Laboratory of Mathematics and its Applications of Pau
University of Pau and Pays de l'Adour

Statistical learning for coastal risks assessment

PhD defense

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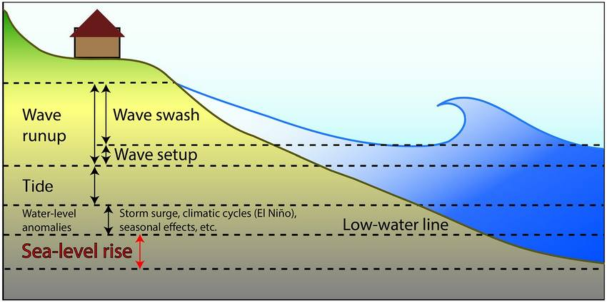
Coastal flooding

Coastal flooding during a storm in Biarritz (Christine storm, March 2014)

Damages to the Casino building (Christine storm, March 2014)

Coastal flooding

Coastal flooding is a temporary inundation resulting from the interaction of several coastal processes: tide, waves, storm surge.



Components of total water level responsible for coastal flooding

→ Occurs when total water level exceeds the elevation of defense infrastructure.

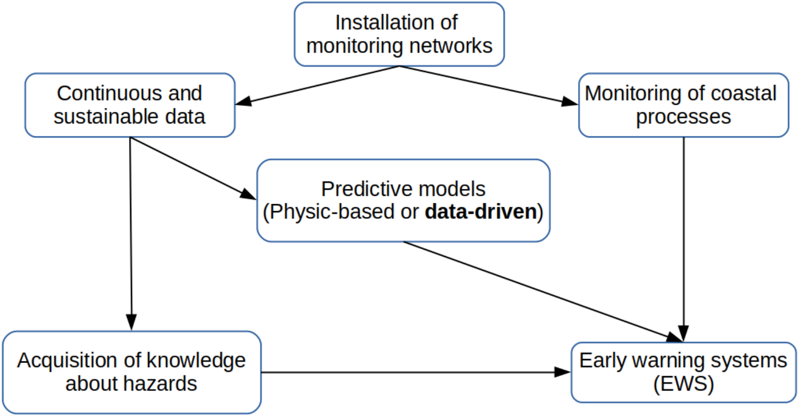
Coastal flooding risk

Flooding risk = **Hazard** x **Exposure** x **Vulnerability**

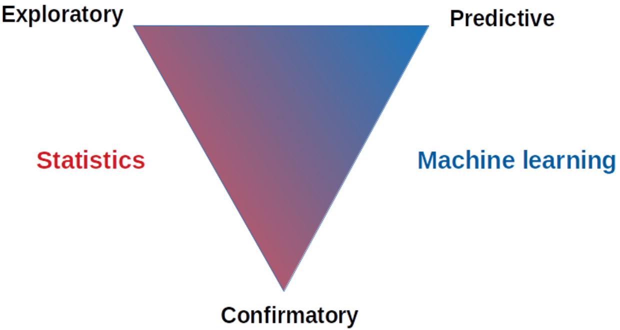
Hazard	Exposure	Vulnerability
Dangerous phenomenon with given intensity and probability	Structures Population Agriculture Business Assets	Physical Social Economic Environmental Coping capacity

→ Coastal flooding risk expected to increase in the future due mainly to sea level rise and on-going urbanization of the coastal areas.

How to prepare for coastal flooding disaster?



Statistical learning methods

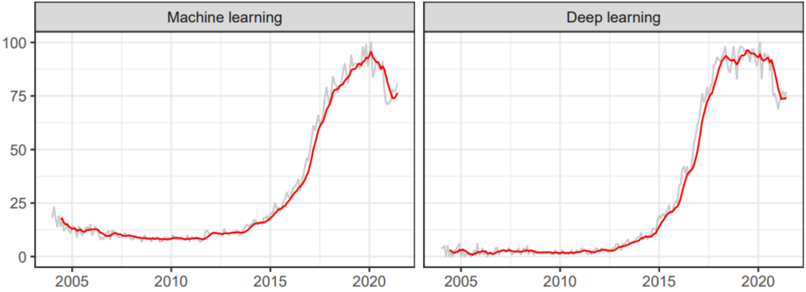


Representation of statistical learning domain

Statistical learning methods (SLMs): Tools and methods for modeling, predicting and understanding complex data.

