From model-based to data-driven remote sensing in environmental management

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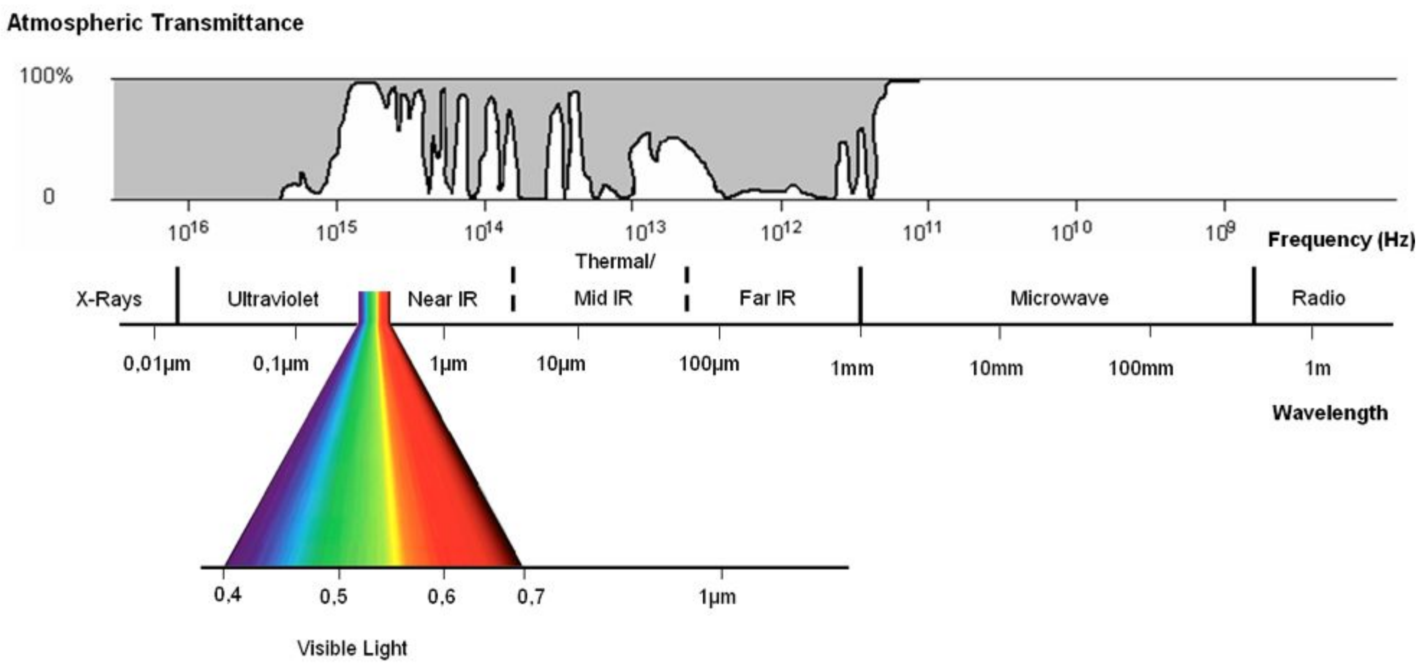
Remote Sensing

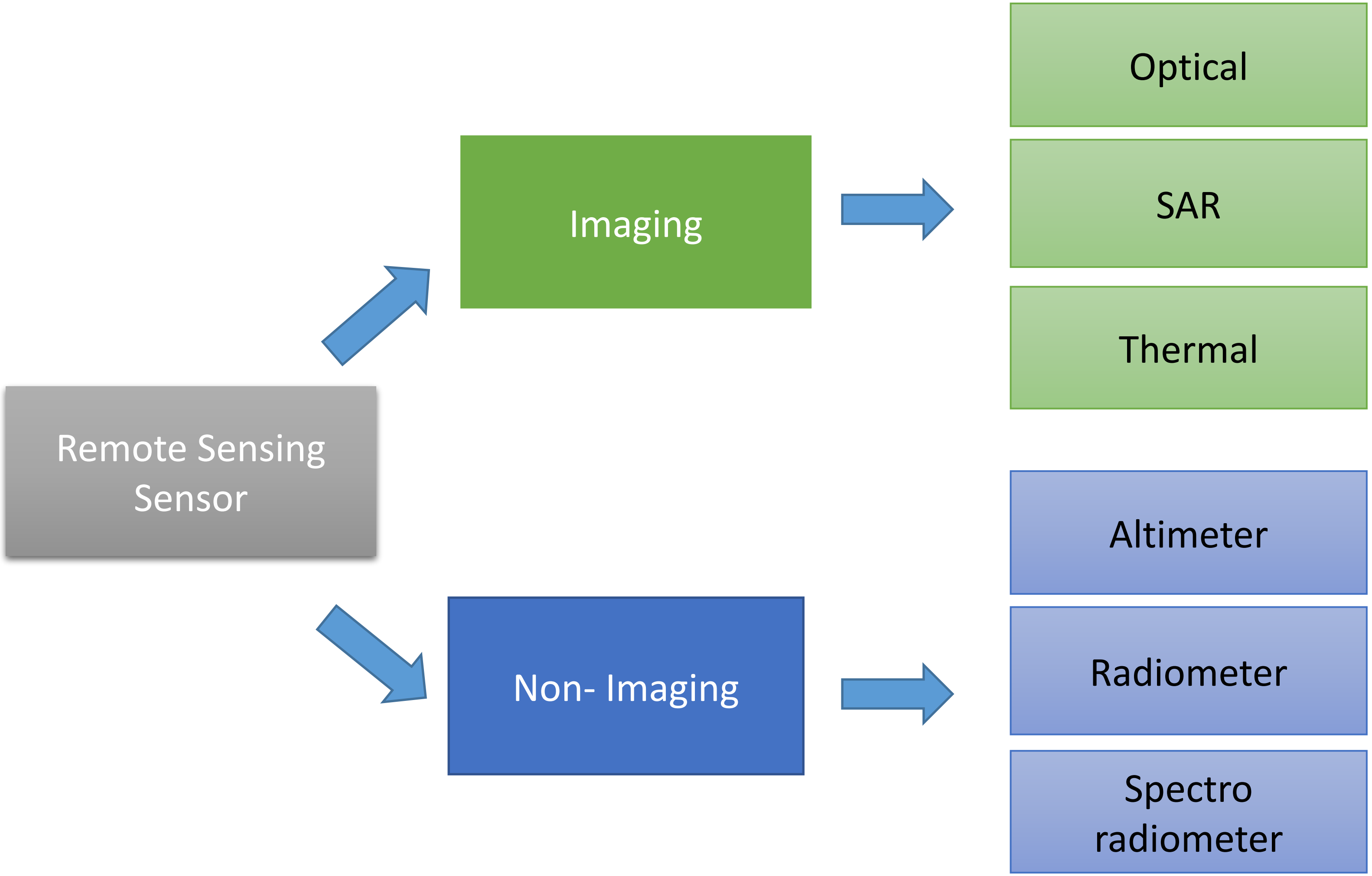
"the practice of deriving information about the Earth's land and water surfaces using images acquired from an overhead perspective, by employing electromagnetic radiation in one or more regions of the electromagnetic spectrum, reflected or emitted from the Earth's surface"

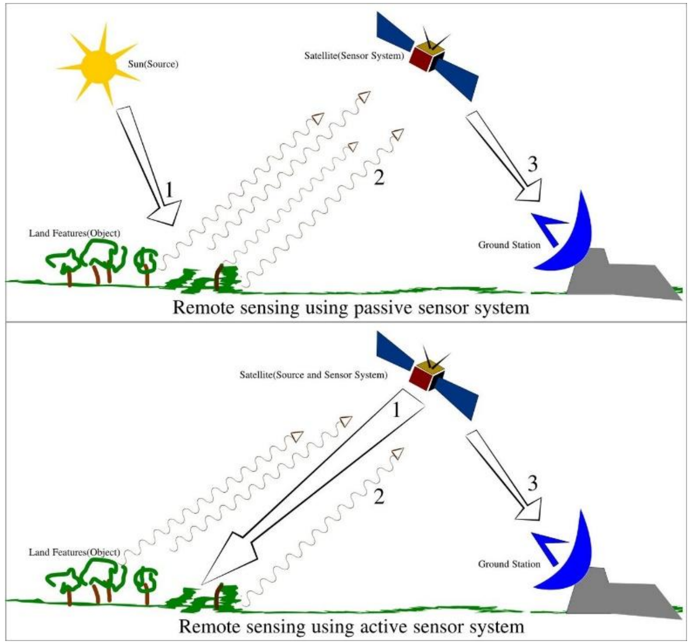
Introduction to Remote Sensing by Campbell and Wynne (2011)



Remote Sensing Sensors

A sensor detects and measures the radiation that is reflected or backscattered from the Earth's land and water surfaces or the object or scene being observed.

