ICDAR 2025
Wuhan, China

Segmenting France Across Four Centuries

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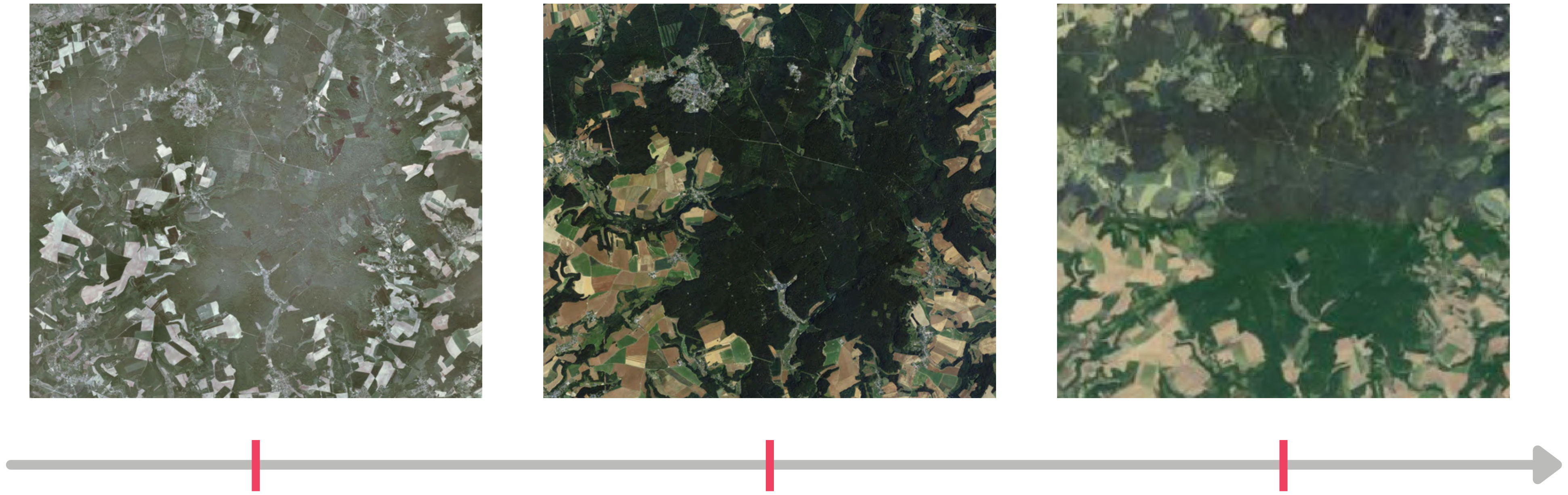
September 18, 2025

Motivation

Track changes in land cover

2000 2006 2012



Satellites were invented in the **1950s**

- Deforestation
- Urban sprawl
- Transportation network expansion

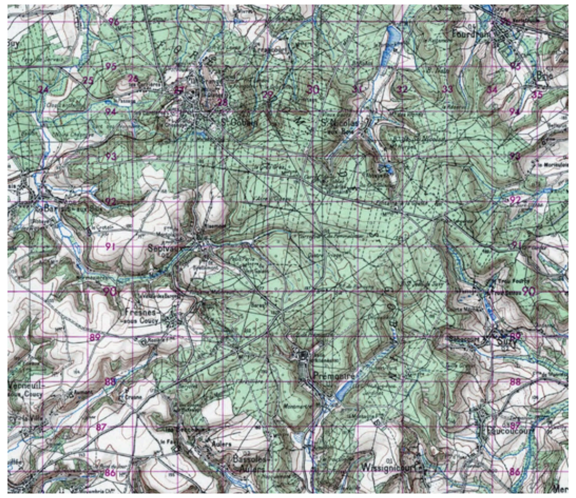
Satellite images: Institut national de l'information géographique et forestière (IGN)

Motivation

Track **long-term** changes in land cover 🌱 🌊 🏢

18th century

19th century



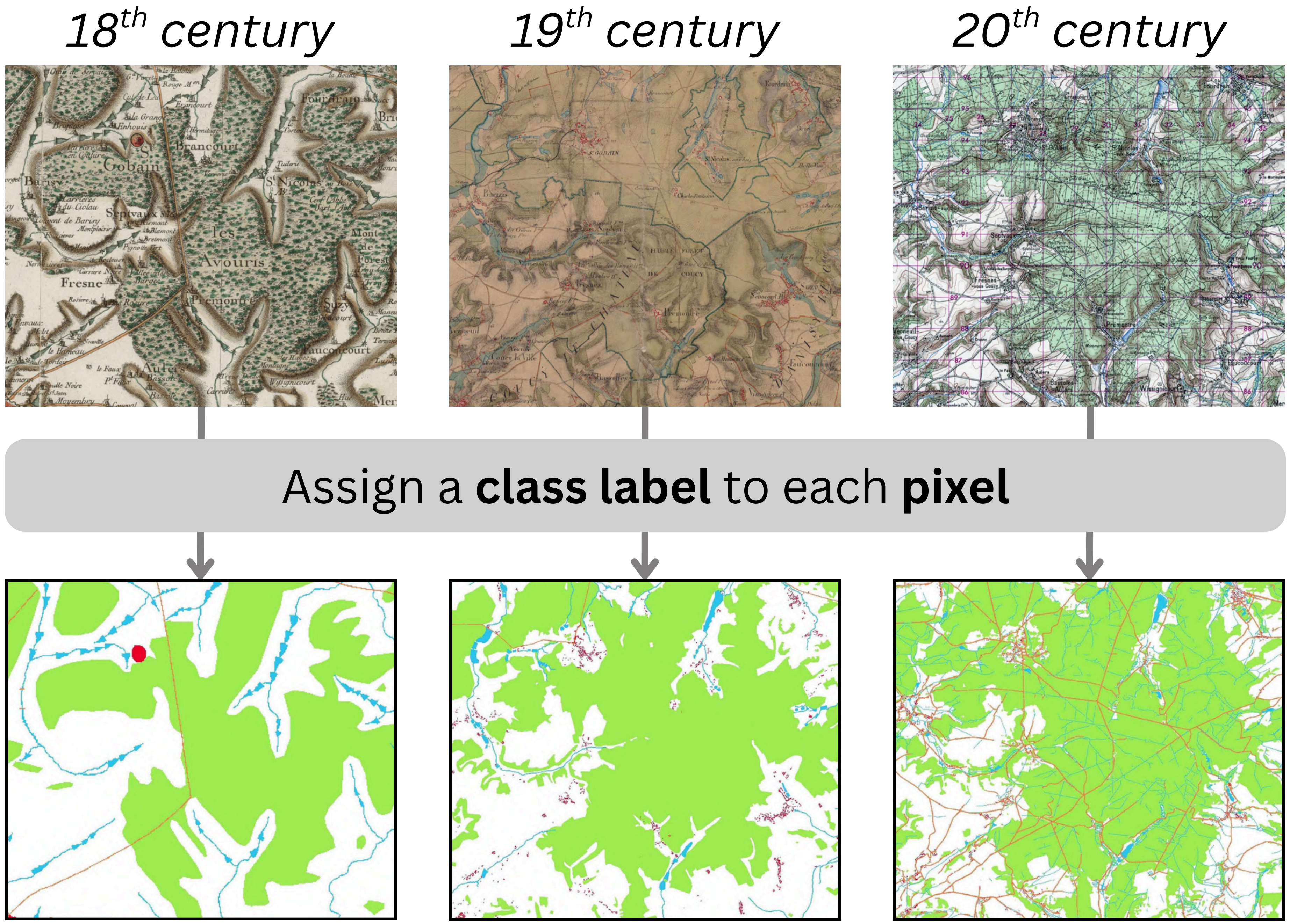
20th century

Historical maps

- Deforestation
- Urban sprawl
- Transportation network expansion

Motivation

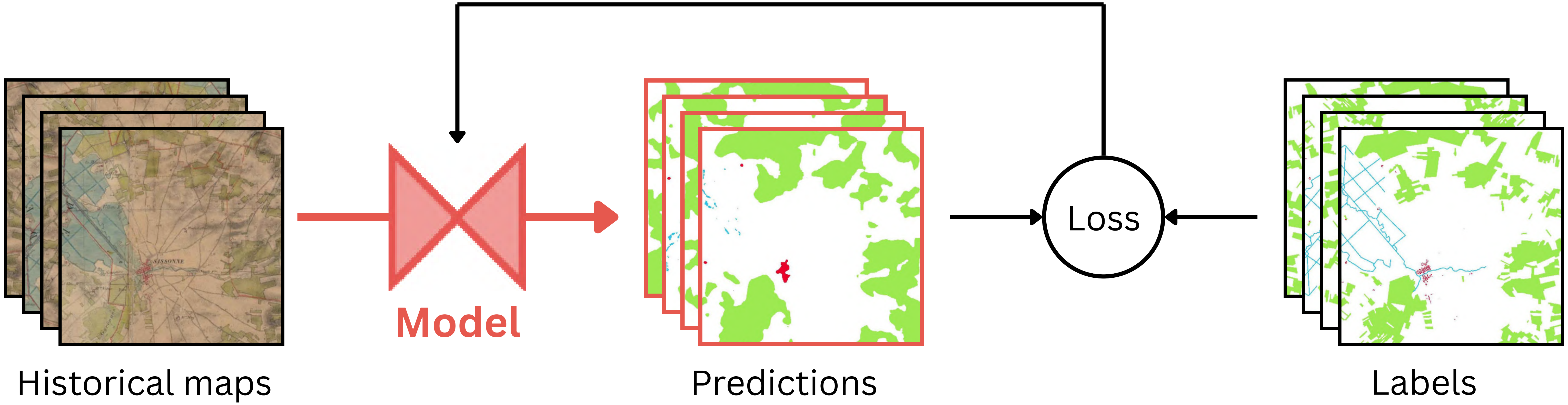
Track **long-term** changes in land cover 🌱🌊🏢



