Constraint Based Evaluation of Generalised Images Generated by Deep Learning.

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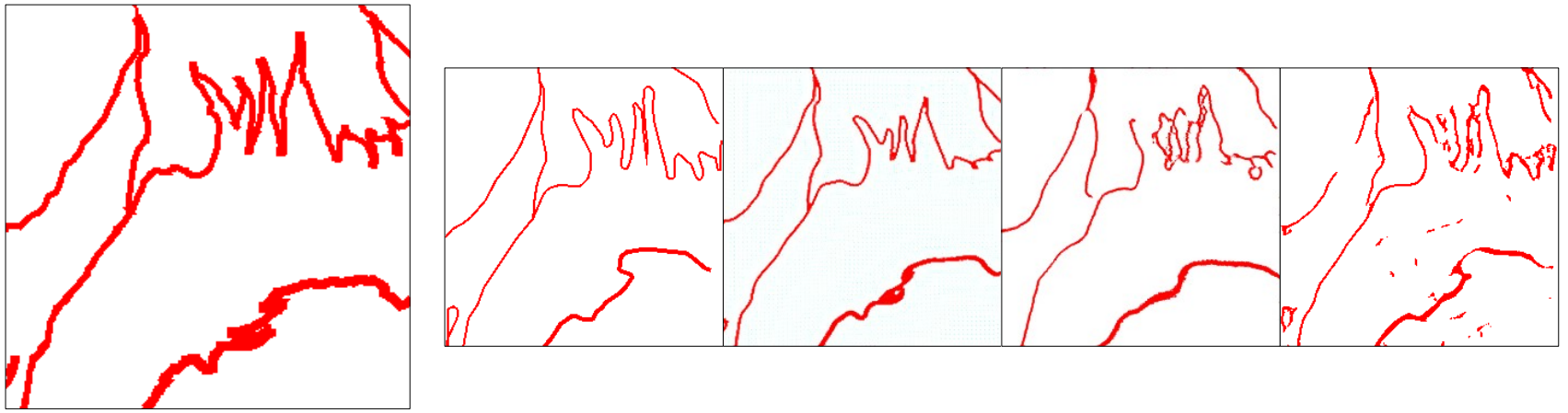
Context

Provide tools for the evaluation of generalisation by deep learning.