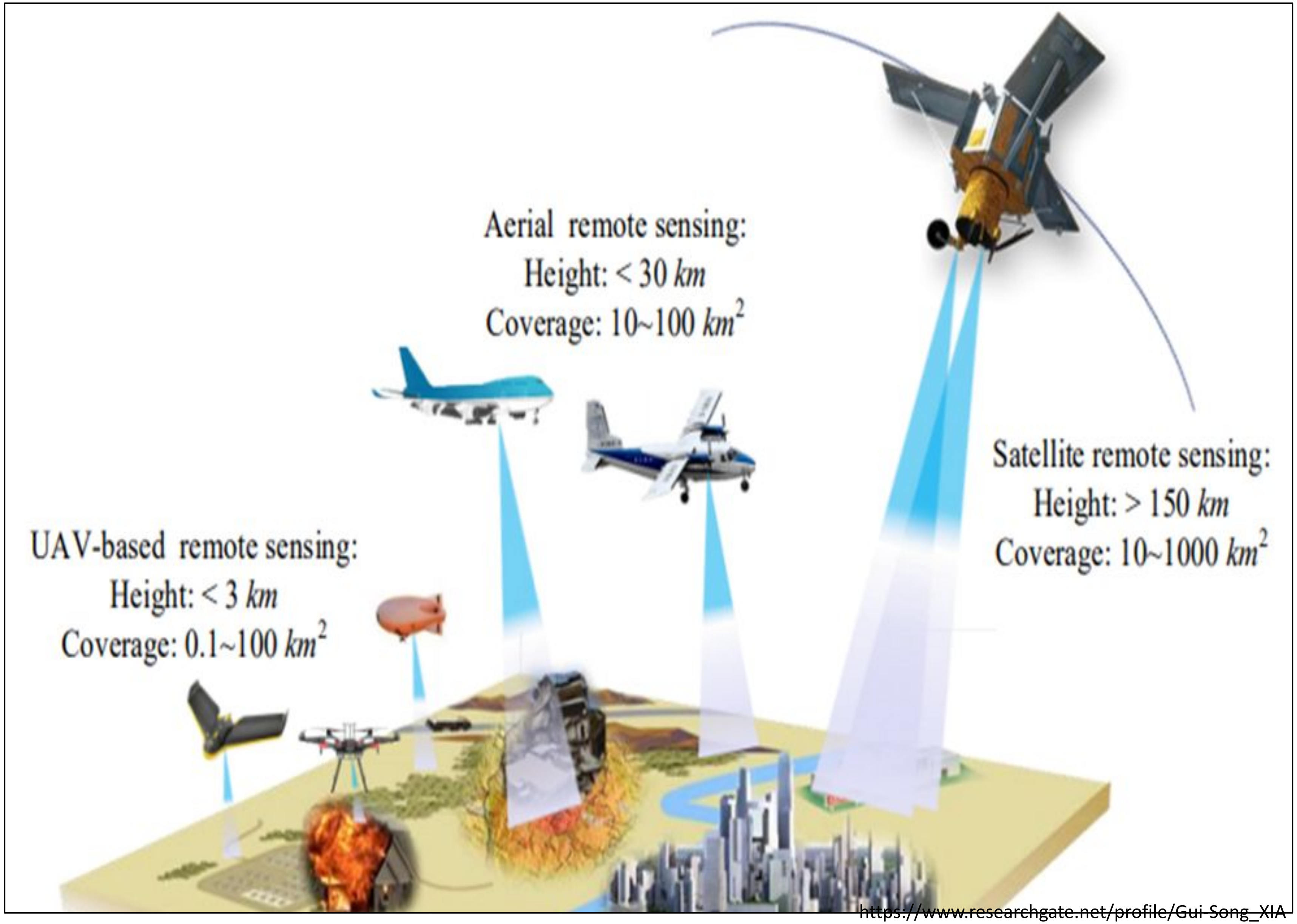




Imaging Remote Sensing Sensors

Sensor	Application Examples	pros and cons
Optical	landuse and landcover, agriculture, features such as coastlines, pipelines, roads, and borders	Easy to use for different applications. Affected by sun illumination and cloud coverage.
SAR X C S L P	• sea-ice surveillance • meteorological applications (e.g. rainfall measurement) • Monitoring vegetated surfaces and ice sheet and glacier dynamics • vegetation canopy, sea ice, soil, and glaciers	can be operated day and night. Radar signals contain no spectral characteristics.
Thermal	Identify surface materials and features such as rock types, soil moisture, air leakages, documenting irregular heat dispersion	See in any lighting conditions - Day and Night, and through smoke, fog and dust. Image requires some training to interpret

Remote Sensing Platforms



https://www.researchgate.net/profile/Gui-Song_XIA

Remote Sensing Data

- Remote sensing data are carriers of spatial information and geographical knowledge about those objects.
- The quality of remote sensing data is closely related to data resolutions:
  - Spatial resolution: size of pixel of remote sensing data
  - Spectral resolution: what colors – bands
  - Temporal resolution: how frequently were data collected? Daily, monthly, yearly?

Environmental Remote Sensing

- The recent proliferation of remote sensing (RS) platforms (e.g., satellites, aircraft, and UAVs) equipped with advanced sensor technologies (e.g., optical, hyperspectral, SAR, LiDAR) has enabled systematic production of massive amounts of high spatial, spectral and temporal data.

- Extracting and combining the information contained in these rich multisource data enable novel views and creating a comprehensive and detailed knowledge basis of the environmental dynamics for both rapid changing event (i.e. Flood) and steady progressions (e.g., erosion monitoring).

Remote Sensing Data Processing

- Model-based: image processing as an ill-posed inverse problem considering the imaging mechanism
  - deterministic and theoretically reasonable
  - cannot easily model complicated nonlinear problems

- Data Driven: data-driven deep learning methods that learn features automatically
  - knowledge learning capability for huge data, especially for nonlinear statistical features
  - over-dependent on training data