Historical maps

Semantic segmentation

DL-based semantic segmentation

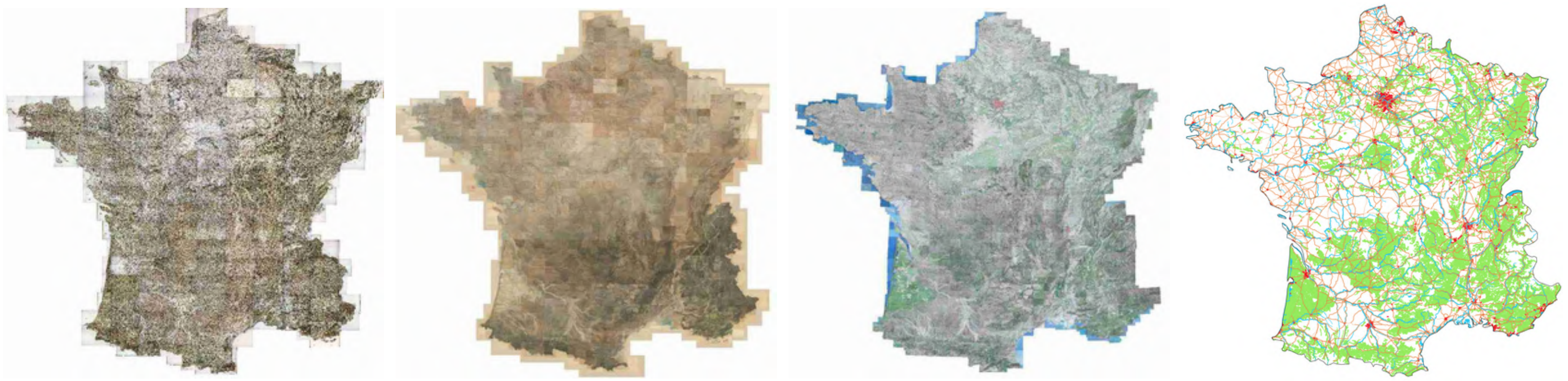


Ståhl, N., Weimann, L.: *Identifying wetland areas in historical maps using deep convolutional neural networks.* Ecol. Inform. (2022) – **Avcı, C.** et al.: *Deep learning-based road extraction from historical maps.* GRSL (2022) – **Martinez, T.** et al.: *Deep learning ancient map segmentation to assess historical landscape changes.* JoM (2023) – **Wu, S.** et al.: *Leveraging uncertainty estimation and spatial pyramid pooling for extracting hydrological features from scanned historical topographic maps.* GIScience & Remote Sensing (2022) – **Can, Y.S.** et al.: *Automatic detection of road types from the third military mapping survey of Austria-Hungary historical map series with deep convolutional neural networks.* IEEE Access (2021) – **Saeedimoghaddam, M.**, Stepinski, T.F.: *Automatic extraction of road intersection points from USGS historical map series using deep convolutional neural networks.* Int. J. Geogr. Inf. Sci. (2020)

Contributions

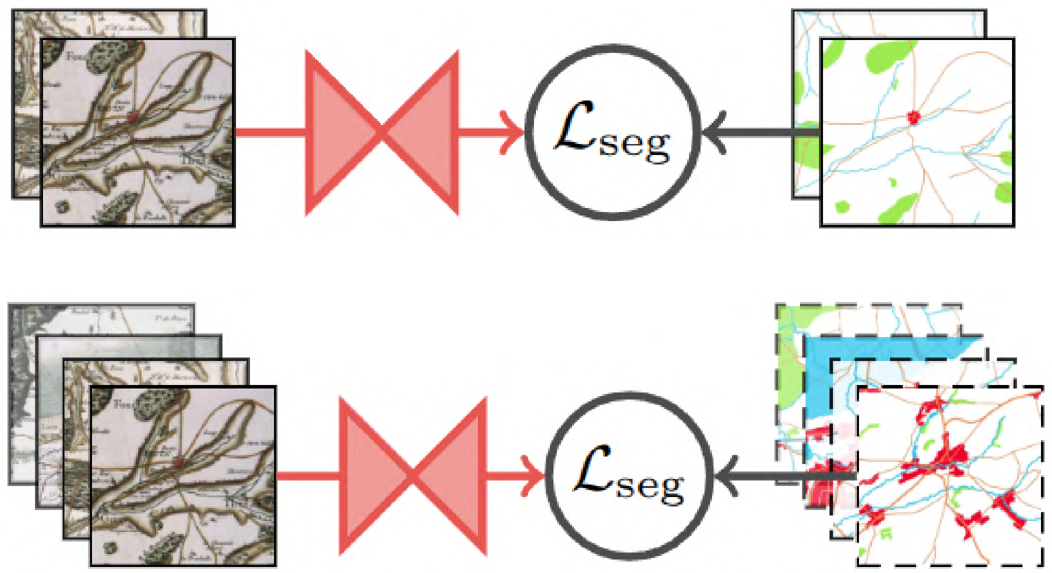
1. Historical map segmentation **dataset**

- Countrywide
- Multi-class
- Spanning four centuries



2. Segmentation baseline **benchmark**

- One supervised
- Two weakly-supervised



Strong supervision

- Historical labels

Weak supervision

- Present-day labels

Historical map segmentation datasets

Dataset	Multi-period	Collection	Period	Location	Extent in km²	Labels x10⁶ px	Classes
Wu et al.	✗	Siegfried	1880	Switzerland	23,048	3,715	hydrography
Martínez et al.	✗	Cassini	1750-1815	France	10,000	134	vegetation, hydrography
Can et al.	✗	Generalkarte	1884-1918	Hungary	321,146	115	roads
Ekim et al.	✗	DHK Turkey	1941-1943	Turkey	132,970	464	roads
Hosseini et al.	✗	Ordnance Survey	1888-1913	UK	620	1,490	buildings, rail
Petitpierre et al., *Paris*	~	Maps of Paris	1765-1994	France	≤105	330	buildings, hydrography, roads
Petitpierre et al., *World*	~	Several	1720-1950	World	-	305	buildings, hydrography, roads
Ours	✓	Cassini	1750-1815	France	548,305	499	vegetation, buildings, hydrography, roads
		État-Major	1820-1866	France	548,305	499	vegetation, buildings, hydrography, roads
		SCAN50	1889-1922	France	548,305	0	vegetation, buildings, hydrography, roads
		Present-day maps	2019	France	548,305	11,963	vegetation, buildings, hydrography, roads

✗ single time period

~ multiple time periods, unaligned

✓ multiple time periods, aligned

hydrography · vegetation · roads · buildings · rail

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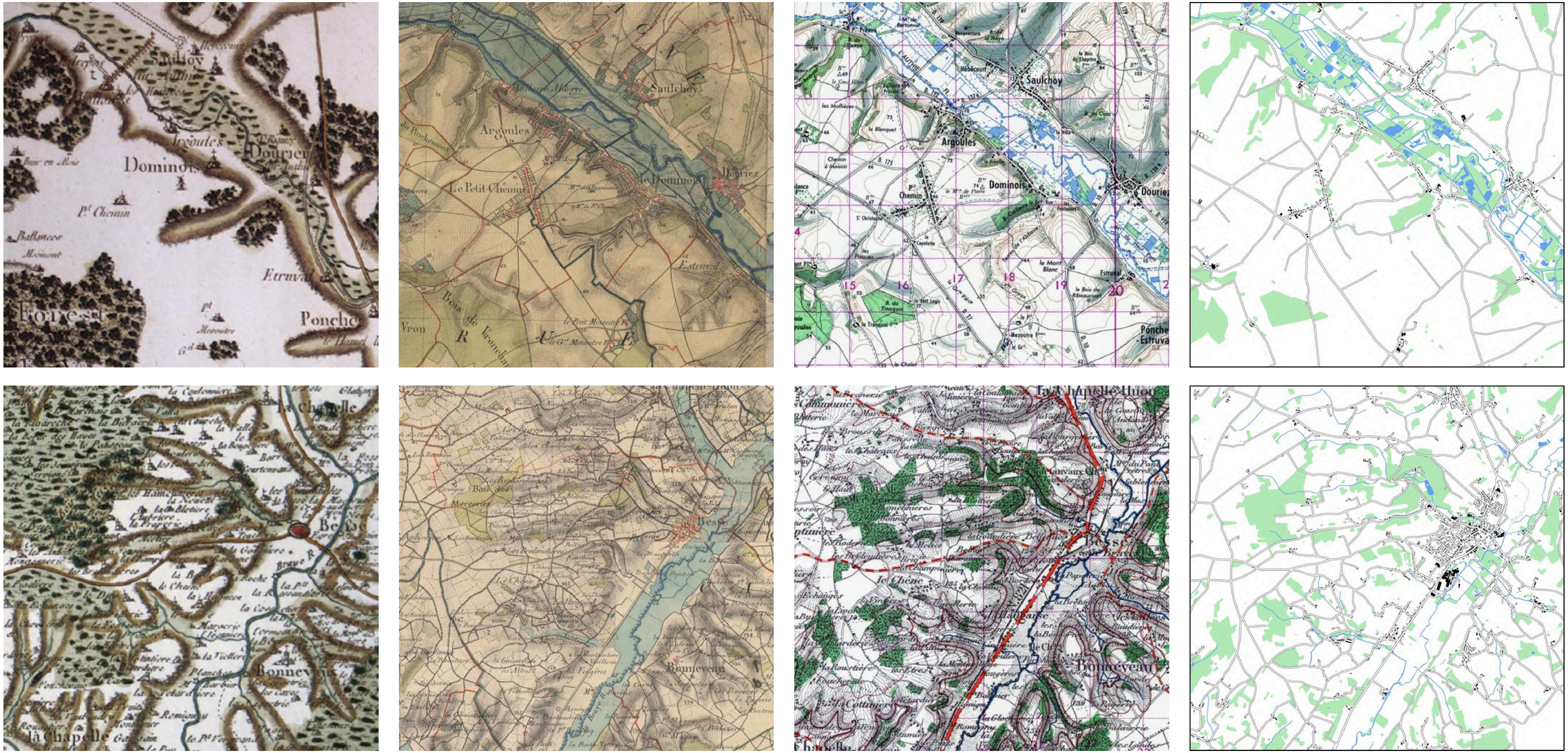
Cassini
18th century