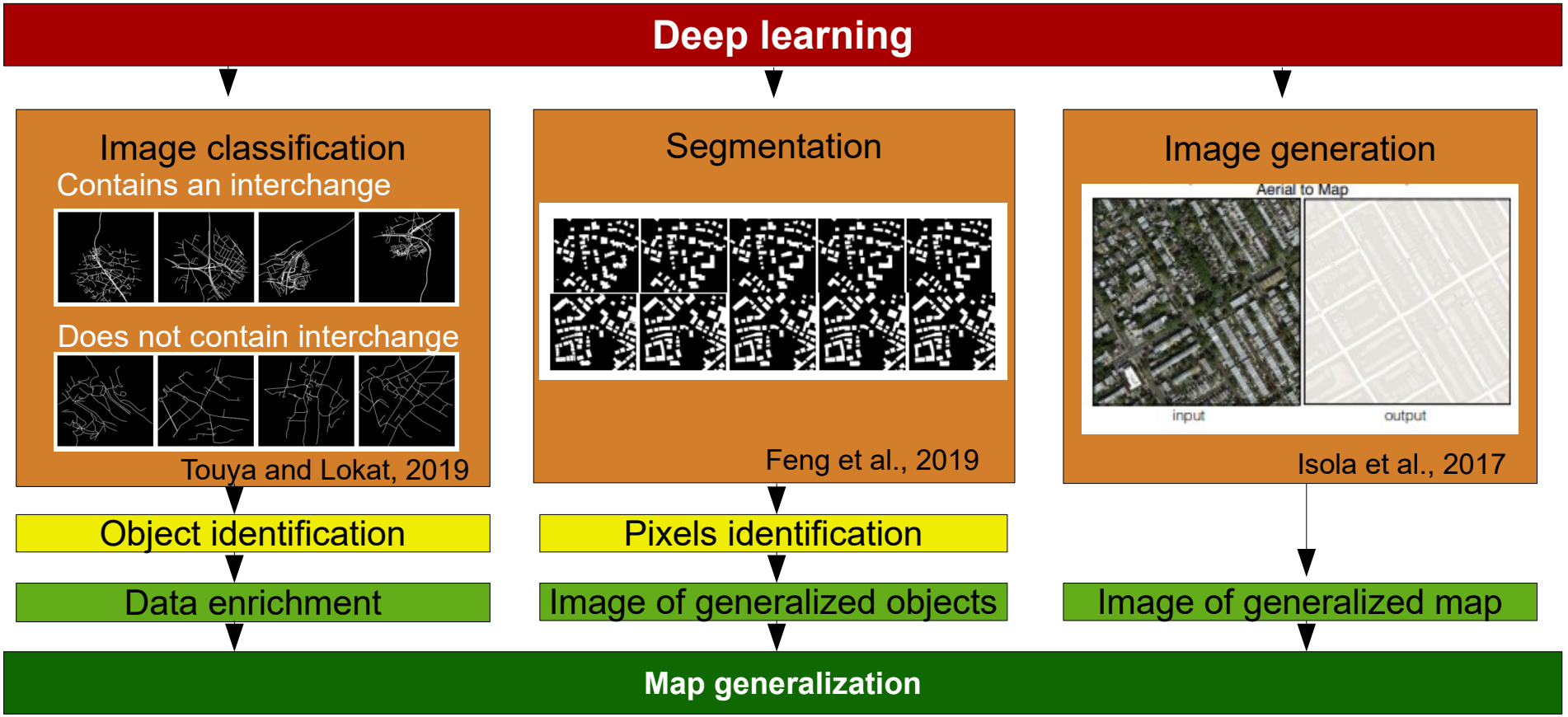


Presentation

1. Motivation
2. Constraint
3. Validation
4. Interest and limits
5. Conclusion

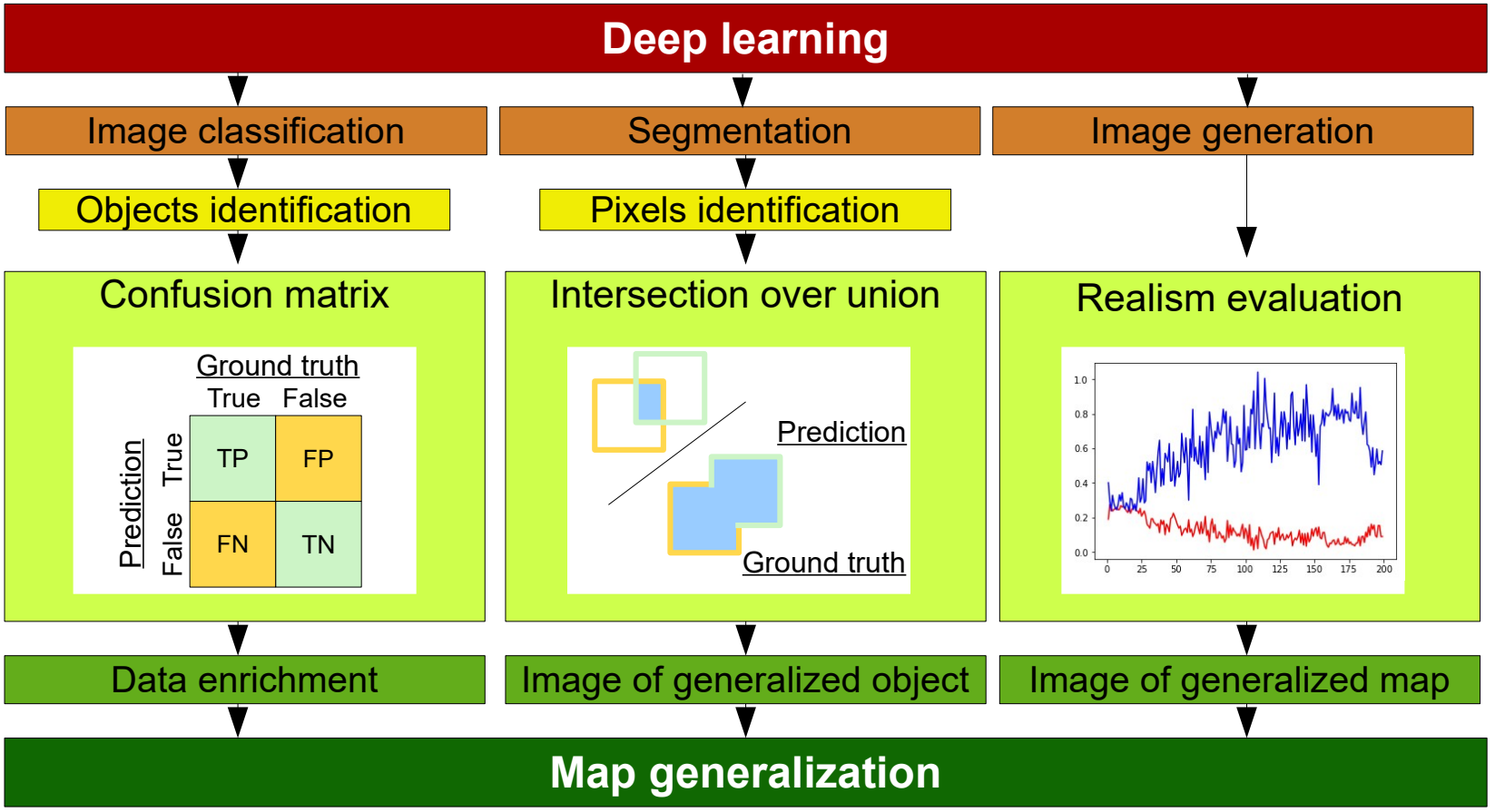
Motivation

Emergence of generalization methods including deep learning.