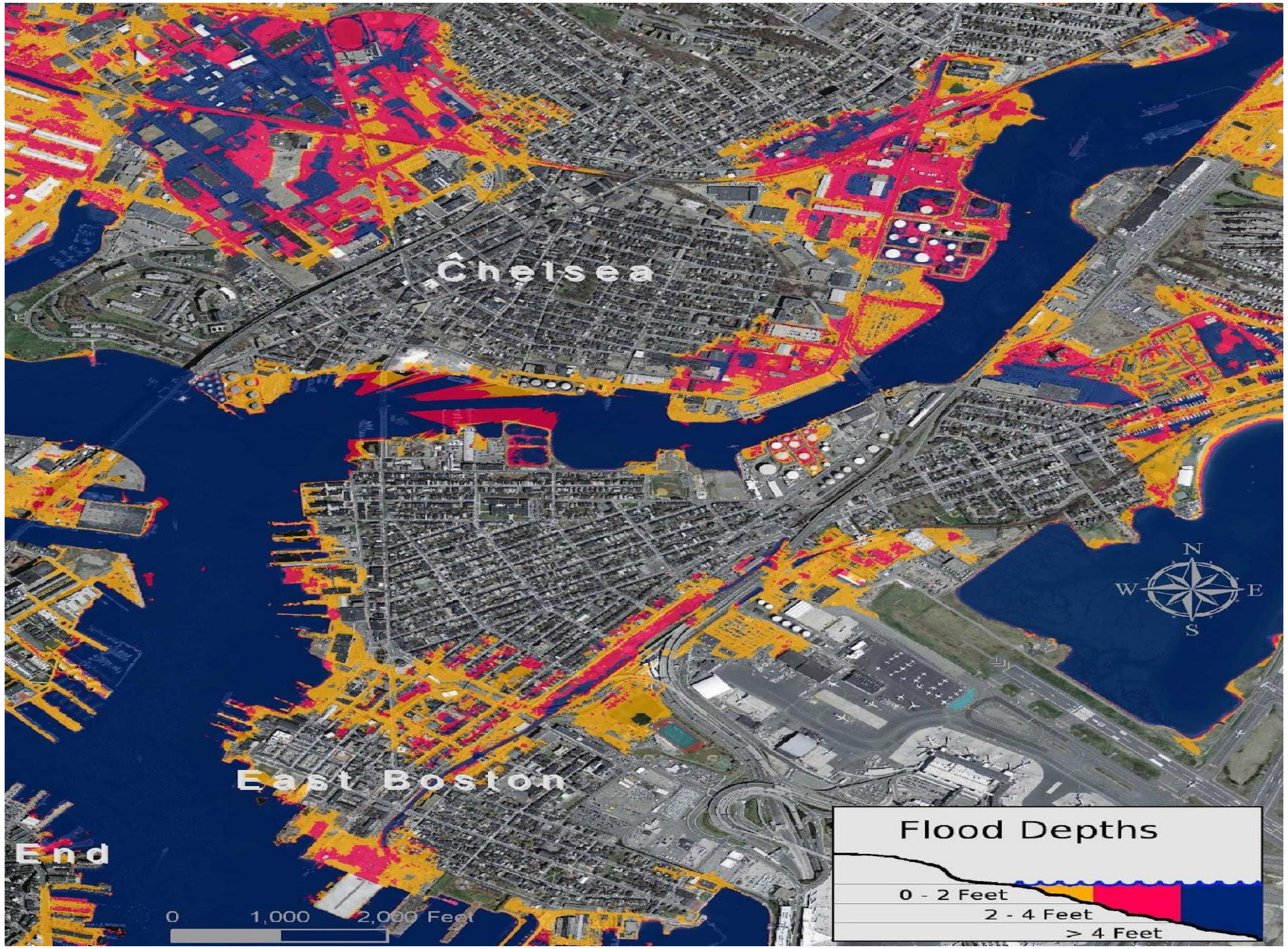
Flooding: Most common and frequent natural disaster

- Hurricane Harvey (2017): $125 billion in damage, 88 deaths in Houston, TX (source: NHC)

Source: HTTPs://help.floodfactor.com/hc/en us/articles/360051062333-Adaptation-types

Flood map: the extent and depth of floods:

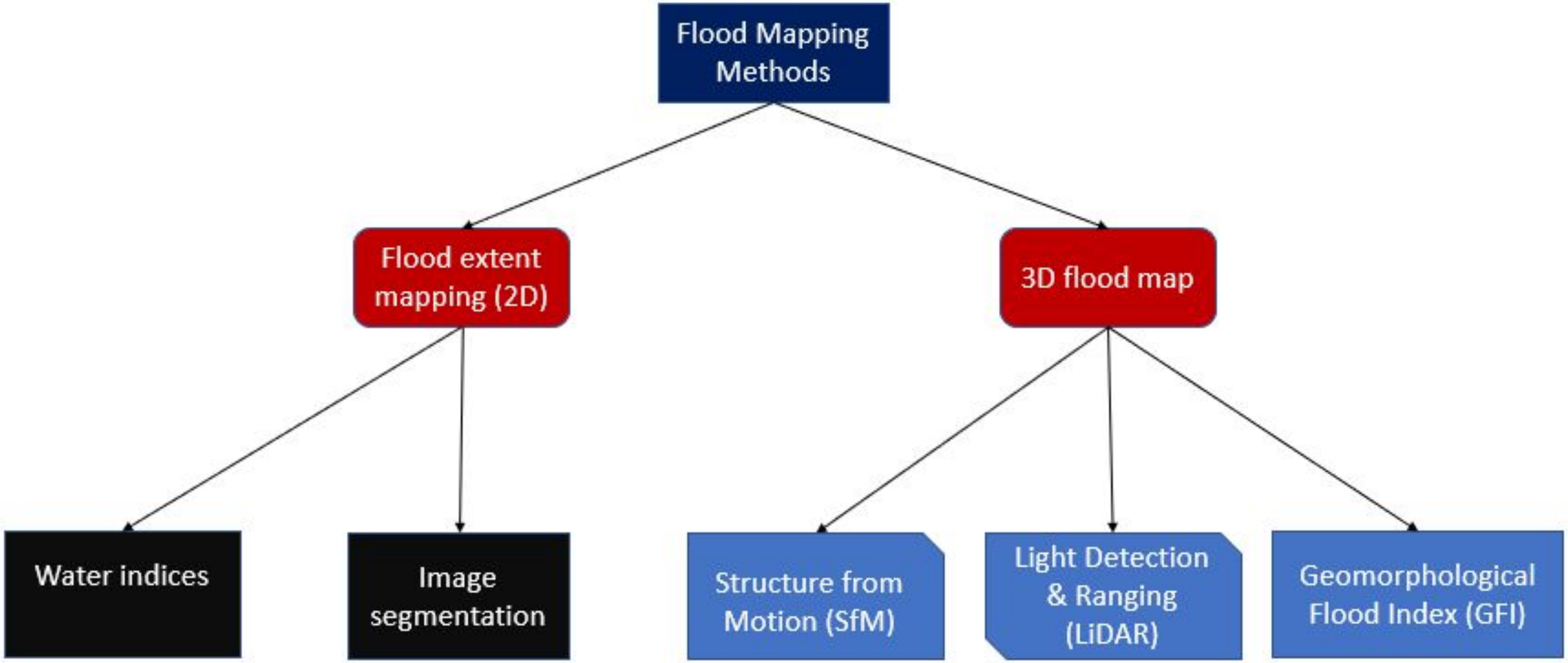
- for emergency response; damage assessment; planning; decision making
- should be accurate and real-time



Boston flood map in 3D

https://www.bostonharbornow.org/what-we-do/work/climate-change-preparedness/maps/

Flood Mapping in Remote Sensing



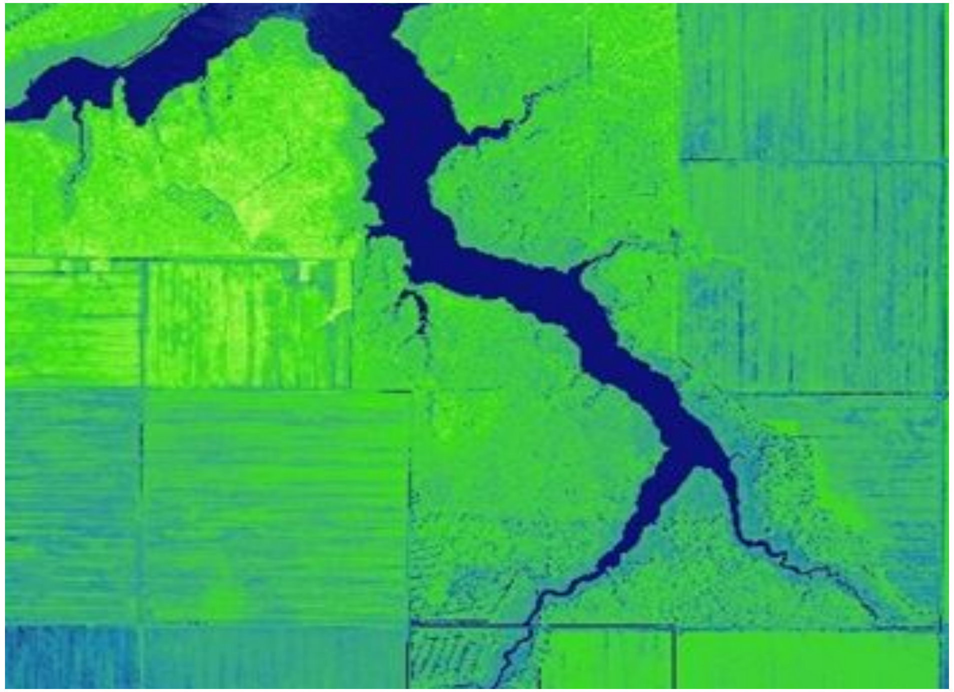
Inundation mapping using water indices

- The Normalized Difference Water Index (NDWI):

$$NDWI = \frac{(Green - NIR)}{}$$

Where the Green and NIR refer to the reflection in the green and near-infrared spectra, respectively.