État-Major
19th century

SCAN50
20th century

2019 map
21st century



Cassini: EHESS/CRH
État-Major, SCAN50, 2019 map: Institut national de l'information géographique et forestière (IGN)

Variation within a map collection - Cassini

Cassini: EHESS/CRH

Contribution 1 - Dataset

FRAx4

A multi-date historical map segmentation dataset

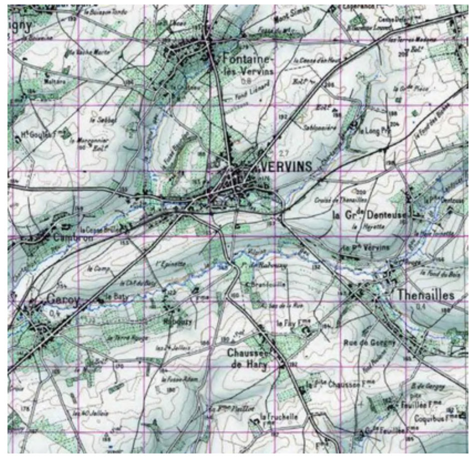
- Metropolitan **France** (548,305 km^2)
- **18th to 21st** centuries
- **Four classes**
  - Forest
  - Buildings
  - Hydrography
  - Roads
- Partial **historical labels** (4.2%)
- Comprehensive **present-day labels**

Historical map

Cassini 18th century

État-Major 19th century

SCAN50 20th century



3 x 10,952 tiles

Cassini: EHESS/CRH
État-Major, SCAN50: Institut national de l'information géographique et forestière (IGN)

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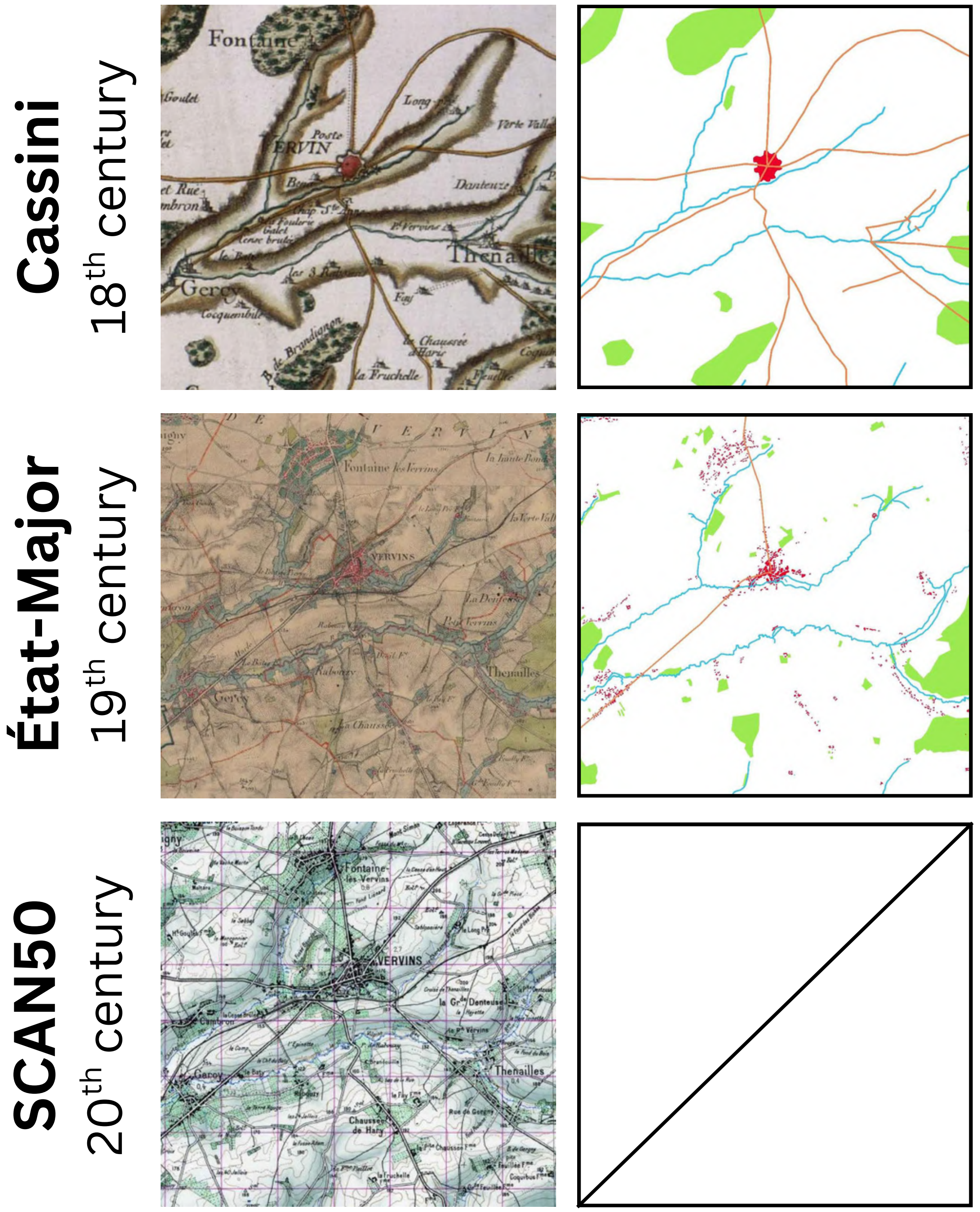
Historical map | Historical labels



3 x 10,952 tiles | *2 x 470 tiles*

Historical label sources

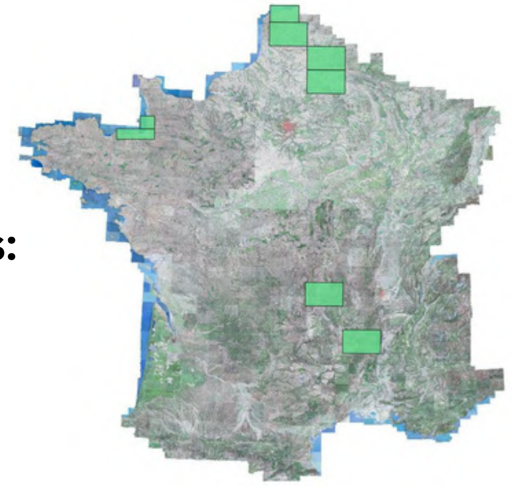
Cassini

- **Vallauri, D.** et al.: *Les forêts de Cassini. Analyse quantitative et comparaison avec les forêts actuelles.* Rapport Technique, WWF (2012)
- **Perret, J.** et al.: *Roads and cities of 18th century France.* Scientific data (2015)

État-Major

- Institut national de l'information géographique et forestière (**IGN**)

Labeled areas:



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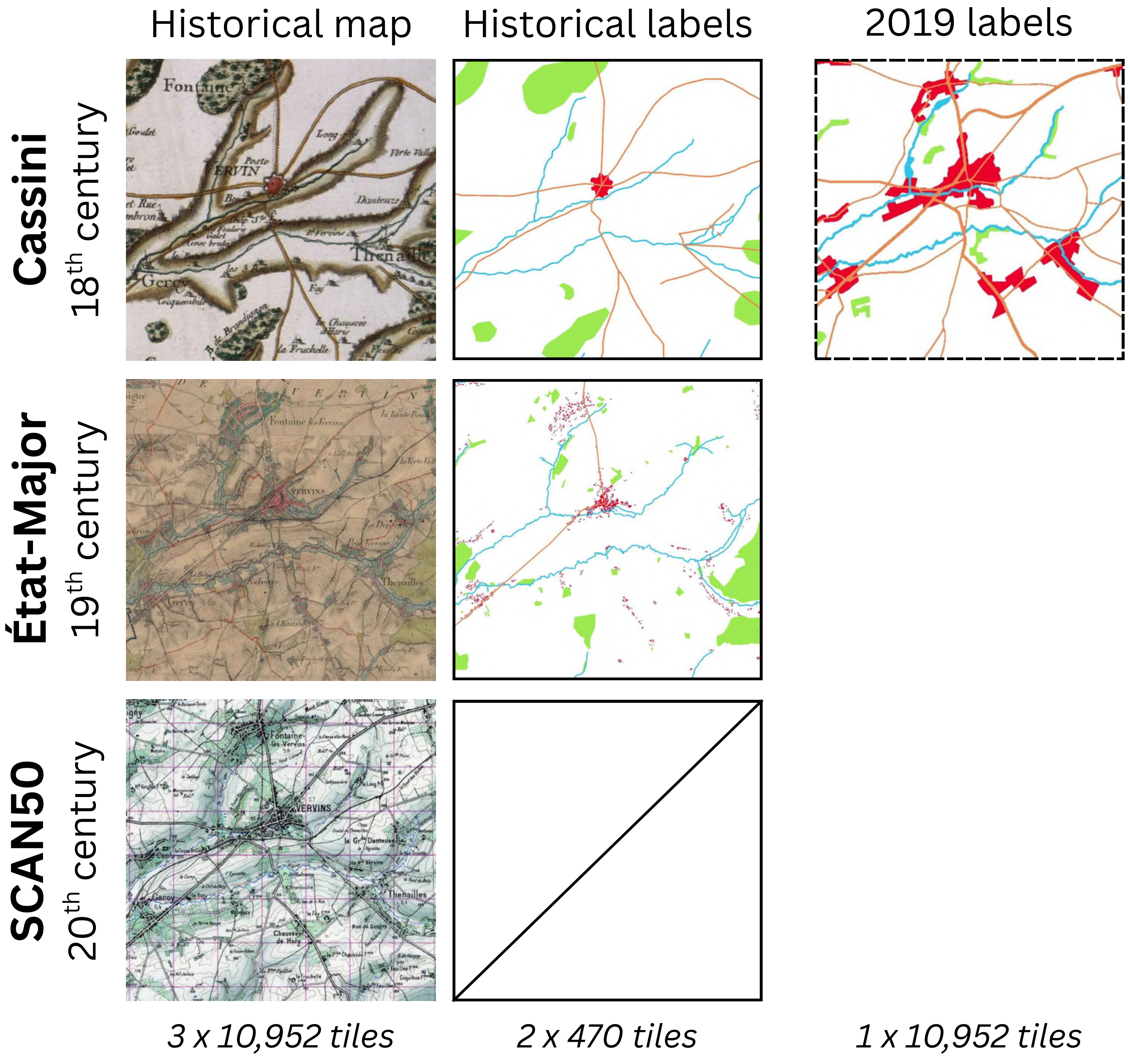

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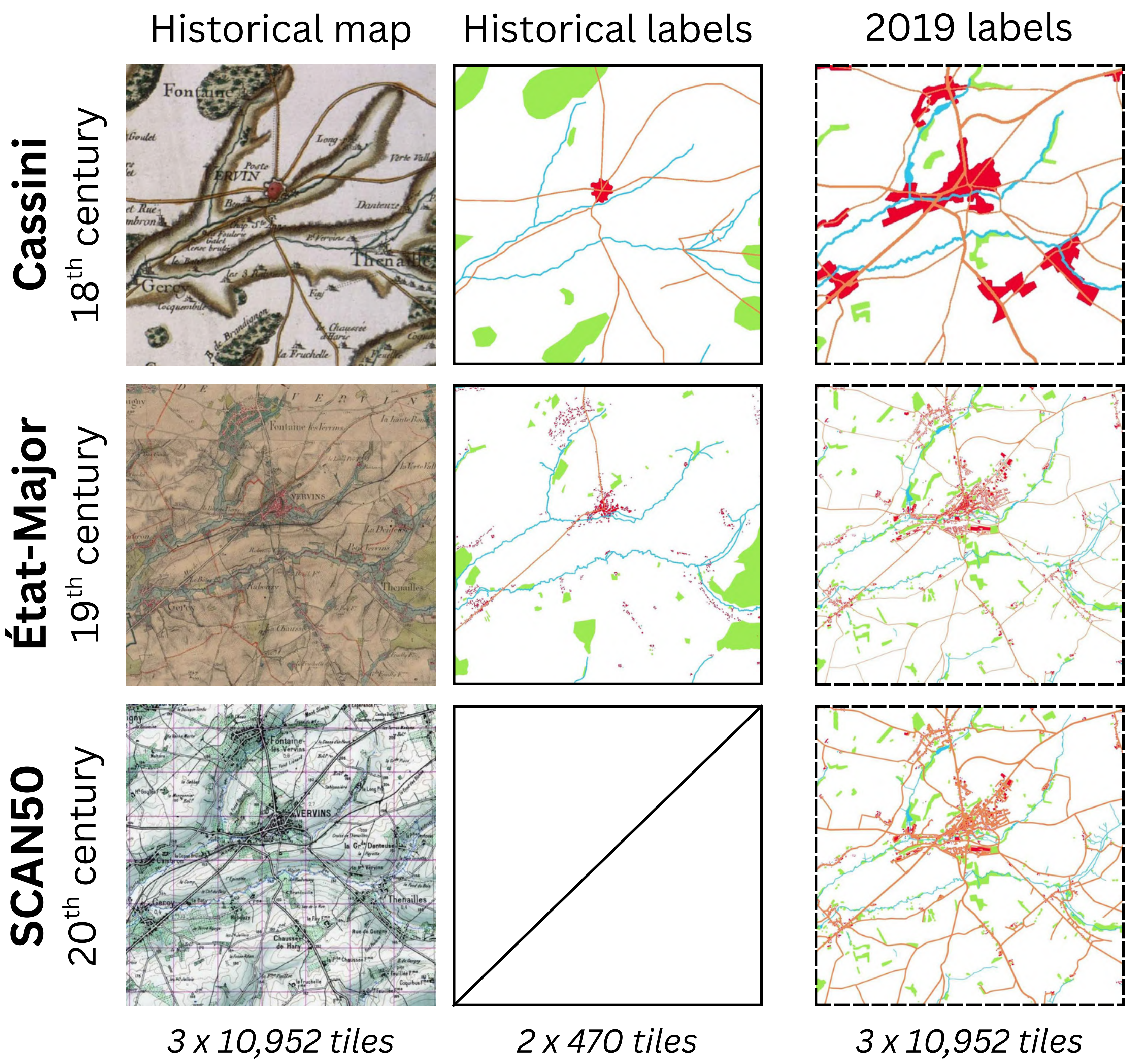

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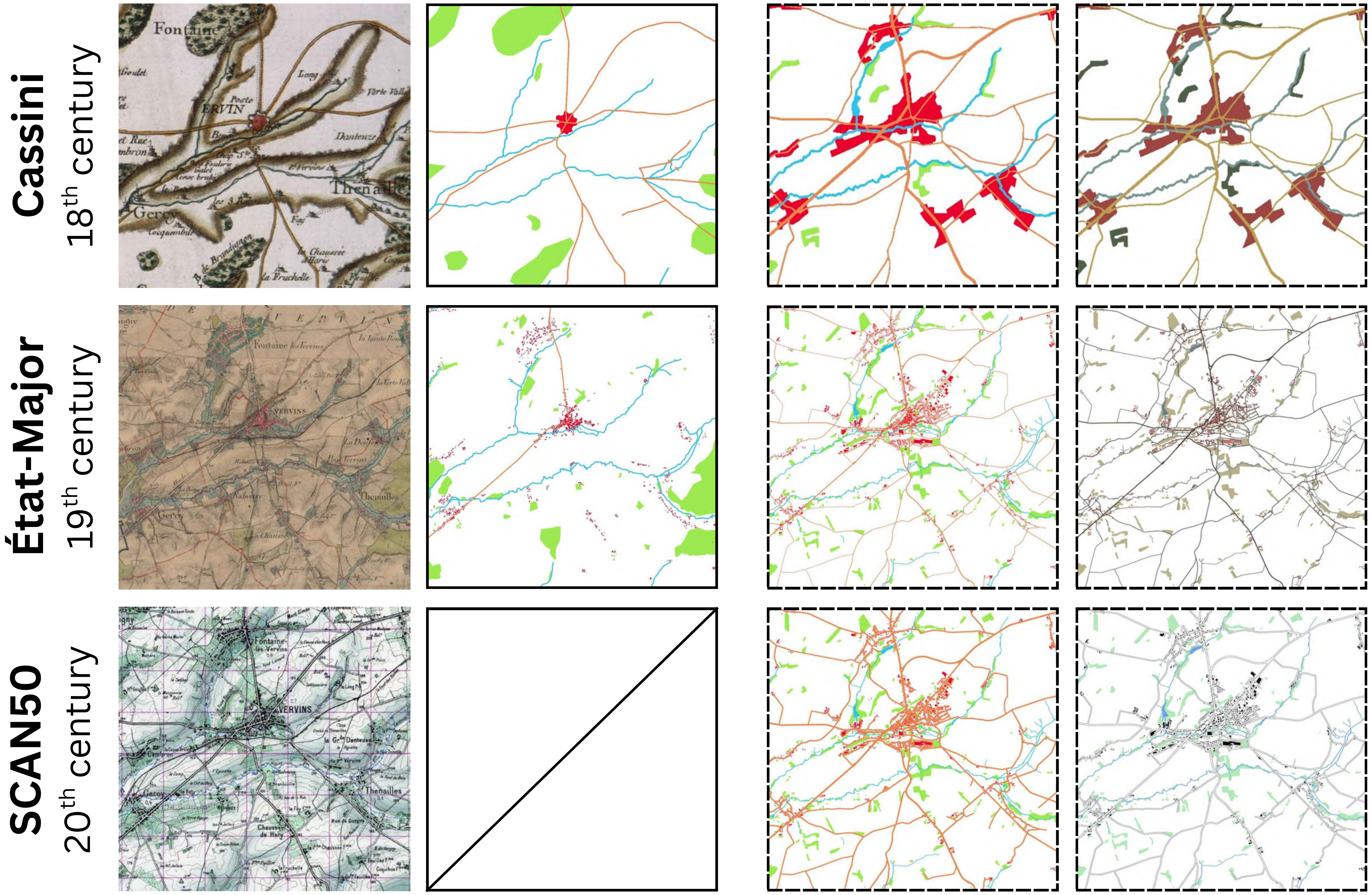