SLMs

→ With more data available, the use of SLMs for predictive models in various domain becomes more legitimate and justified.



Interest in Google searches

SLMs and coastal flooding

	Machine learning	Deep learning	Statistical models
Definition	Algorithms learning patterns from data	Sub-class of ML able to detect features and learn from complex data	Models based on statistics
Aim	Make the most accurate predictions		Understand the data and study relationships between variables
Use	**Predictive models** for tide (*Granata et al., 2021*), wave height (*Makarynskyy, 2005*) or storm surge (*Lee et al., 2018*) **Data assimilation** for wave models (*Moeini et al., 2012*)	**Predictive models** for wave height time-series (*Sadeghifar et al., 2017*) **Image analysis** to estimate nearshore bathymetry (*Benshila et al., 2020*)	**Storm impact models** with Bayesian networks: -Shoreline retreat (*Beuzen et al., 2018*) - Prediction of coastal hazards (*Poelhekke et al., 2016*)

Problematic

How SLMs can contribute to the improvement of coastal risk assessment tools and more particularly in the development of an EWS which aims to reduce coastal flooding risk?

Outline of the thesis

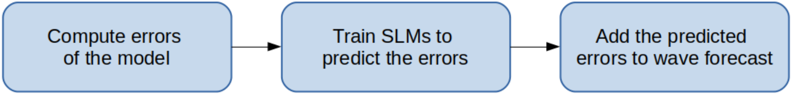
1. SLMs to improve wave forecast at a specific location
2. Automatic creation of a storm impact database from images generated by video monitoring stations
3. Development of a storm impact model using data from monitoring networks and data extended by SLMs

Improving wave forecast with SLMs

Improving locally wave forecast

Numerical wave models have a tendency to underestimate the wave parameters in energetic conditions (Arnoux et al., 2018).

Method:



Error prediction method

Main results: we reduced the RMSE of the MFWAM wave model by 40% for wave height and 30% for wave period with gradient boosting trees (Callens et al., 2020).

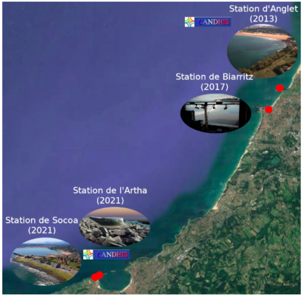
Storm impact database

Data about storm impact

Storm impact databases are rare, sparse and mostly come from archives (Abadie et al., 2018) or insurance data (Naulin et al., 2016).

We do not have direct observations!

→ Can we use video monitoring networks already deployed to create routinely storm impact databases?

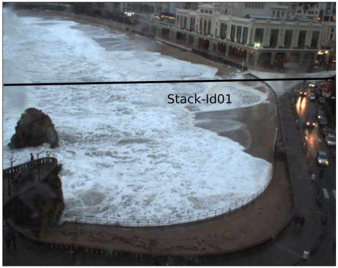


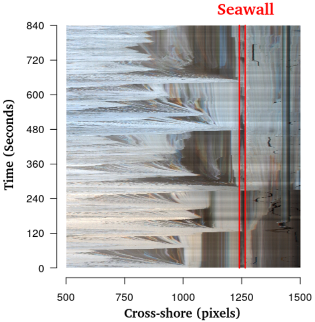
SIRENA network

Video station of Biarritz

Video monitoring and timestacks

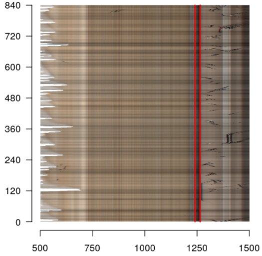
Video monitoring systems create different types of images including timestacks.
Timestacks: time varying pixel intensities along a particular cross-shore transect.