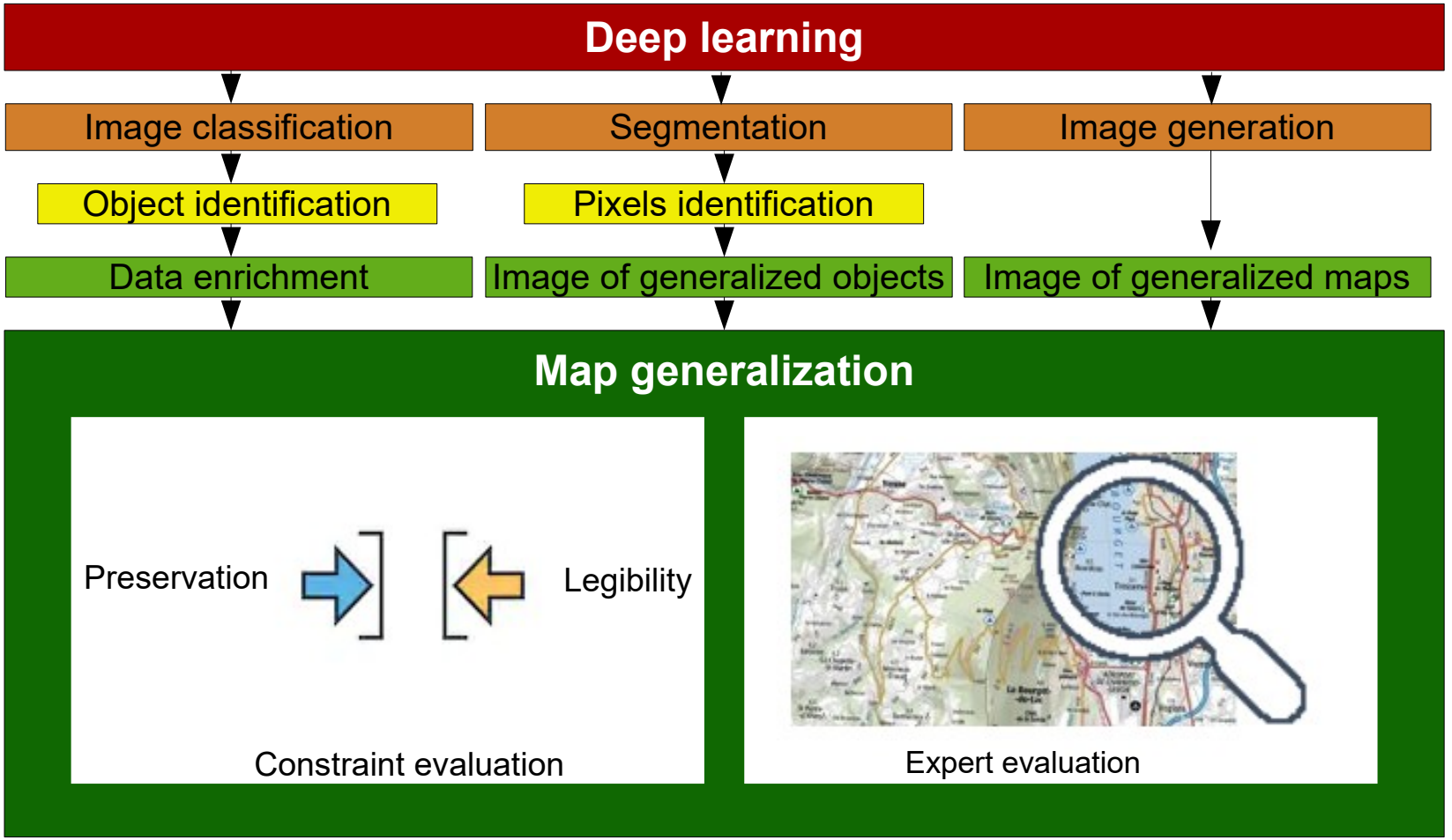
Existing evaluation methods

Evaluation form deep learning methods are not adapted for map.