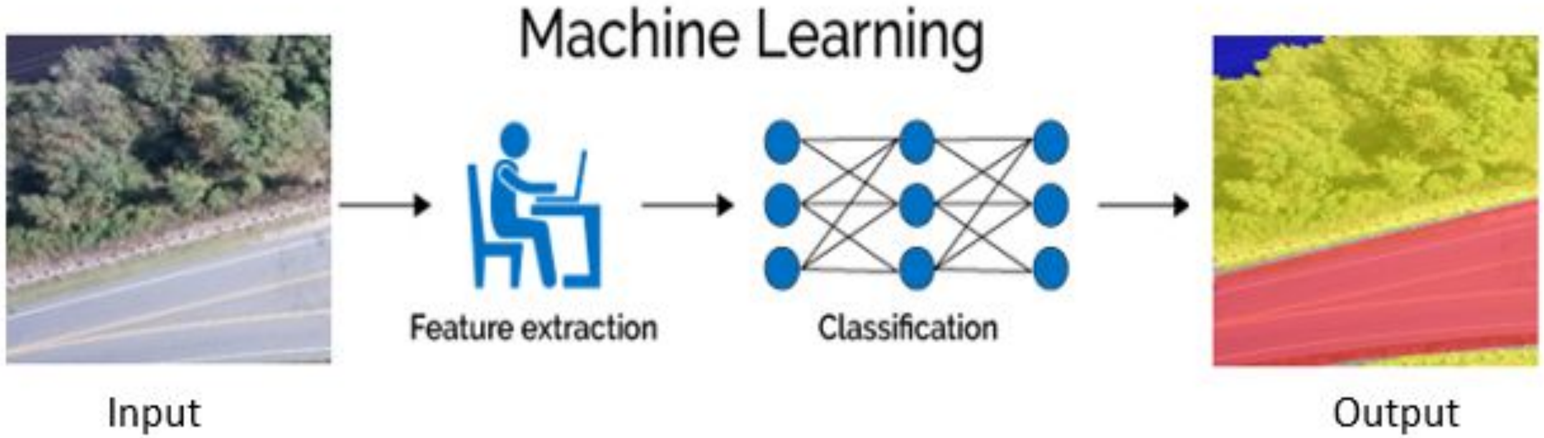
Limitation: overestimation of floods



Inundation mapping using image segmentation

Conventional Machine Learning: e.g., Random Forest (RF) and Support Vector Machine(SVM)

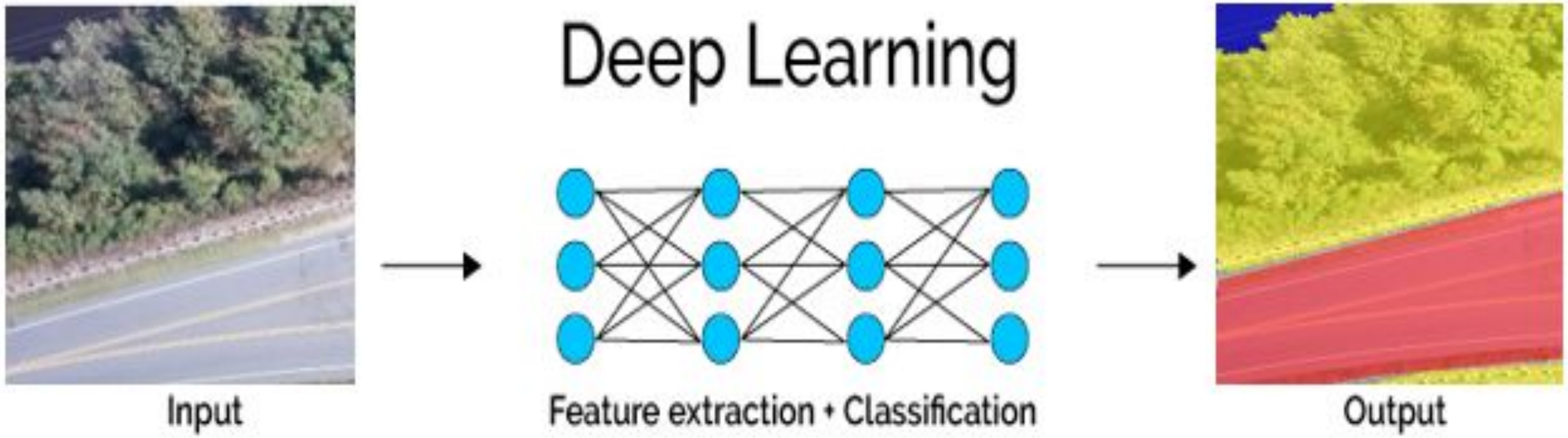
Limitation: Dependent on hand crafted features; can not handle large dataset



https://deepai.org/publication/techniques-for-interpretable-machine-learning

Inundation mapping using Deep Learning

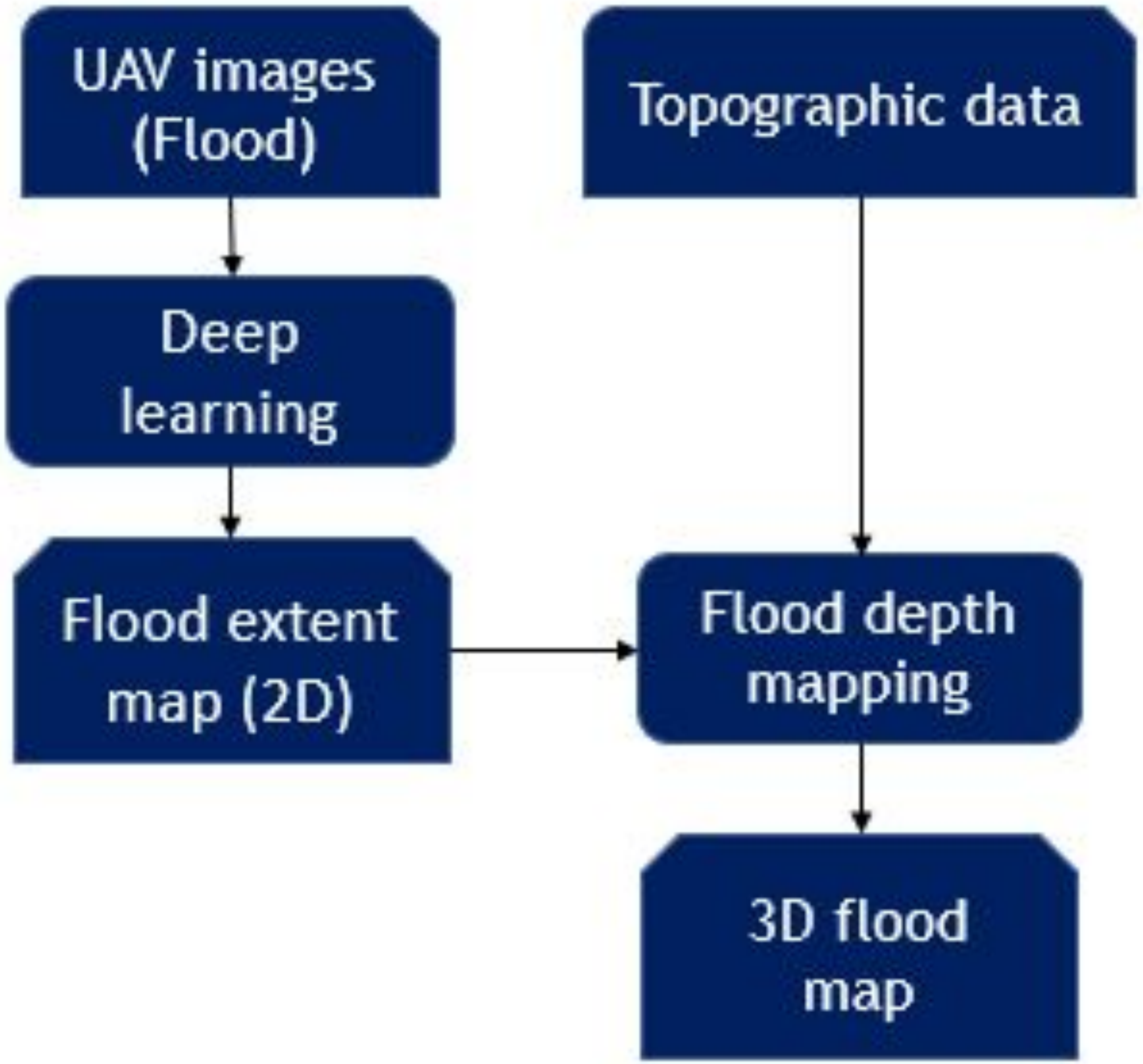
- Can automatically learn feature representation directly from a big data
- Performance improves as the data size increases
- Requires a large training data