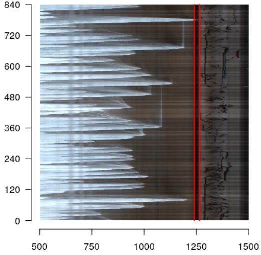


Contribution

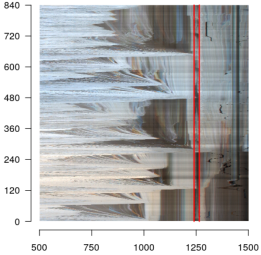
Methodology based on convolutional neural networks (deep learning) to classify automatically timestacks into 3 storm impact regimes based on the scale of Sallenger (2000):



(a) Swash regime



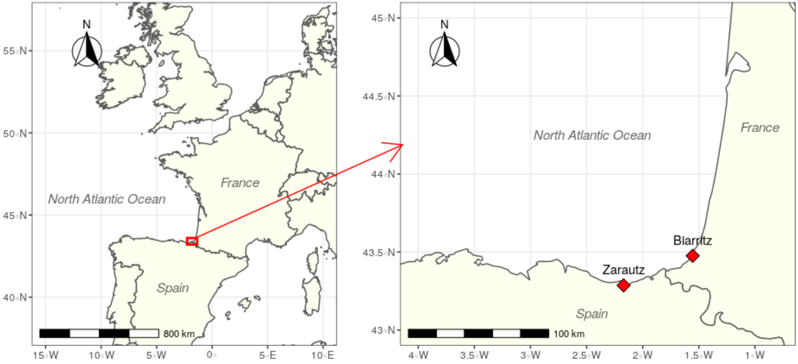
(b) Collision regime



(c) Overwash regime

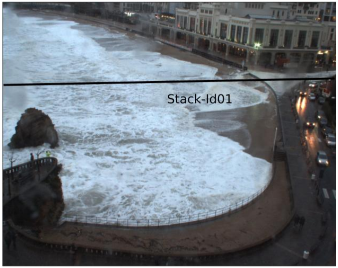
The study sites

Biarritz (France) and Zarautz (Spain)



The study sites

Biarritz



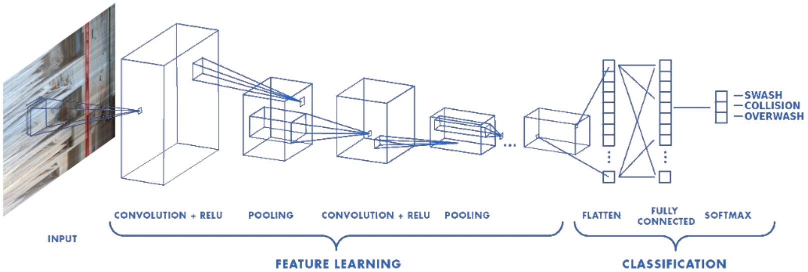
7907 Swash, 211 Collision, 54 Overwash between 2017 and nowadays

Zarautz

19596 Swash, 2776 Collision, 162 Overwash between 2015 and nowadays

→ **Class imbalance!**

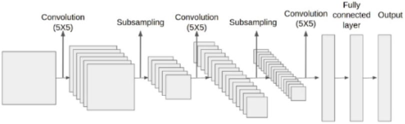
Short introduction on CNN



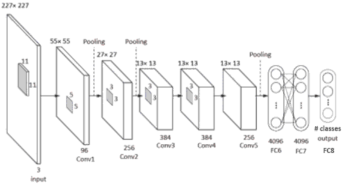
Simplified convolutional neural network

→ Update in iterative manner the weights to minimize a cost function (Categorical Cross-Entropy for multi-class classification).