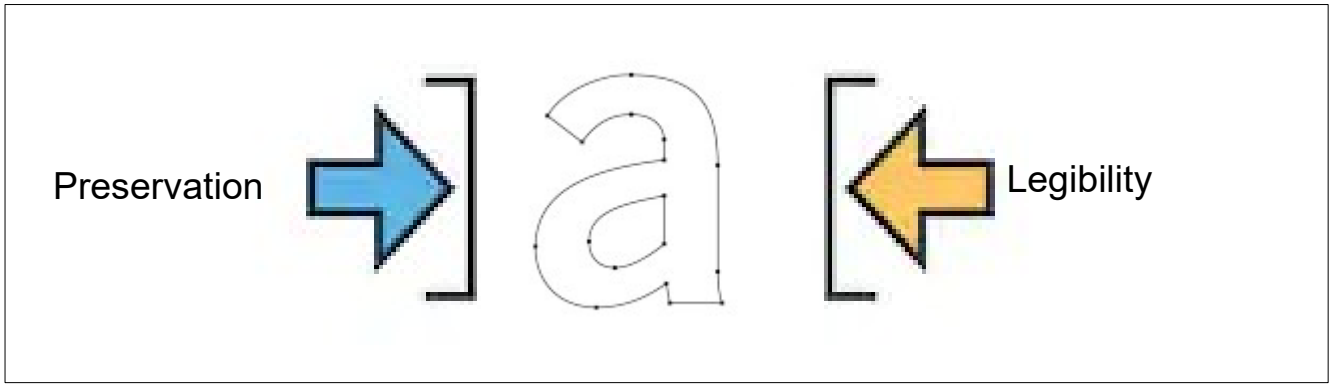


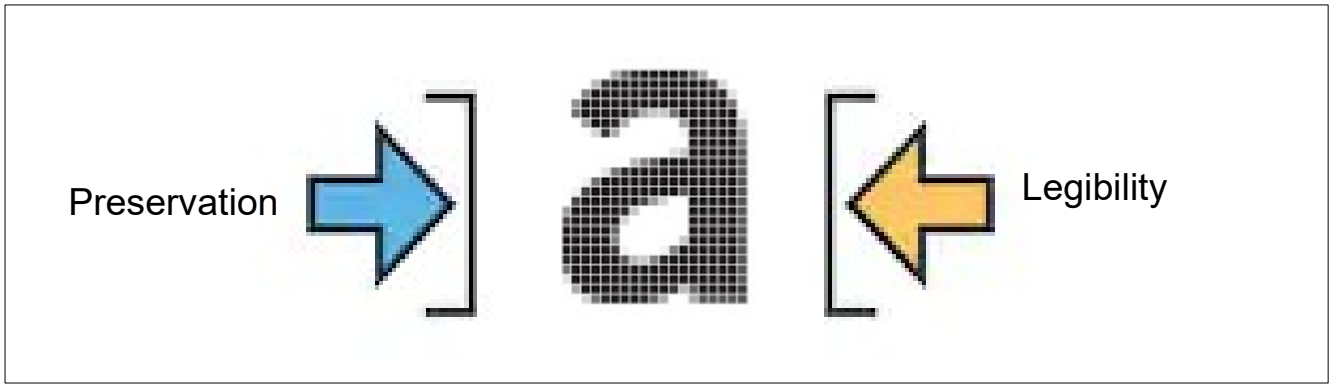
Existing evaluation

Evaluation from map generalization are not adapted for images or for controling deep learning.

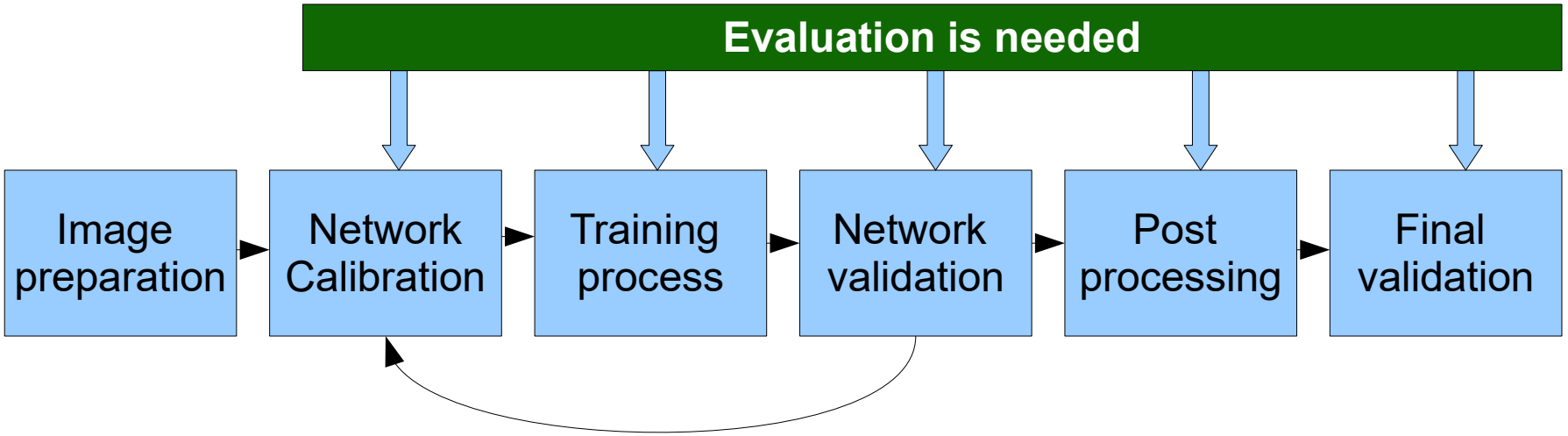


Challenge





Where to evaluate ?



Use case

Mountain roads generalisation from a precise data at 1:25 000 to image legible at 1:250 000.

