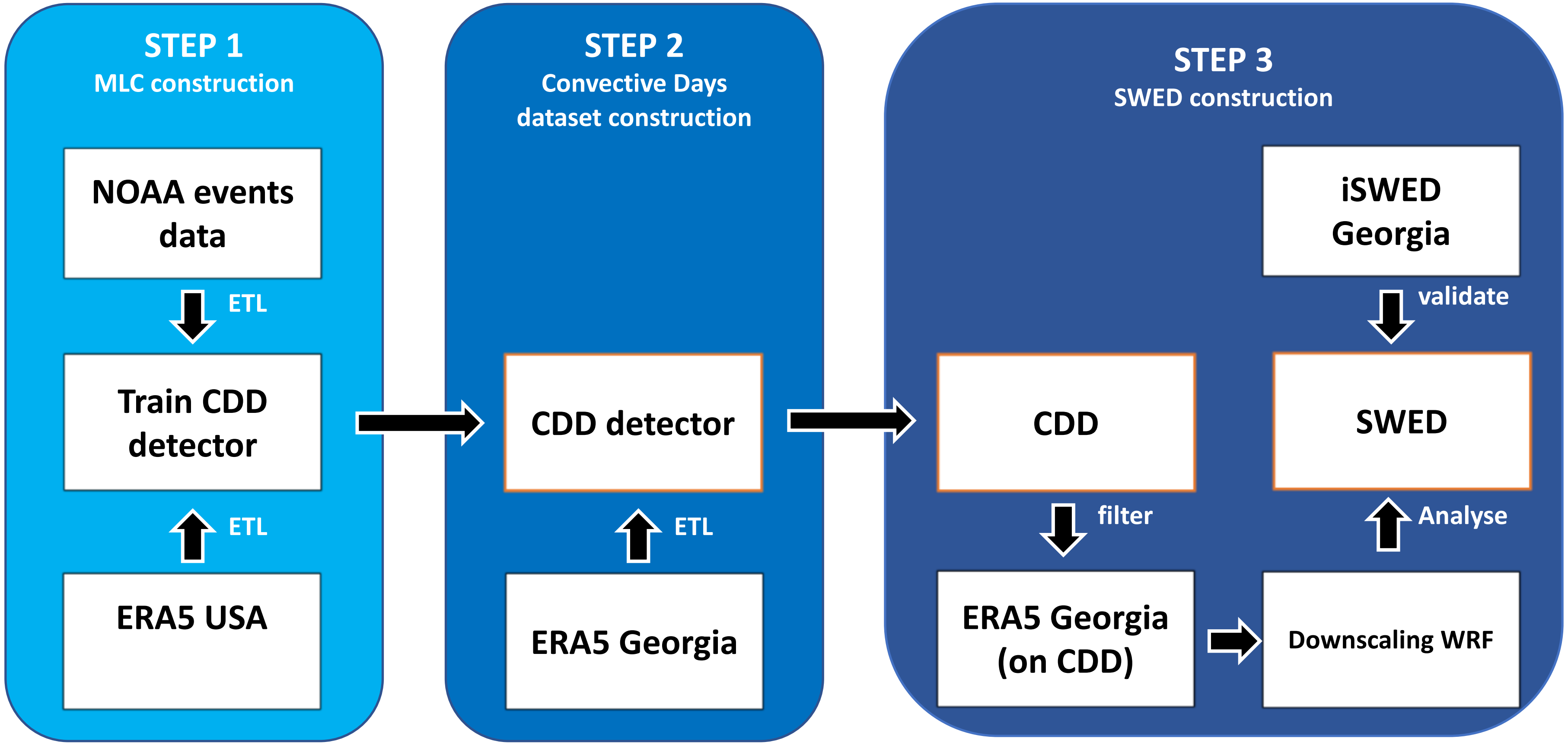
NOAA events data
ETL
Train CDD detector
ETL
ERA5 USA
STEP 2
Convective Days dataset construction
CDD detector
ETL
ERA5 Georgia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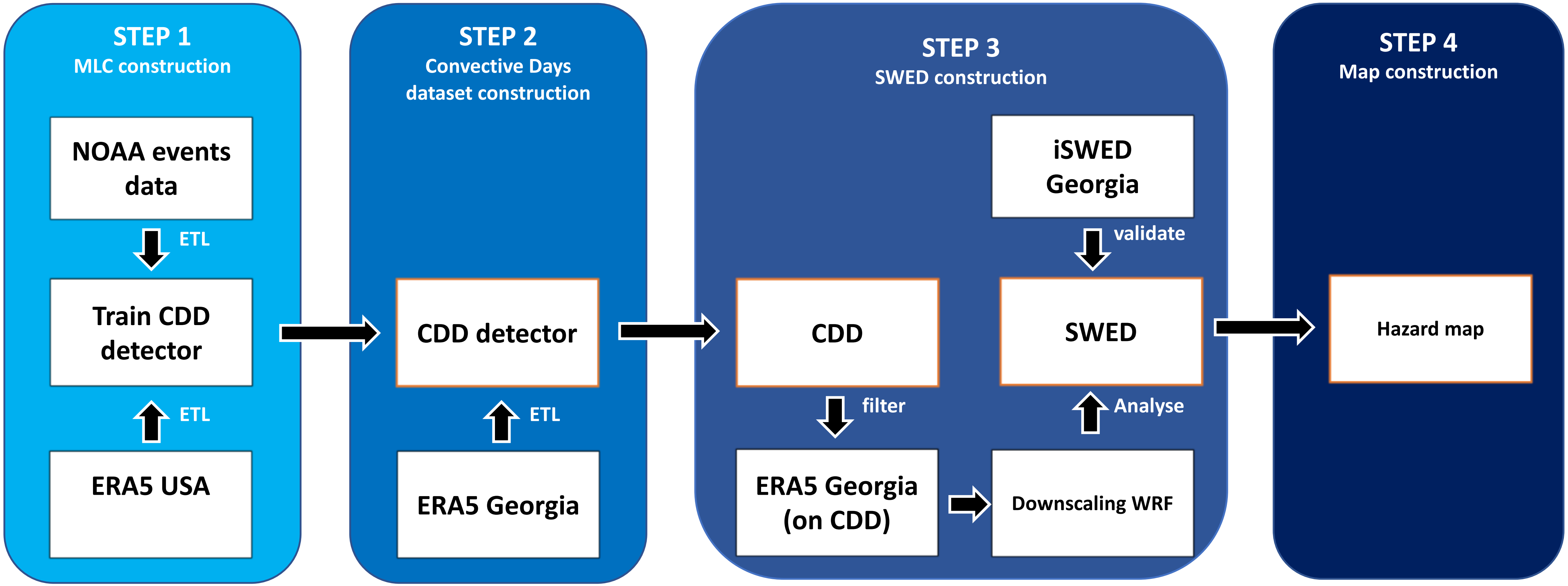
ETL
ERA5 Georgia
STEP 3
SWED construction
iSWED Georgia
validate
CDD
SWED
filter
Analyse
ERA5 Georgia (on CDD)
Downscaling WRF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ERA5 Georgia (on CDD)