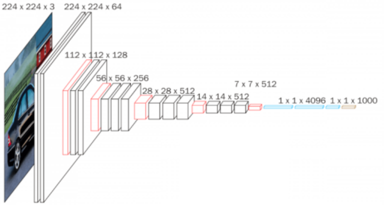
What is the best CNN architecture?



LeNet (Lecun et al., 1998)



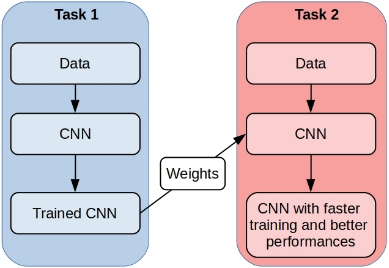
AlexNet (Krizhevsky et al., 2012)



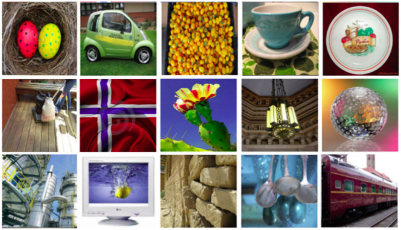
VGG16 (Simonyan et al., 2014)

Inception v3 (Szegedy et al., 2016)

Transfer learning



Transfer learning concept



Images from ImageNet (Ahmed et al. 2017)

The efficiency of pretraining will be tested twice:

- From ImageNet (largest labeled image dataset) to our task
- Between sites

Class imbalance problem

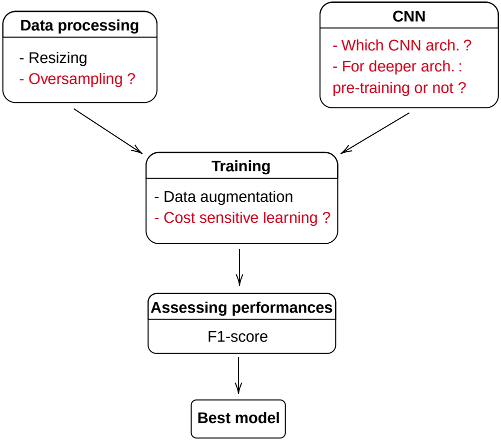
Limited number of Collision and Overwash events for both sites (class imbalance). We will test two methods to cope with this problem:

- **Oversampling:** oversampling of the minority classes (change in class distribution) to reduce imbalance ratio
- **Cost-sensitive learning:** puts more weight on the minority classes during the training of the CNN

We choose **F1-score** to compare the CNNs due to its robustness to class imbalance.

General workflow

Data divided into training (65%), validation (15%) and testing set (20%).



Best model for Biarritz

→ VGG16 with oversampling and transfer learning (ImageNet): F_1-score of 0.866 in 20 epochs.

Confusion matrix Biarritz test data

		Predicted		
		Swash	Collision	Overwash
Observed	Swash	**1576**	7	0
	Collision	4	**34**	2
	Overwash	1	2	**9**

Best model for Zarautz

→ VGG16 with oversampling and transfer learning (ImageNet): F_1-score of 0.858 in 13 epochs.

Confusion matrix for Zarautz test data

		Predicted		
		Swash	Impact	Overwash
Observed	Swash	**4265**	40	0
	Impact	13	**617**	8
	Overwash	0	25	**30**

Transfer learning

CNN	Time (min)	Epochs	F_1-score
Biarritz			
VGG16 (OV)	69.6	28	0.813
VGG16 (OV, ImageNet)	**49.9**	**20**	**0.866**
VGG16 (OV, Zarautz)	47	19	0.823
Zarautz			
VGG16 (OV)	146.6	22	0.792
VGG16 (OV, ImageNet)	86.5	13	0.858
VGG16 (OV, Biarritz)	**92**	**14**	**0.885**

$\rightarrow$ Better results than training from scratch and better results than pretraining with ImageNet for Zarautz!