Cassini: EHESS/CRH
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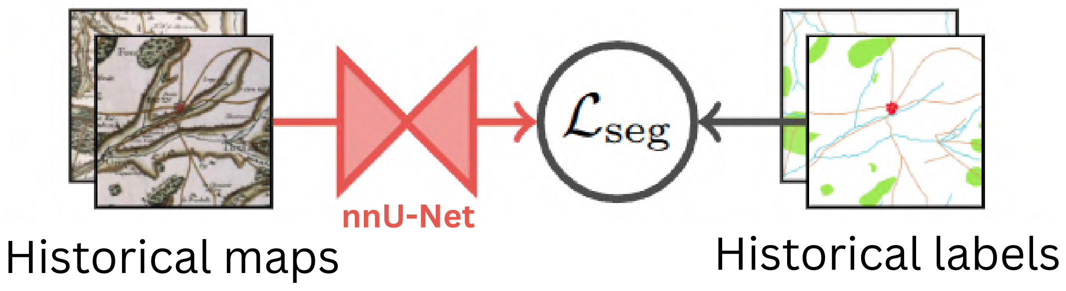
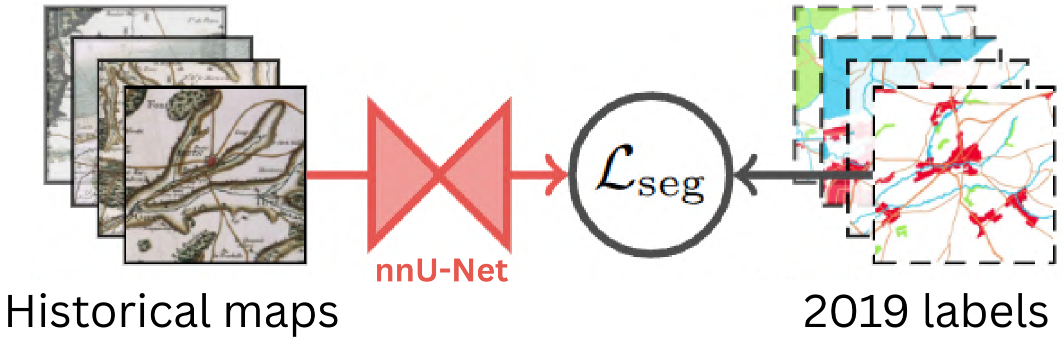
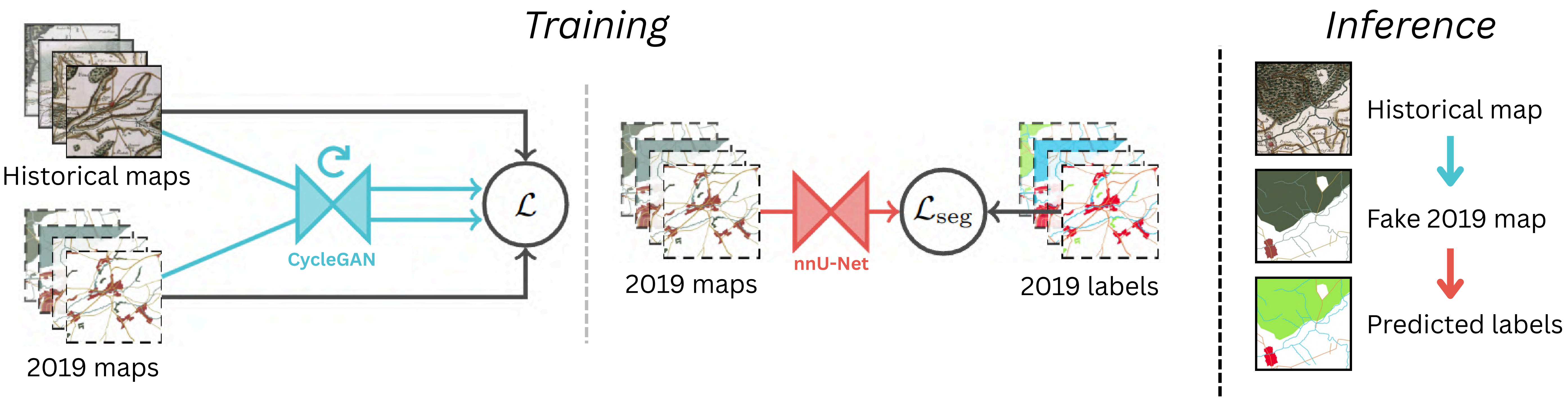
Contribution 2 - Baselines



A) Supervised Segmentation



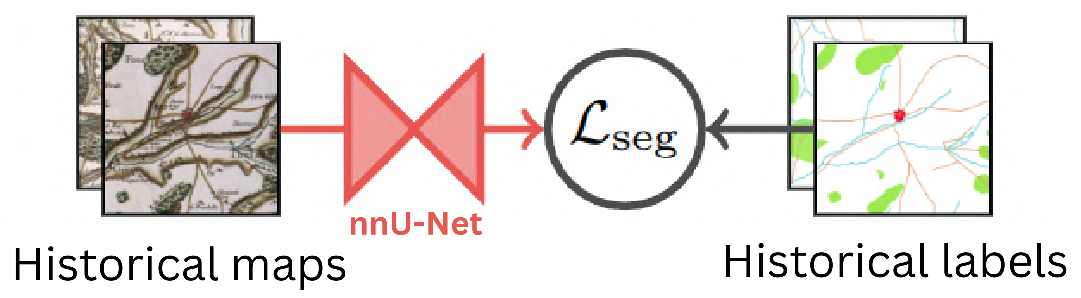
B) Direct Weakly-Supervised Segmentation



C) Translation + Segmentation

CycleGAN: Zhu, J.Y. et al.: *Unpaired image-to-image translation using cycle-consistent adversarial networks*. IEEE ICCV (2017)
nnU-Net: Isensee, F. et al.: *nnU-Net: A self-configuring method for deep learning-based biomedical image segmentation*. Nat. Methods (2021)

Contribution 2 - Baselines



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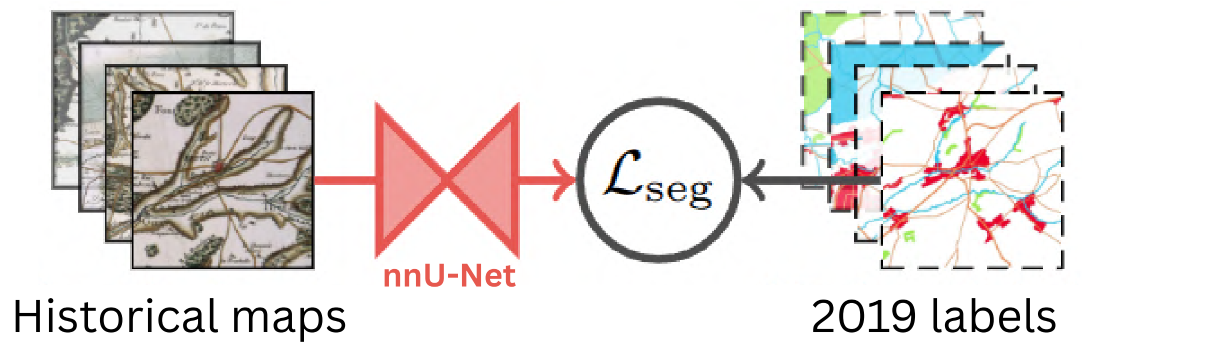