https://deepai.org/publication/techniques-for-interpretable-machine-learning

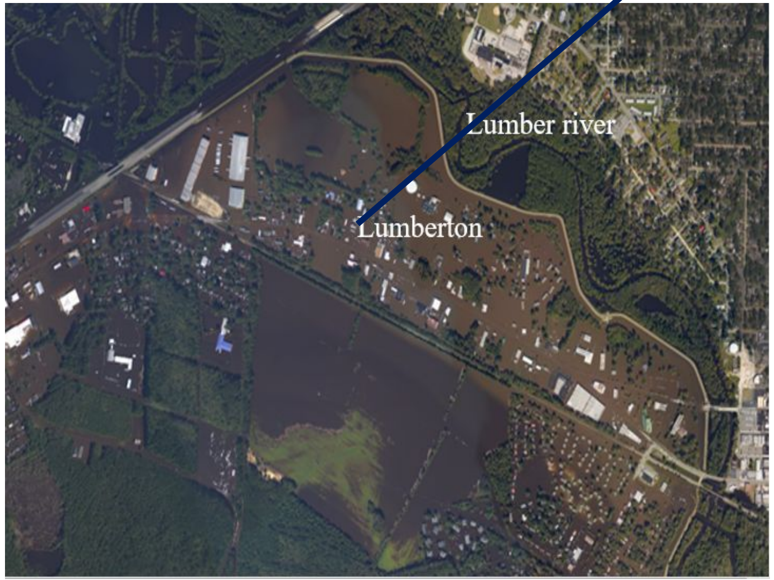
Research Objectives

- To investigate the performance of deep learning for automated flood extent mapping using images from UAV
- To investigate an integrated method for mapping floods in open area and underneath vegetation canopy


UAV images (Flood)
Topographic data
Deep learning
Flood extent map (2D)
Flood depth mapping
3D flood map

Study Area

https://geology.com/lakes-rivers-water/north-carolina.shtml



Lumberton during Hurricane Florence (2018)

Princeville during Hurricane Matthew (2016)

Research Data

i. **LiDAR (North Carolina Emergency Management (NCEM))**
ii. **High-resolution UAV images (NCEM)**
iii. **Flood-gauge reading data (USGS)**

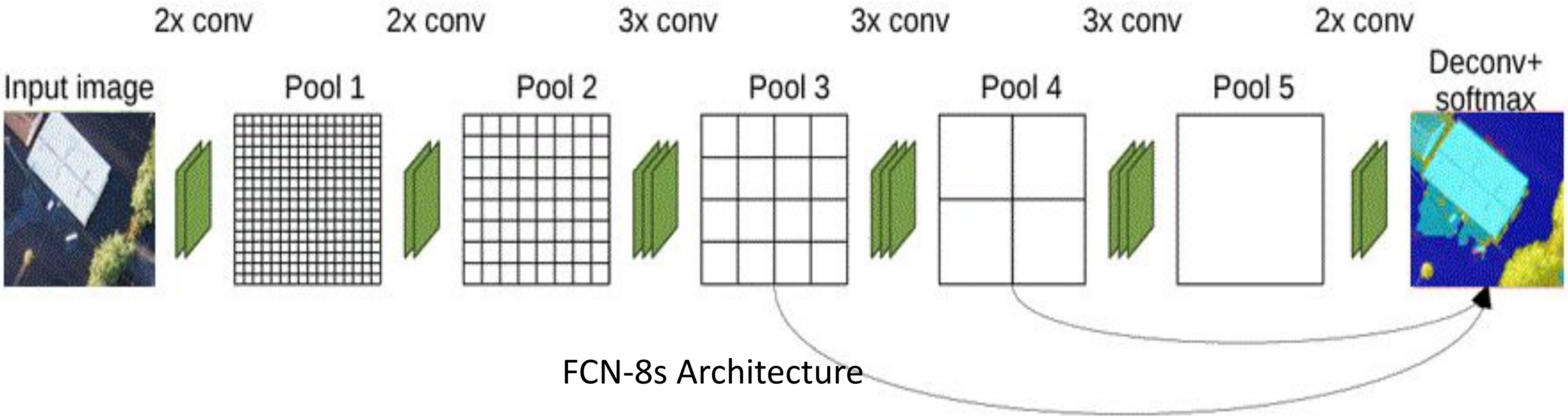
		Spatial Resolution	**Land coverage**	**Flood events**	**Data collection date**
UAV Imagery	Princeville	2.6 cm	0.64 km^2	Matthew	10/16/2016
	Lumberton	1.5 cm	0.52 km^2	Florence	9/23/2018
	Fair Bluff	1.5 cm	0.49 km^2	Florence	9/26/2018

2D Flood extent mapping

Research approach: Fine-tuning pre-trained FCN-8s model (Long et al., 2015)

Fine tuning: Tuning a model to perform a second similar task.

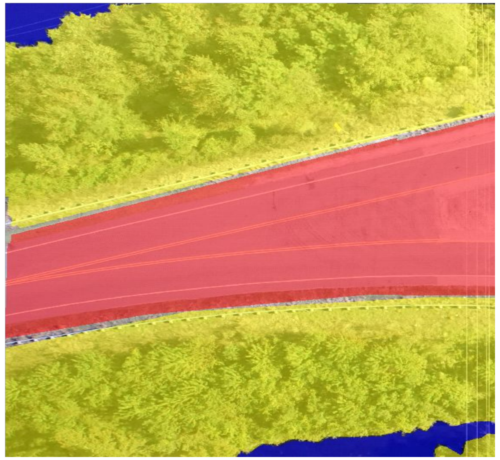
Advantage of fine tuning: Speed up the training; overcome small training data issue



FCN-8s Architecture

Annotating stage:

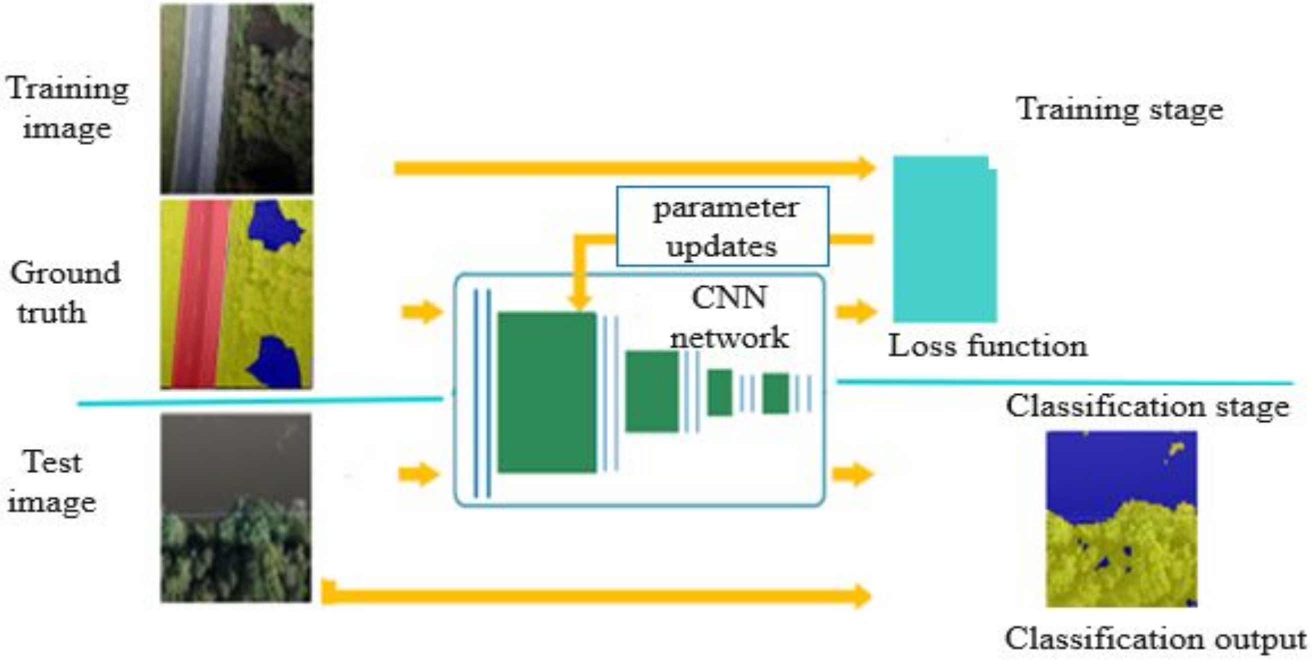
- 150 UAV images (4,000 x 4,000 pixels each)