Advantages and limitations

Advantages

- Transferability of the method to new sites facilitated with pre-training
- Room for improvements:
  - Hyperparameters
  - Data augmentation
- As more data are collected, CNN are expected to yield better results

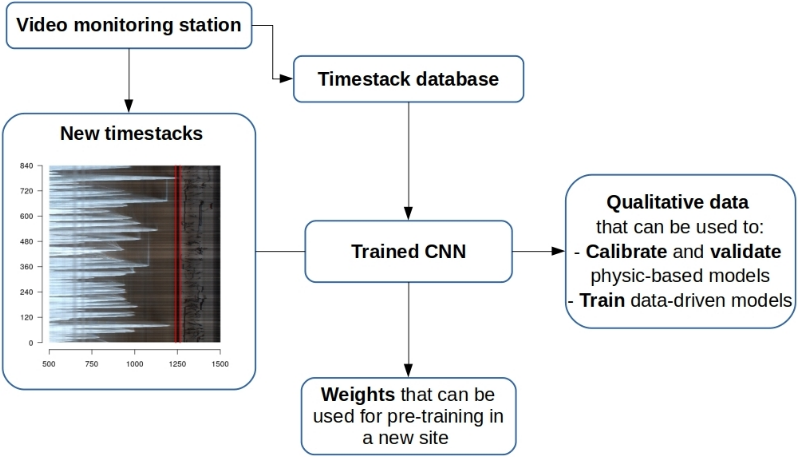
Limitations

- Lack of comparison with human level performance or other image processing techniques
- Image annotation is tedious and time consuming
- Extract only qualitative information on coastal flooding

Perspectives

- Compare this methodology with other image processing techniques
- Extend this work to detect and count the number of Collision or Overwash events
- Explore semi-supervised learning which aims to learn form labeled and unlabeled data (Baur et al. 2017) to adapt this methodology for new sites

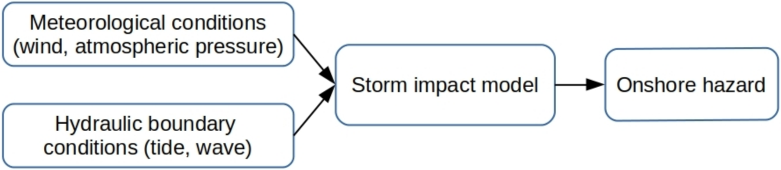
Conclusion


Video monitoring station
Timestack database
New timestacks
840
720
600
480
360
240
120
0
500
750
1000
1250
1500
Trained CNN
Qualitative data
that can be used to:
- Calibrate and validate
physic-based models
- Train data-driven models
Weights that can be
used for pre-training in
a new site

Storm impact model

Storm impact model

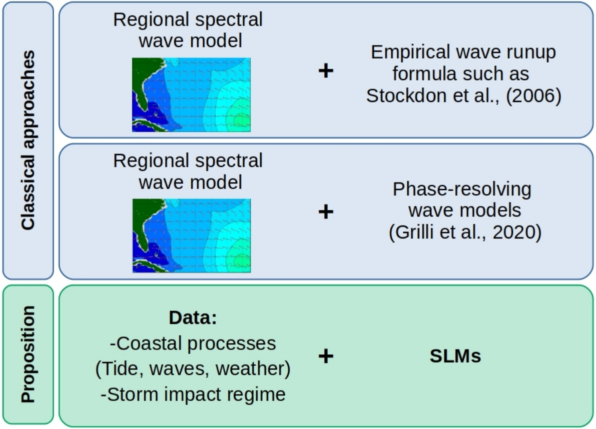
One objective of the thesis: develop a storm impact model.