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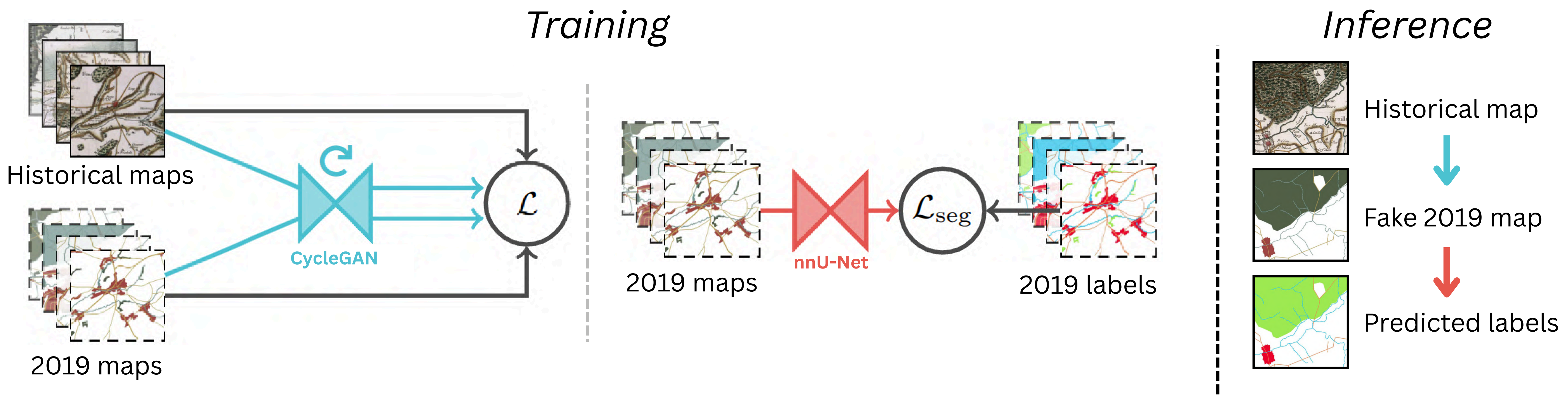

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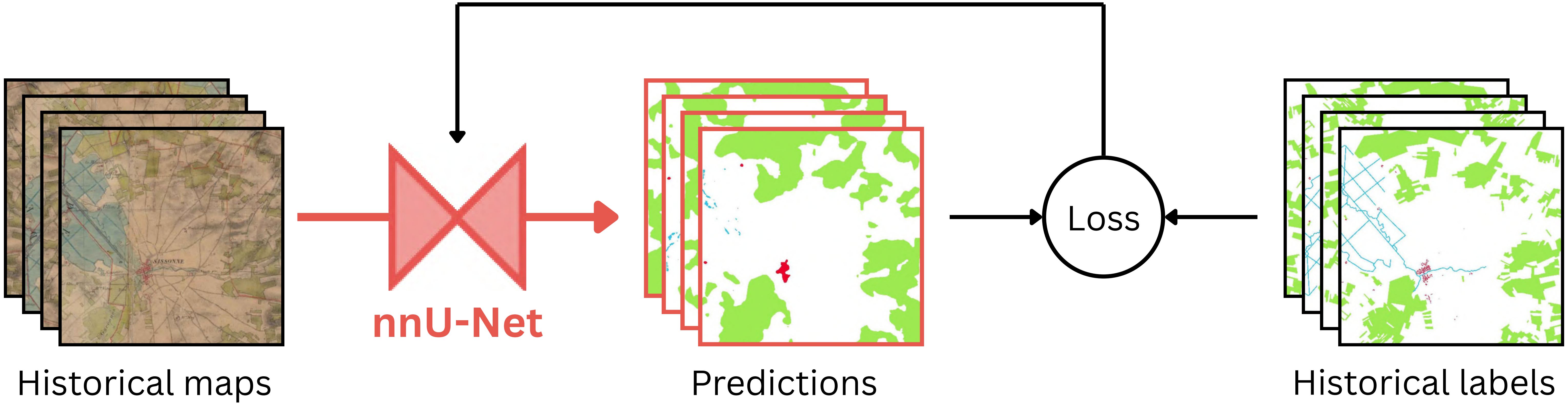

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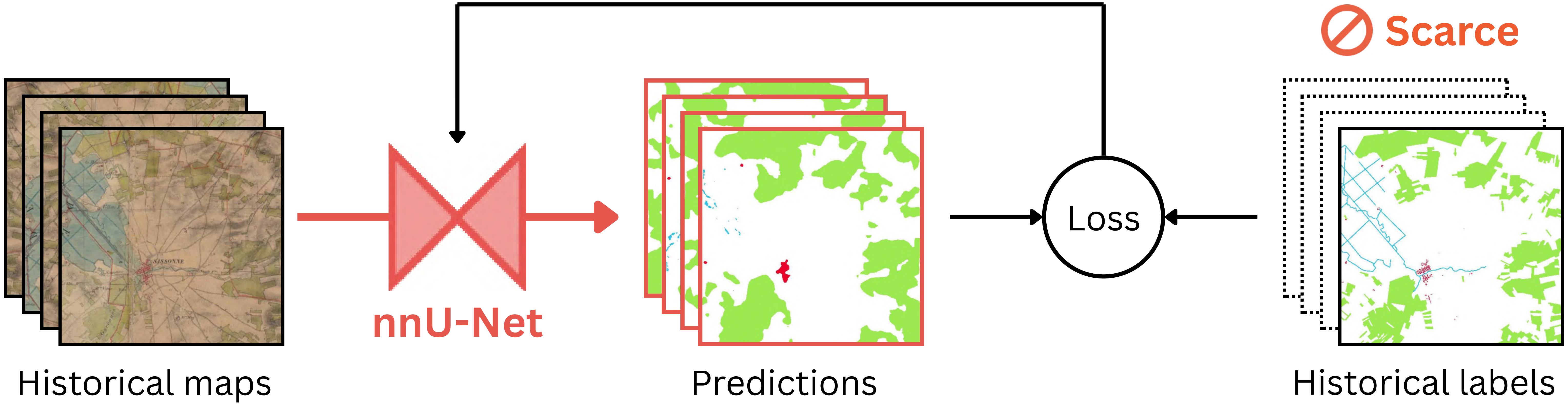
A) Supervised Segmentation

Challenge - Lack of annotated data



- **Historical** map annotation is **very costly**

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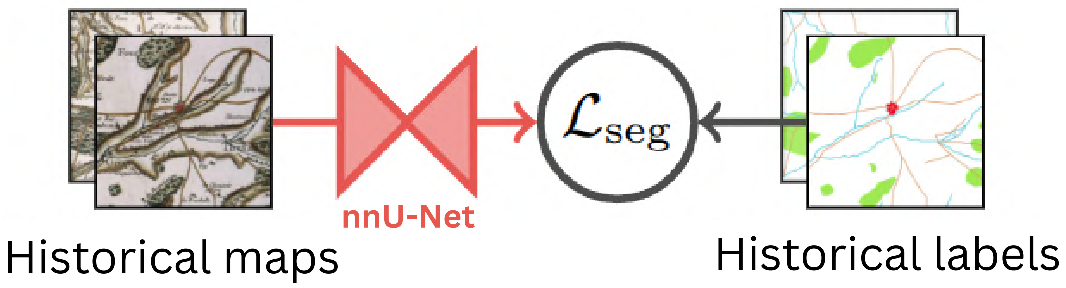

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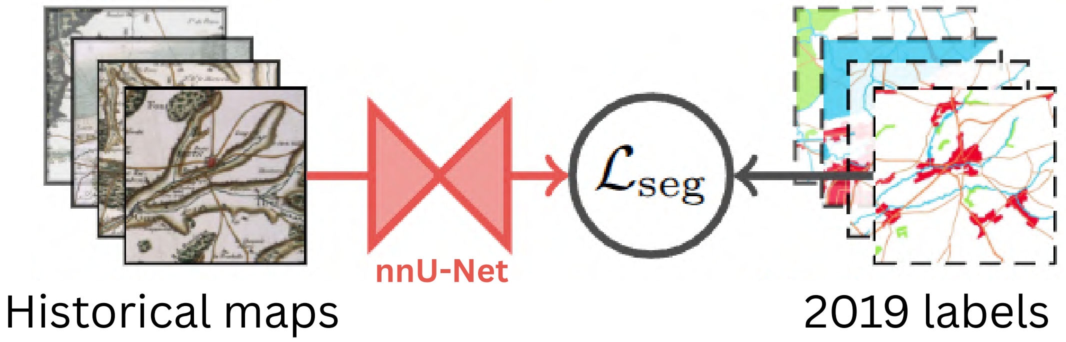

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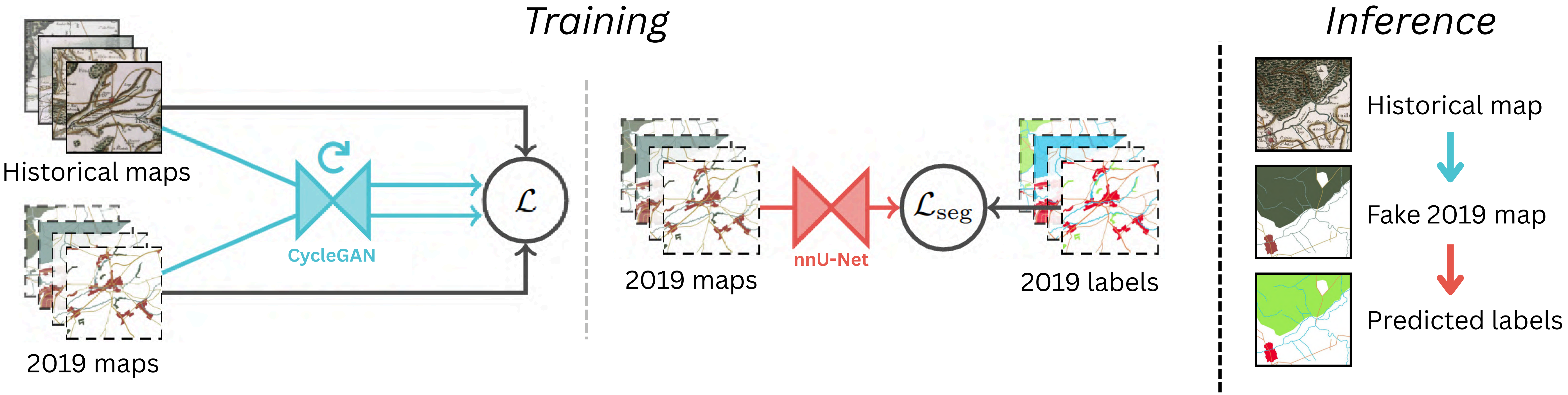