Sample portion of training image   Annotated image

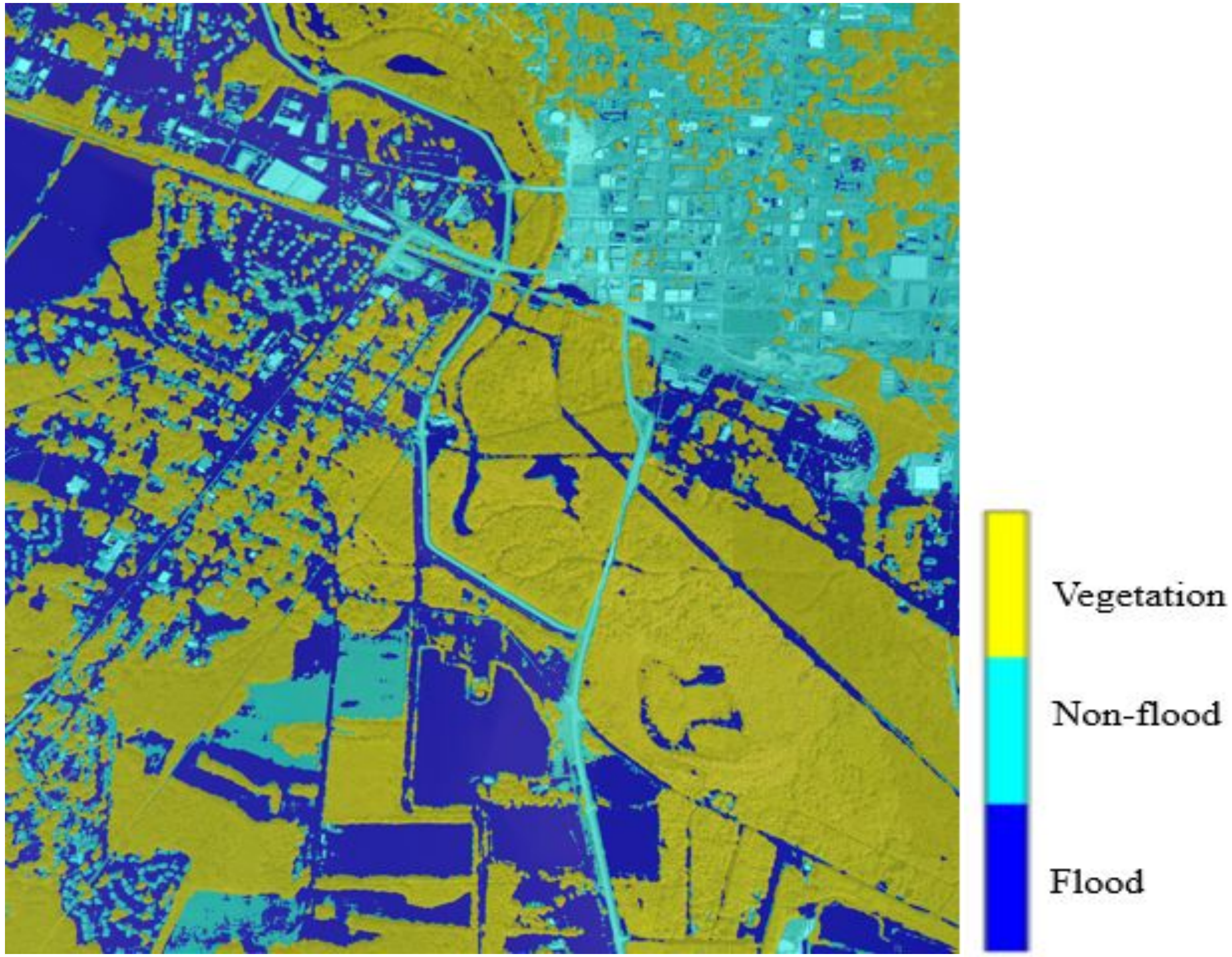
Training and accuracy Assessment Stages:

- Fine-tuning FCN-8s
- Data augmentation
- K-fold cross validation
- Confusion matrix used for accuracy assessment



The general pipeline of the methodology

Test image (Lumberton during Hurricane Florence)



FCN-8s classification result

FCN-8s result: (unit: percentage)

- FCN-8s achieved 98.7% accuracy for detecting water applying data augmentation
- Data augmentation improved the classification results of deep learning

	Water	Building	Vegetation	Road
Water	**97.5**	1.4	1.0	0.1
Building	2.5	**87.0**	2.72	7.8
Vegetation	1.2	1.4	**97.2**	0.1
Road	0.3	3.2	1.0	**95.5**

FCN-8s classification result

	FCN-8s	FCN-8s (data augmentation)
Water	97.5	98.7
Building	87.0	95.2
Vegetation	97.2	98.4
Road	95.5	97.9

FCN-8s result without and with data augmentation

Overall accuracy:

- FCN-8s achieved better overall accuracy

Performance of Model-based and Deep Learning Classifiers

	Overall accuracy (%)	Kappa index
FCN-16s	95	0.90
FCN-8s	95.5	0.91
FCN-32s	92	0.87
U-Net	91.7	0.89
RF	85.4	0.88
SVM	87.5	0.79
NDWI	92	0.89

An Integrated Method for Flood Extent Mapping in Open area and Underneath Vegetation Canopy