Simplified storm impact model

→ **Crucial step in early warning systems!**

Storm impact model

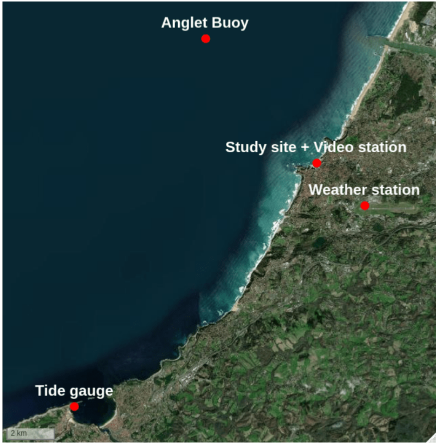


→ Storm impact model on the Grande Plage of Biarritz

Monitoring networks near Biarritz

Data collected routinely for decades by monitoring networks:

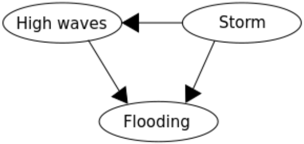
- Tide gauge (Shom) for water level
- Wave buoy (Candhis) for offshore wave characteristics
- Weather station (MeteoFrance) for meteorological variables
- Video station for storm impact regime



Bayesian networks

Probabilistic graphical models representing a set of variables and the dependencies between those variables.

Storm	High waves T	High waves F
F	0.01	0.99
T	0.6	0.4



T	F
0.2	0.8

High waves	Storm	Flooding T	Flooding F
F	F	0.0	1.0
F	T	0.8	0.2
T	F	0.9	0.1
T	T	0.99	0.01

Bayesian networks

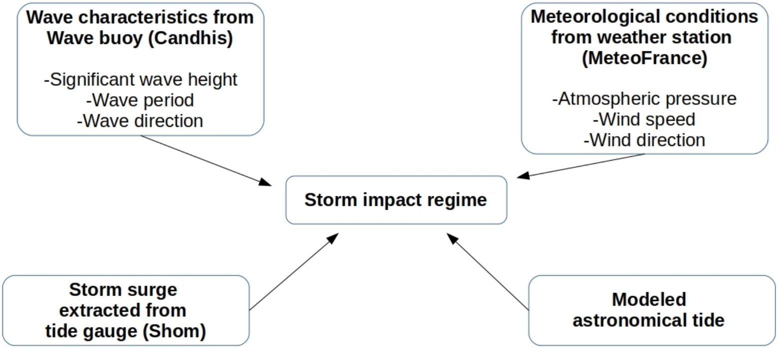
Advantages:

- Instantaneous predictions when evidences are provided to the networks
- Summarize complex systems into intuitive graphs
- Great tools for decision making, communication with stakeholders

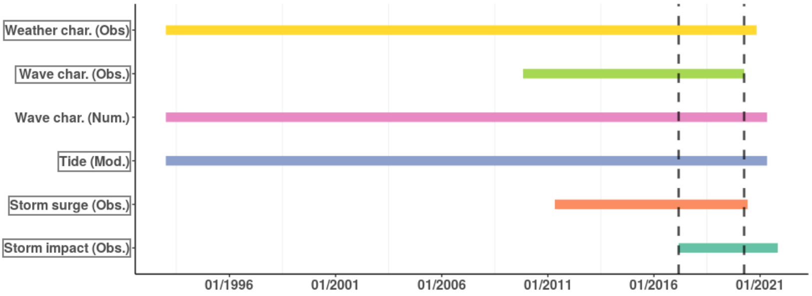
→ Commonly used as storm impact model (Poelhekke et al., 2016)

Bayesian networks

Our goal:

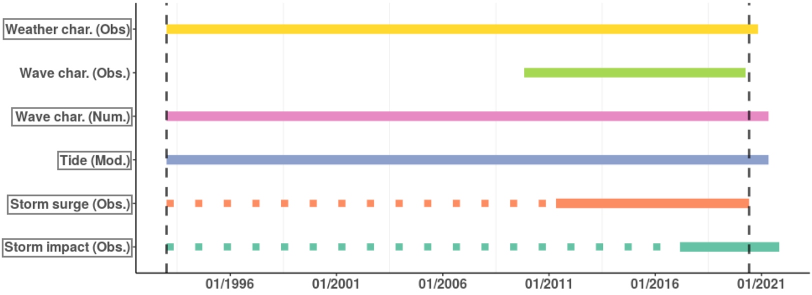


BN based on observational data



→ From 03/2017 to 11/2020 with 80% training set, 20% testing set.