Our constraints

Legibility constraint

- Smothness
- Coalescence

Preservation constraint

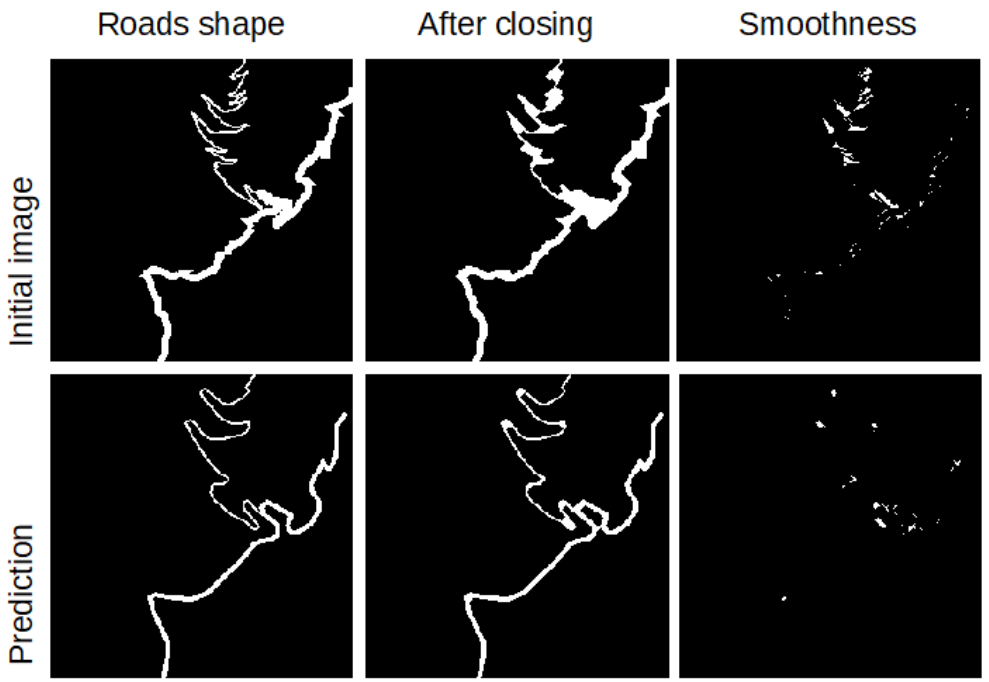
- Position accuracy
- Continuity preservation

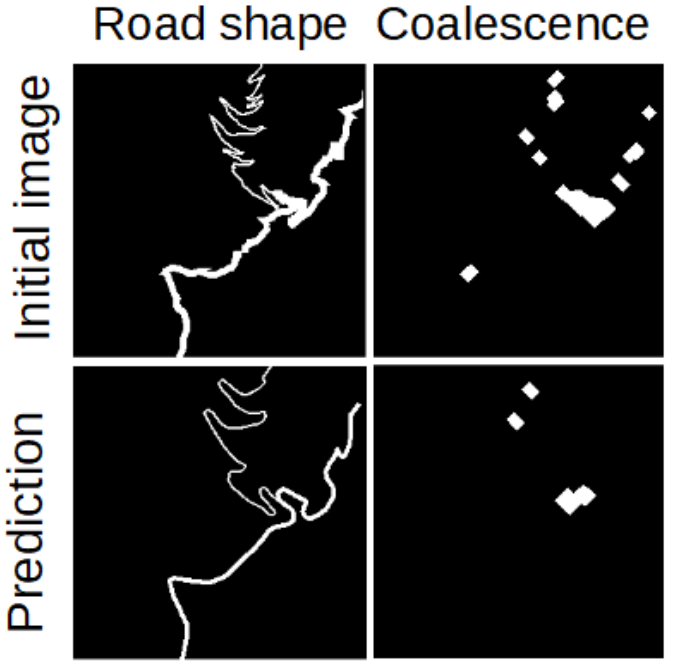
Realism constraint

- Noise
- Color

Legibility constraints

We use morphological mathematic to identify pixels that make the image legiblility decrease.





Preservation constraints

We combine a position accuracy constraint with a structure persevervation constraint based on statisitics on pixels sets.

Initial image
1 road set
3 background sets

Continuity loss
2 road sets
2 background sets

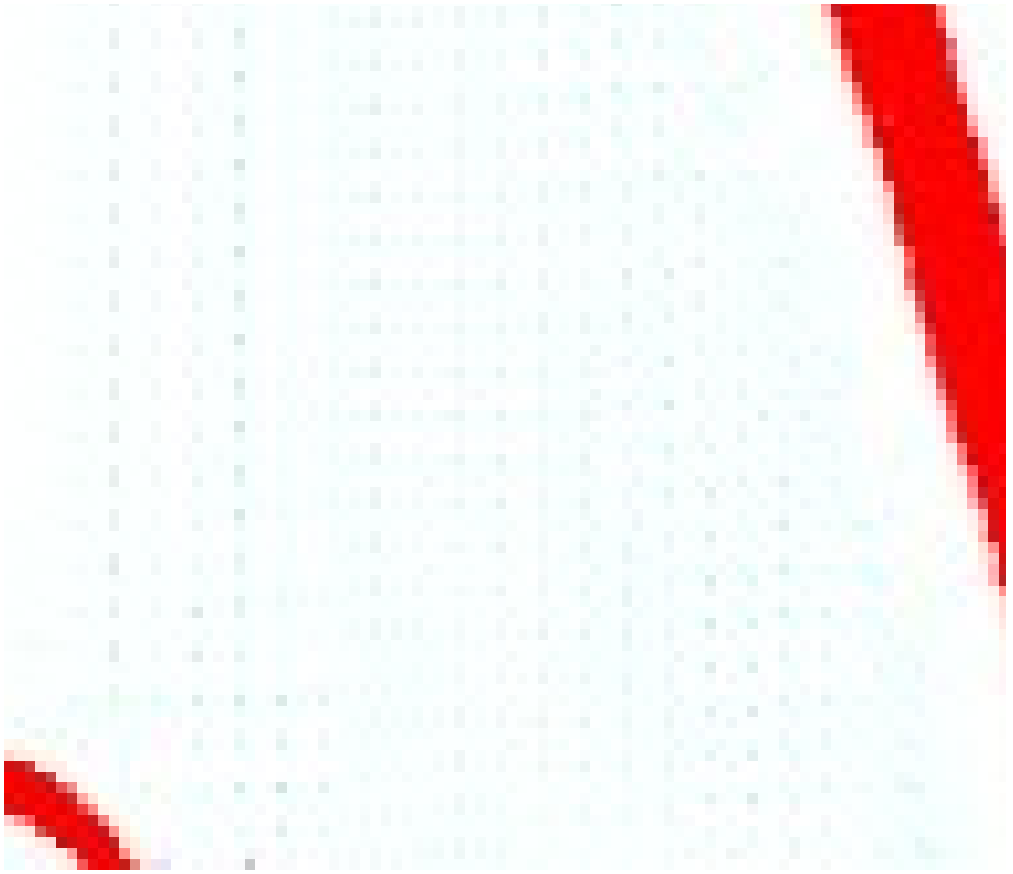
Road disappearance
1 road set
2 background sets