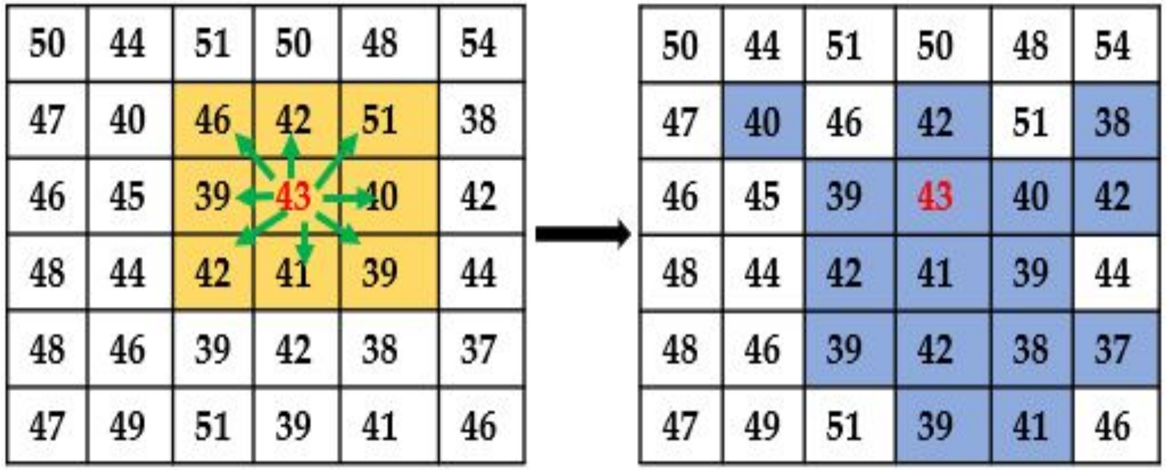
Open area flood

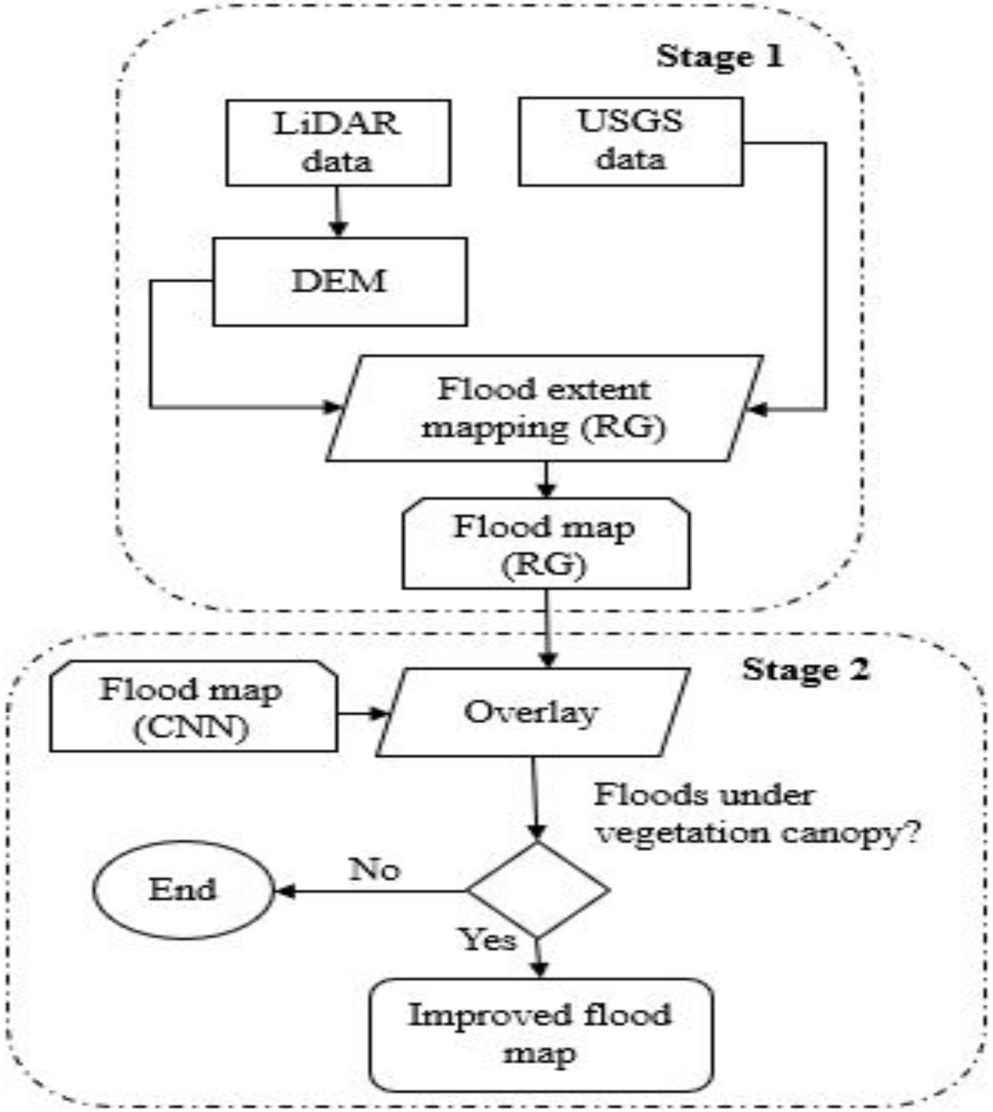
Flood in underneath vegetation canopy

Source: HTTPs://help.floodfactor.com/hc/en us/articles/360051062333-Adaptation-types

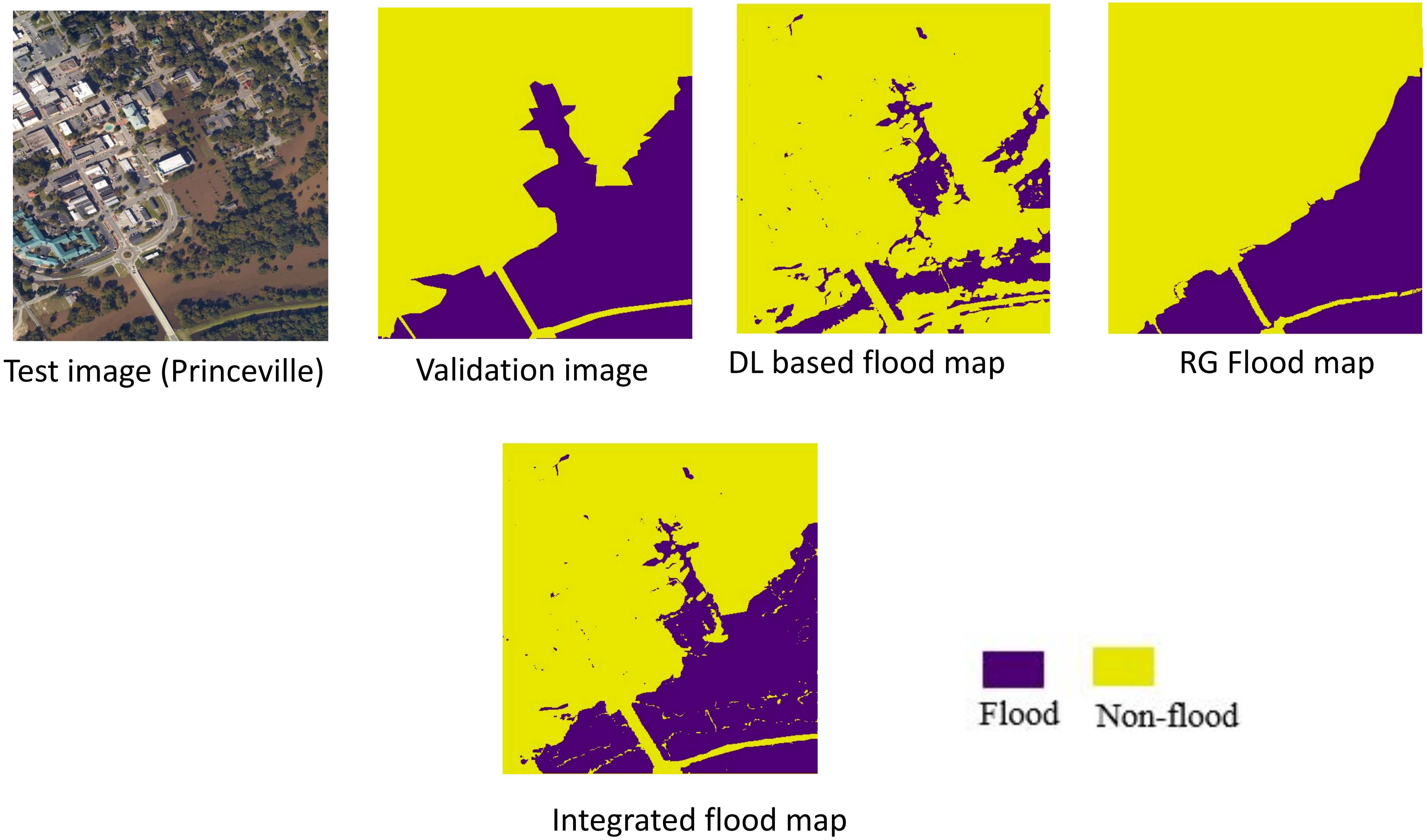
Stage 1: **Mapping vegetation floods using RG**:

- Selection of Initial point (water level)
- Searching 8 immediate neighbors
- Adding/removing from the region based on the topography