BN based on observational and extended data



Wave char. (Num): Reanalysis from MFWAM wave model improved by our method (Callens et al., 2020).

From 01/1993 to 11/2020 with **same testing set** than the first BN.

Performances of the bayesian networks

Descriptive performance (training set)			
	Precision	Recall	F1-score
BN based on obs. data	0.743	0.709	0.72
BN based on obs. and ext. data	**0.871**	**0.88**	**0.875**

Predictive performance (test set)			
	Precision	Recall	F1-score
BN based on obs. data	0.594	0.673	0.628
BN based on obs. and ext. data	**0.63**	**0.789**	**0.691**

Predictive performances

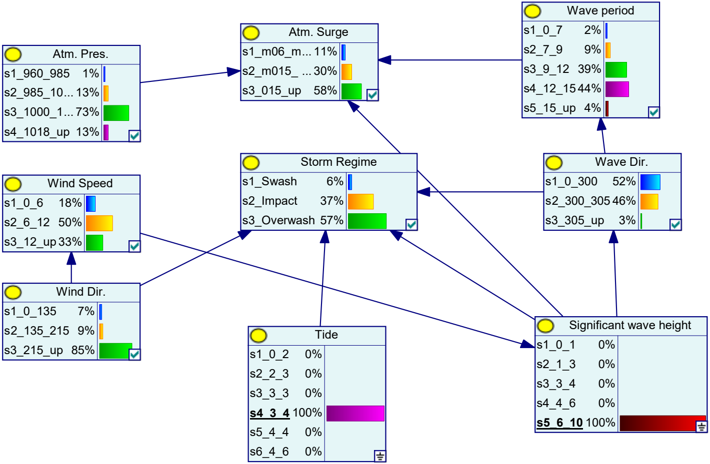
BN based on observational data

		Predicted		
		Swash	Collision	Overwash
Observed	Swash	**1209**	24	1
	Collision	10	**15**	6
	Overwash	3	1	**5**

BN based on observational and extended data

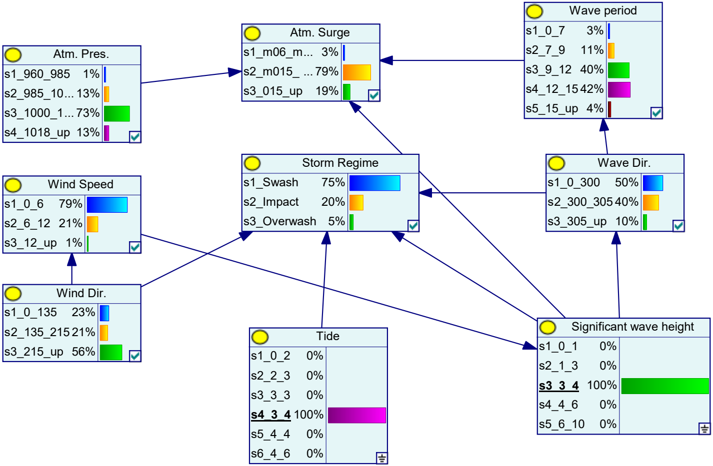
		Predicted		
		Swash	Collision	Overwash
Observed	Swash	**1205**	23	6
	Collision	10	**19**	2
	Overwash	0	2	**7**

Bayesian network predictions



BN obtained with observed and extended data

Bayesian network predictions



BN obtained with observed and extended data

Advantages and limitations

Advantages

- We avoid potential bias related to numerical models
- Instantaneous prediction for coastal flooding
- Take advantage of the networks already installed