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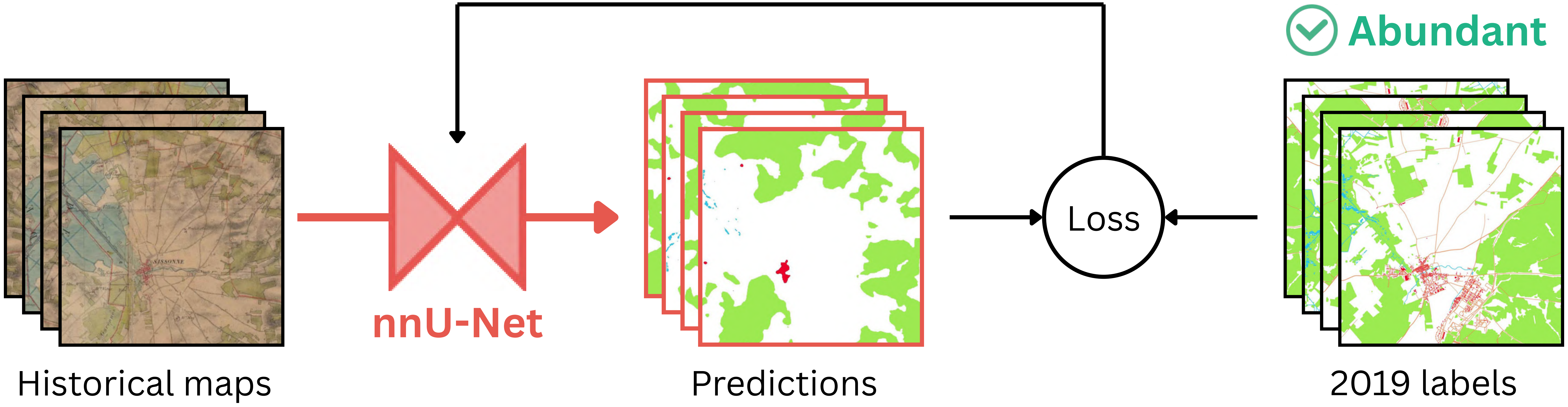
B) Direct Weakly-Supervised Segmentation

Solution - Use present-day labels

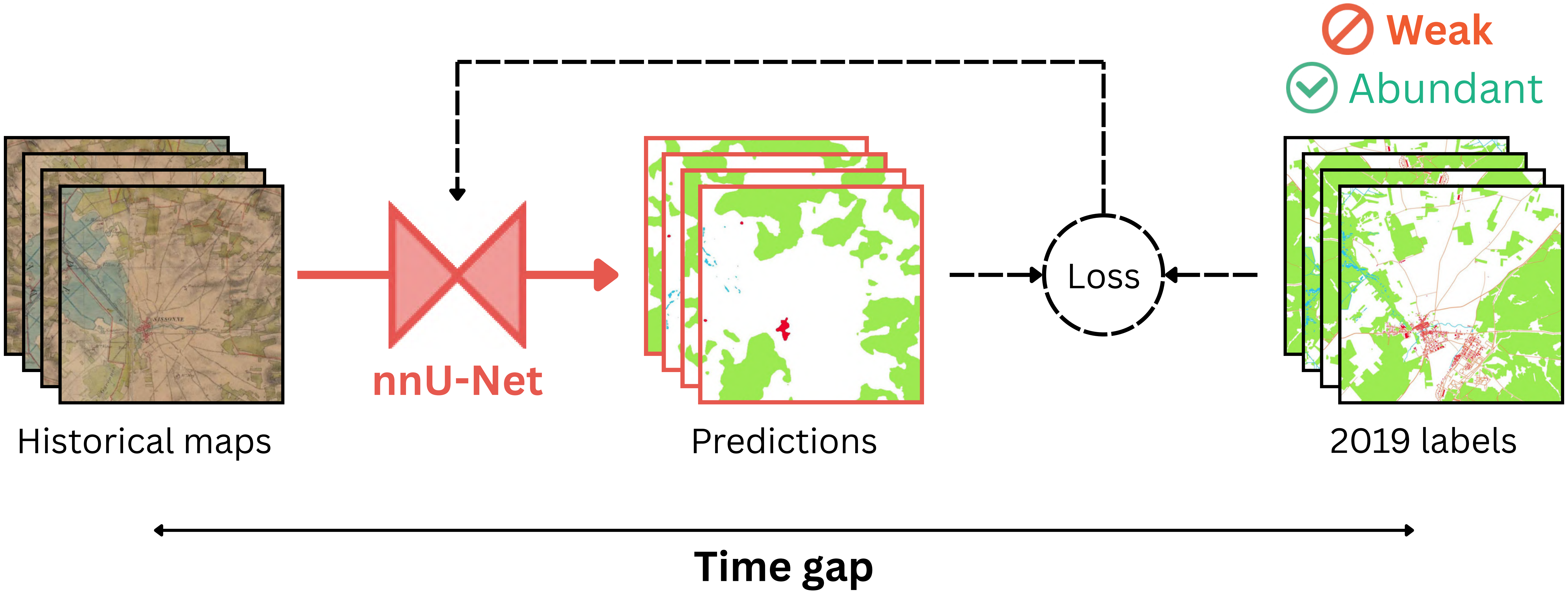


- Historical map annotation is very costly
- **Modern** remote sensing imagery is **easy to obtain**

Uhl, J.H. et al.: *Towards the automated largescale reconstruction of past road networks from historical maps*. CEUS (2022) – **Uhl, J.H.** et al.: *Automated extraction of human settlement patterns from historical topographic map series using weakly supervised convolutional neural networks*. IEEE Access (2019) – **Briand, S.** et al.: *LULC segmentation in historical images under domain shift: An empirical study*. IGARSS (2024) – **Duan, W.** et al.: *Automatic alignment of contemporary vector data and georeferenced historical maps using reinforcement learning*. Int. J. Geogr. Inf. (2020)

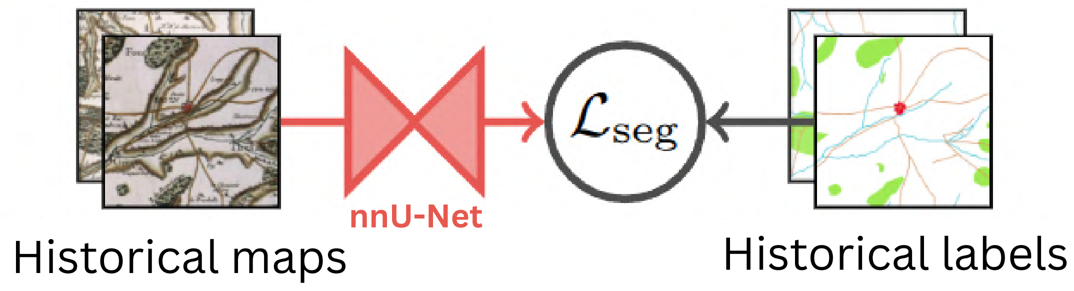
B) Direct Weakly-Supervised Segmentation

Challenge - Weak supervision

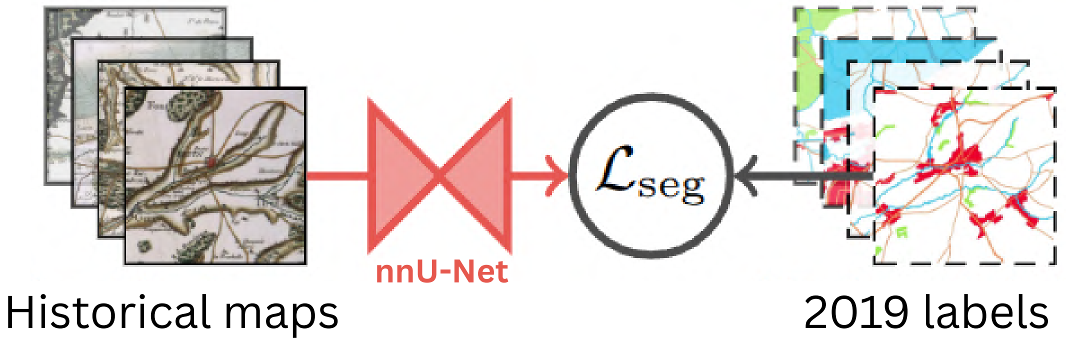


Uhl, J.H. et al.: *Towards the automated largescale reconstruction of past road networks from historical maps*. CEUS (2022) – **Uhl, J.H.** et al.: *Automated extraction of human settlement patterns from historical topographic map series using weakly supervised convolutional neural networks*. IEEE Access (2019) – **Briand, S.** et al.: *LULC segmentation in historical images under domain shift: An empirical study*. IGARSS (2024) – **Duan, W.** et al.: *Automatic alignment of contemporary vector data and georeferenced historical maps using reinforcement learning*. Int. J. Geogr. Inf. (2020)