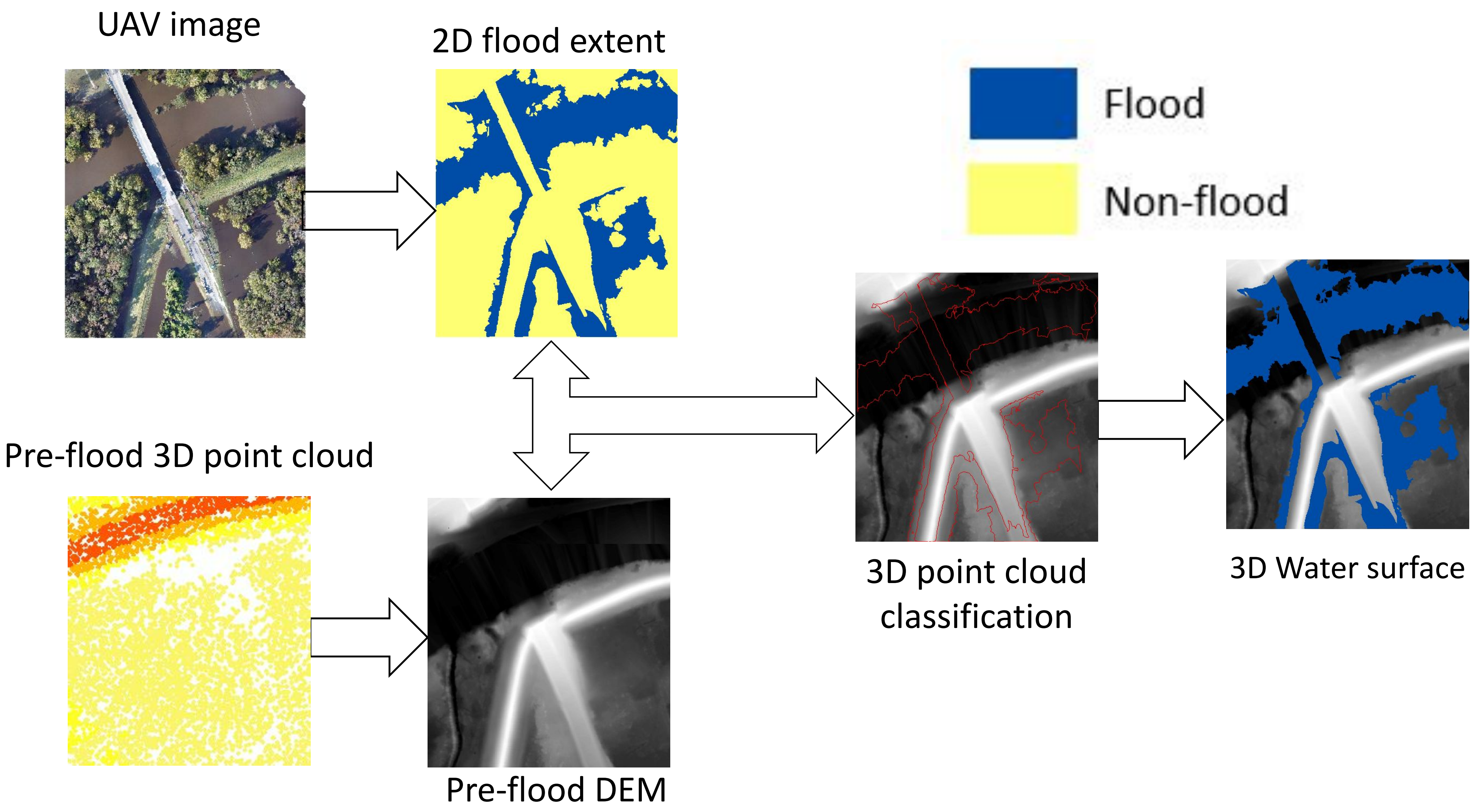




Region growing procedure

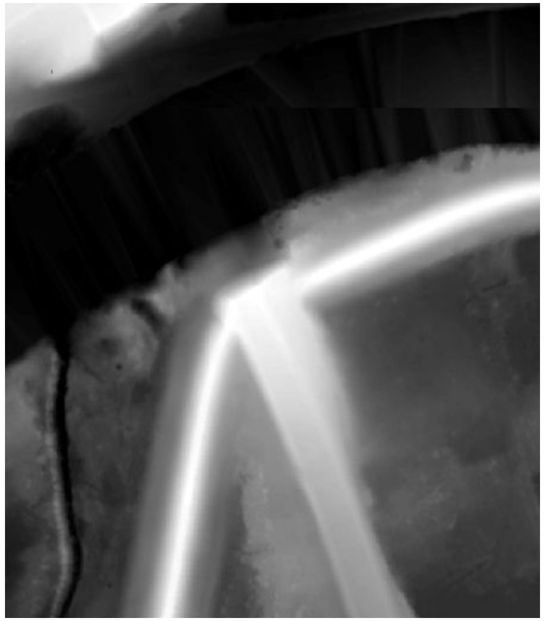

Test image (Princeville)
Validation image
DL based flood map
RG Flood map
Integrated flood map
Flood
Non-flood

3D Water Surface Reconstruction

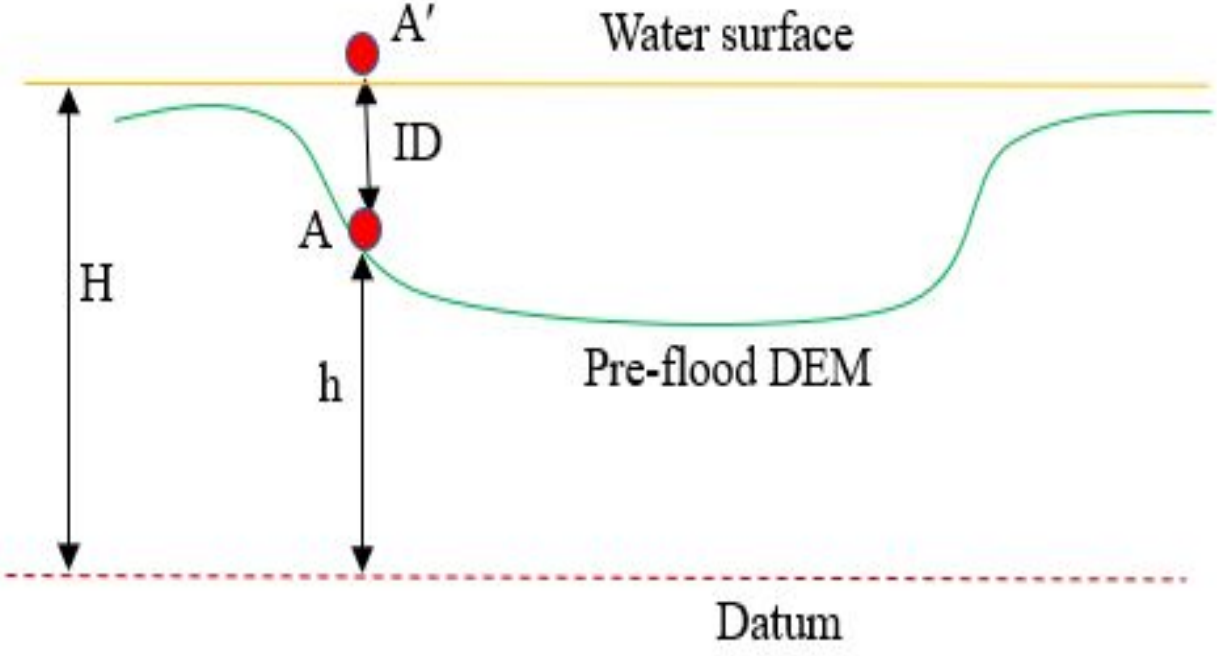


3D Flood Depth Estimation

- Inundation depth (ID) = H - h



Pre-flood DEM



A schematic description of inundation depth estimation

Conclusions

- Deep Learning is an efficient method for accurate, fast and automatic flood mapping in Open areas. Fine-tuning is a suitable approach to overcome data scarcity issues for flood mapping.
- The integrated approach – model-based and deep learning - showed promising results for rapid and accurate mapping of floods in vegetated areas.
- The proposed method’s performance will be compared and tested in several study areas. The method can also be applied for damage assessment after any natural disaster event.

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