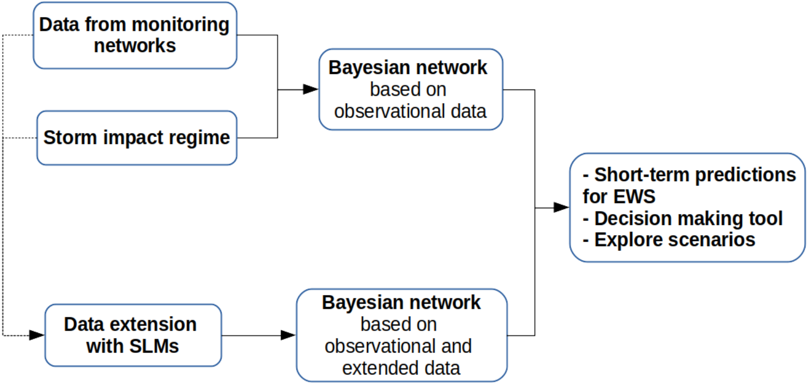
Limitations

- Lack of comparison with classical approaches
- Model to extend storm regime variable has not been validated
- Coastal flooding risk only valid on the transect used to create the timestack images

Perspectives

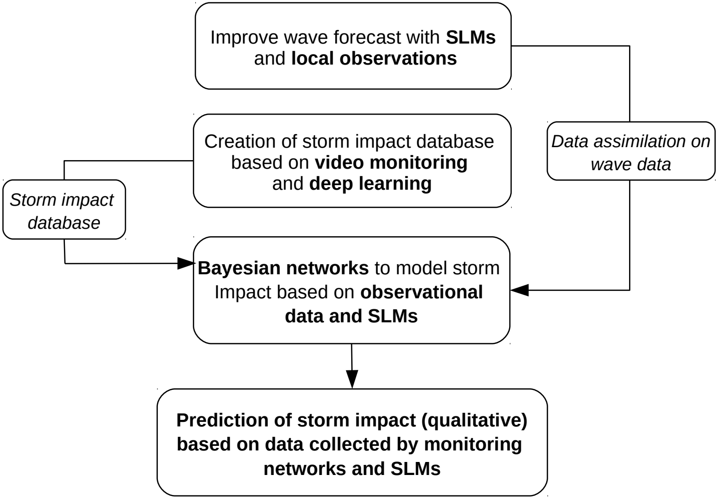
- Observational data could be completed with:
  - Synthetic events and their simulated impact (physic-based modeling)
  - Historical database (Abadie et al., 2018) or expert knowledge
- Comparison with classical approaches that involve numerical modeling
- Integration of temporality with dynamic bayesian networks

Conclusion


Data from monitoring networks
Storm impact regime
Bayesian network based on observational data
Data extension with SLMs
Bayesian network based on observational and extended data
- Short-term predictions for EWS
- Decision making tool
- Explore scenarios

Conclusion

General conclusion



Scientific contributions

- 2 publications in international journals and 1 in preparation

ELSEVIER
Applied Ocean Research
Volume 104, November 2020, 102339

Using Random forest and Gradient boosting trees to improve wave forecast at a specific location

Aurélien Callens [a], Denis Morichon [b], Stéphane Abadie [b], Matthias Delpey [c], Benoit Liquet [a, d]

- 2 communications in national and international conferences

Open Access Article

Automatic Creation of Storm Impact Database Based on Video Monitoring and Convolutional Neural Networks

by Aurelien Callens [1,*], Denis Morichon [2], Pedro Liria [3], Irati Epelde [3] and Benoit Liquet [1,4]

- R + Python code and pre-trained weights for CNN on Github

AurelienCallens / **CNN_Timestacks**

Perspectives

- Include temporality in data assimilation method and storm impact model
- Operational implementation of the proposed methods
- Physic-based modeling to generate more extreme data

Thank you!

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Extension of the database

Aim: Find the best generalizing models for storm surge and storm impact.

Solution: Test several SLMs (random forest, gradient boosting trees, multinomial model, shallow neural networks) and hyperparameters with cross validation.

Explanatory variables	Target variable	Best model
Wave char. (Num.) Meteo. cond. (Obs.) Tide (Mod.)	Storm surge	Random forest
Wave char. (Num.) Meteo. cond. (Obs.) Tide (Mod.) Storm surge (Mod.)	Storm impact	Random forest