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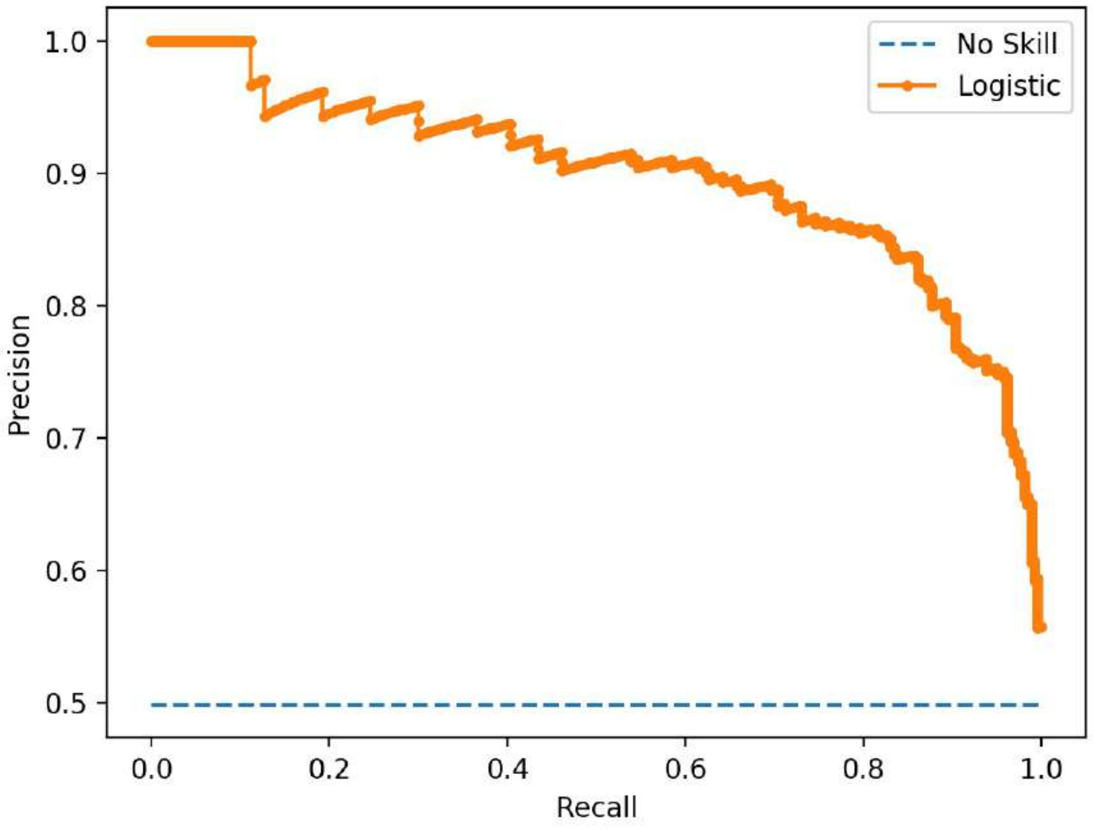
STEP 4
Map construction
Hazard map

AI: Expected result

- Perfrormant Machine Learning Classification with algorithm with a good precision-recall trade-off
- High recall particularly important (capturing as many of the true convective events as possible)



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Thank you

Dr. Alejandro Martí Alejandro.marti@mitigasolutions.com