Loop creation
1 road set
4 background sets

Border effect
2 road sets
4 background sets

Realism constraints

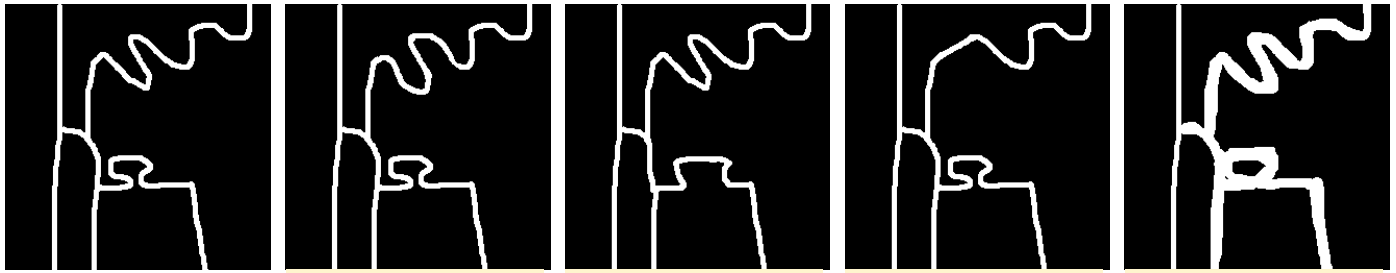
As there is no way to be sure that the deep neural network produce a map we introduce some realism constraint.



Validation

First, we verify that our constraint give the expected result on some extrem fake cases.

Coalescence alteration



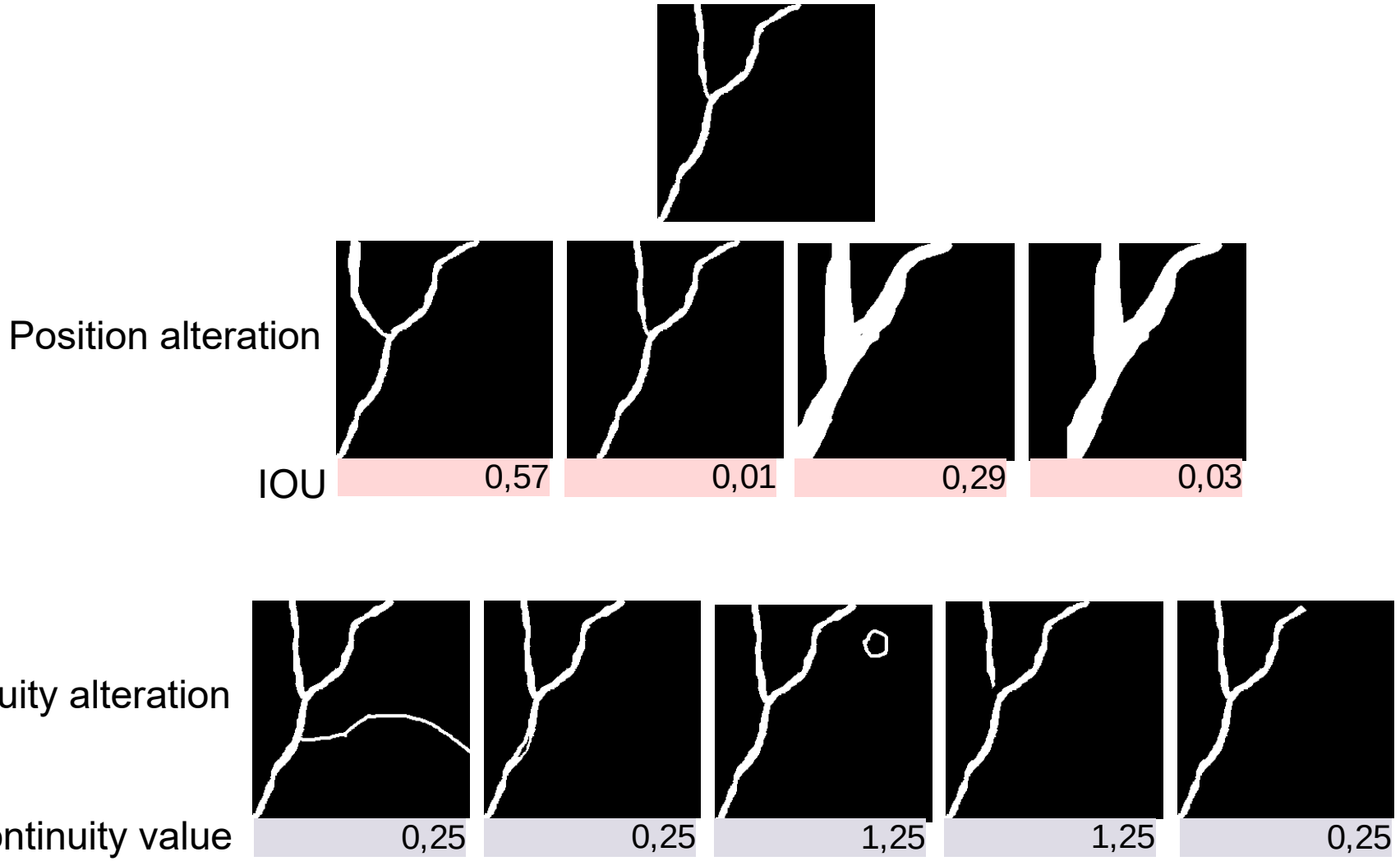
Coalescence value	648	563	591	563	6721

Smoothness alteration

Smoothness value	42	31	33	318

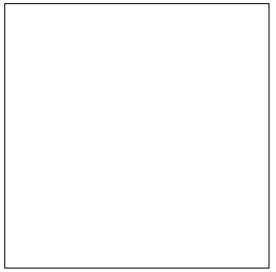
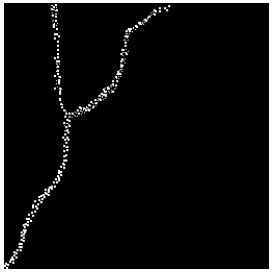
Validation

First, we verify that our constraint give the expected result on some extrem fake cases.



Validation

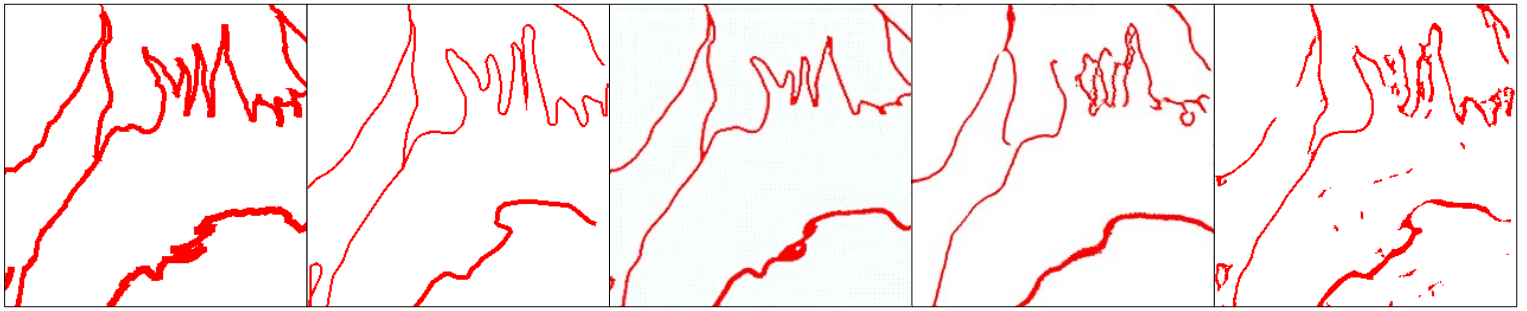
First, we verify that our constraint give the expected result on some extrem fake cases.

Realism alteration					
Coalescence value	633	65025	0	1928	0
Smooth value	42	0	0	195	780
Continuity value		0,75	1,5	64	138,25

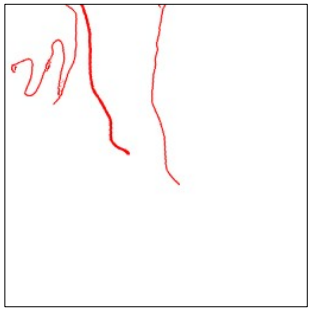
Interest

Compare the metods

Cyclegan > pix2pix > unet



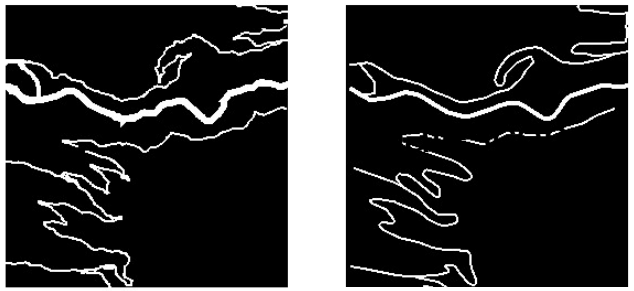
Identifying images that are badly generalized



Constraint	Value
Coalescence	431
Continuity	0,40
Noise	28

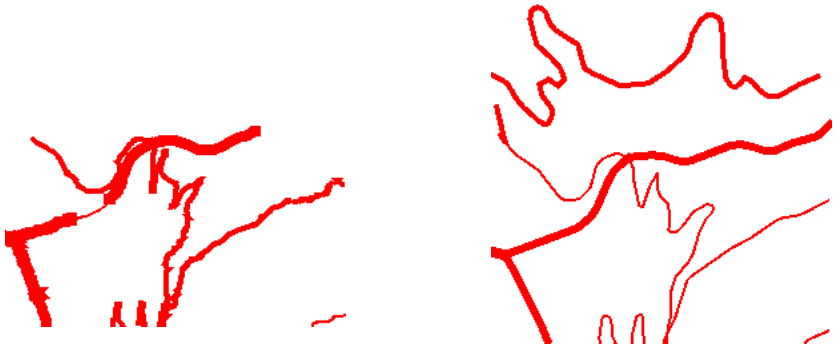
Limits

Why is the measured coalescence greater for the initial image than for the generalized one here?



Threshold effect

Why is the measured smoothness greater for the initial image than for the generalized one here?



Situation effect

Why do the constraint measure an important continuity problem here ?

Border effect

Conclusion

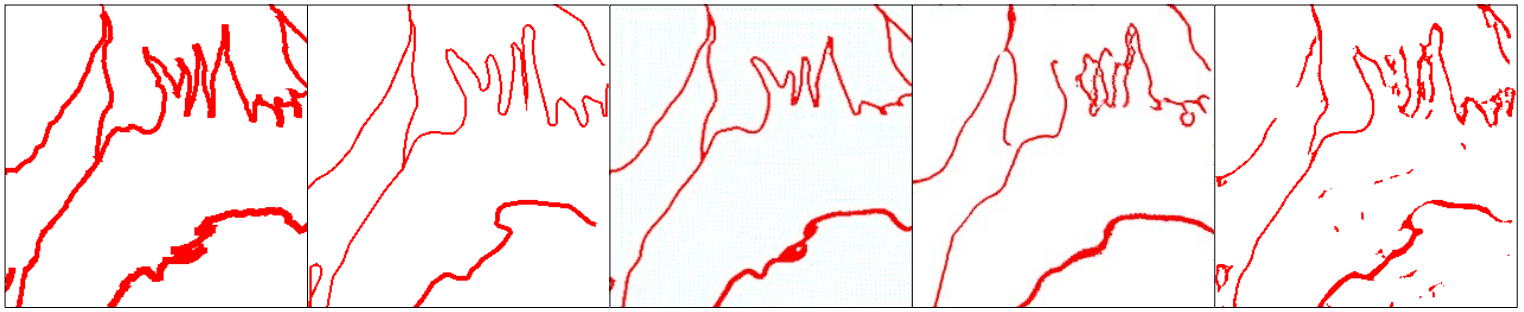
- Pixels based constraint evaluation is possible
- Enable better deep learning models for map generalization
- Remain pixel based issues

Conclusion

- Integrate these constraints as part of the loss function
- User based evaluation

Validation

Then, we verify that our constraints give consistant result with our perception, and especially the legibility value increase with generalisation.



Legibility mean for 12 images	Initial image	Reference	Good prediction	Medium prediction	Bad prediction
Number of coalescent pixel	2682	1275	1139	1153	2345
Part of road pixel that coalesce	0,48	0,32	0,27	0,27	0,53
Number of not smooth pixels	326	42	45	64	79
Part of the roads pixel that are not smooth	4,33	0,96	0,92	1,01	1,72

Validation

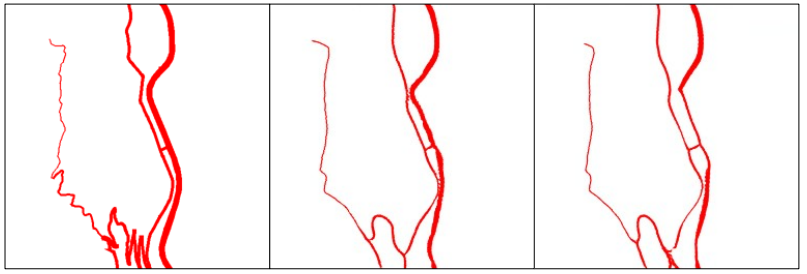
Then, we verify that our constraints give consistant result with our perception, and especially the legibility value increase with generalisation.

Preservation mean for 12 images	Reference	Good prediction	Medium prediction	Bad prediction
Intersection over union	0,19	0,63	0,22	0,23
Continuity constraint	0,35	0,39	0,81	1,85

Un-realism mean for 12 images	Initial image	Reference	Good prediction	Medium prediction	Bad prediction
Noise	0	0,19	0,19	4,69	10,5
Color	0	0	4,78	1,86	0

Use cases

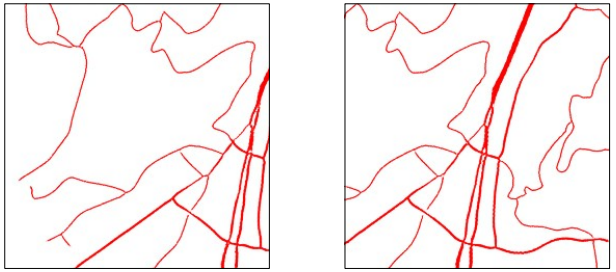
- Add a loss for tuning the learnig process.



- To choose a parameter for the network.
- To confirme the validity of an image.
- To guide the post processing.

  Identify which tiles need to be denoised.

  Identify which shape is better in merging process.



- To identify the weakness of a network.