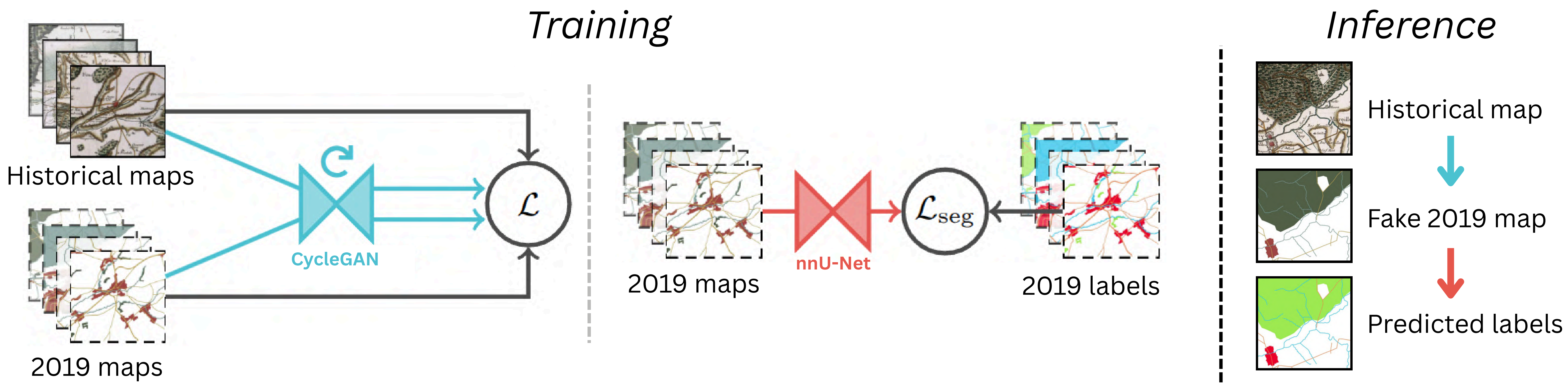
Contribution 2 - Baselines



A) Supervised Segmentation



B) Direct Weakly-Supervised Segmentation

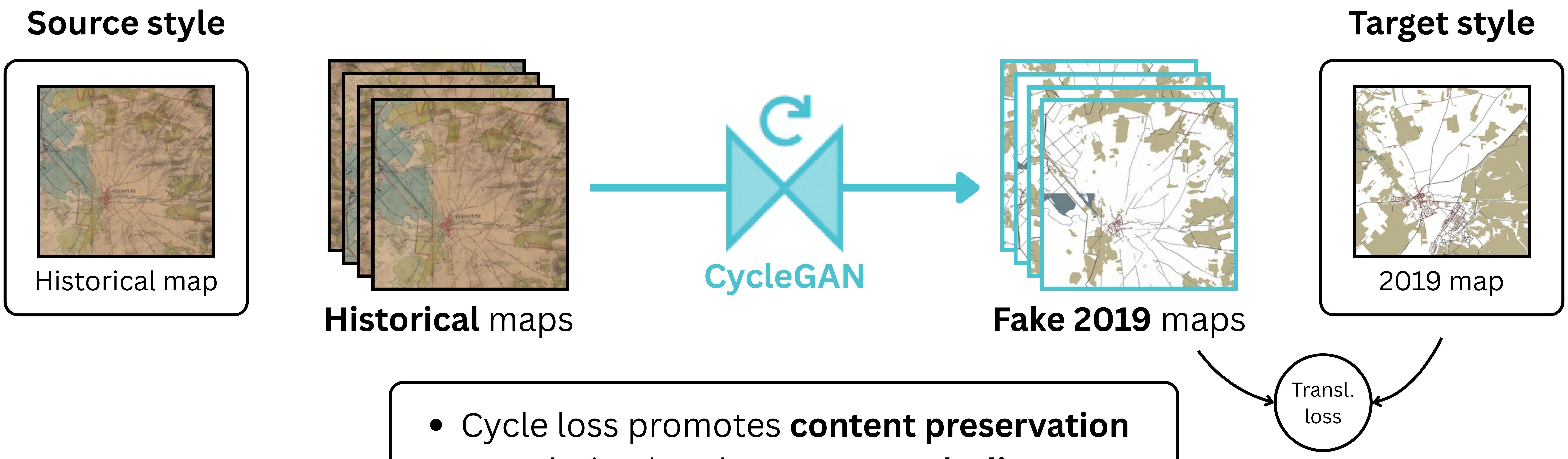


C) Translation + Segmentation

CycleGAN: Zhu, J.Y. et al.: *Unpaired image-to-image translation using cycle-consistent adversarial networks*. IEEE ICCV (2017)
nnU-Net: Isensee, F. et al.: *nnU-Net: A self-configuring method for deep learning-based biomedical image segmentation*. Nat. Methods (2021)

C) Translation + Segmentation

Solution - Image-to-image translation



- Cycle loss promotes **content preservation**
- Translation loss leverages **weak alignment**

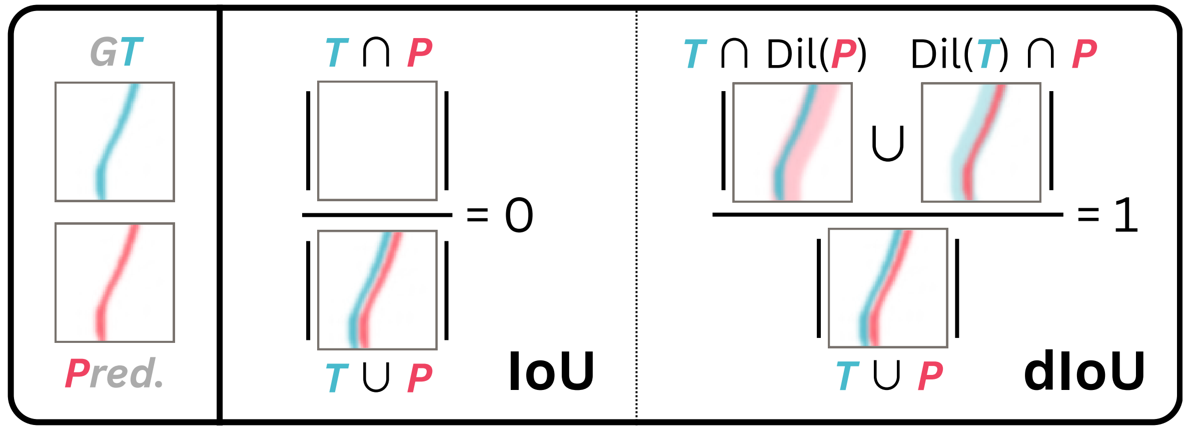
Christophe, S. et al.: *Neural map style transfer exploration with GANs*. Int. J. Cartogr. (2022) – **Andrade, H.J.A.**, Fernandes, B.J.T.: *Synthesis of satellite-like urban images from historical maps using conditional GAN*. GRSL (2022) – **Wong, C.S.** et al.: *Semi-supervised learning for topographic map analysis over time: A study of bridge segmentation*. Sci. Rep. (2022) – **Mühlematter, D.J.** et al.: *Probabilistic road classification in historical maps using synthetic data and deep learning.* arXiv:2410.02250 (2024) – **Arzoumanidis, L.** et al.: *Deep generation of synthetic training data for the automated extraction of semantic knowledge from historical maps.* ICA-Abs (2024) – **Li, Z.** et al.: *Synthetic map generation to provide unlimited training data for historical map text detection*. GeoAI (2021) – **Jiao, C.** et al.: *A fast and effective deep learning approach for road extraction from historical maps by automatically generating training data with symbol reconstruction.* Int. J. Appl. Earth Obs. Geoinf. (2022)

Results - Segmentation

OA: Overall Accuracy **dIoU**: dilated Intersection over Union

Map	Baseline	OA	Mean dIoU	Per-class dIoU			
Cassini	**A)** Supervised	96.7	76.4	88.3	69.8	85.0	62.6
	B) Direct weakly-supervised	79.8	26.1	35.8	**5.3**	63.1	0.0
	C) Translation + segmentation	**85.3**	**36.1**	**56.1**	4.7	**70.9**	**12.7**
État-Major	**A)** Supervised	91.3	61.2	77.4	56.3	65.4	46.0
	B) Direct weakly-supervised	**83.3**	**38.6**	**49.6**	**39.6**	**58.6**	**6.3**
	C) Translation + segmentation	78.4	28.7	43.0	15.6	51.0	5.3

- **Supervised** segmentation works best
- **Weakly-supervised** achieves fair OA
- Results can still be **improved**



Dilated IoU: Cheng, B. et al.: *Boundary IoU: Improving object-centric image segmentation evaluation*. IEEE/CVF CCVPR (2021)

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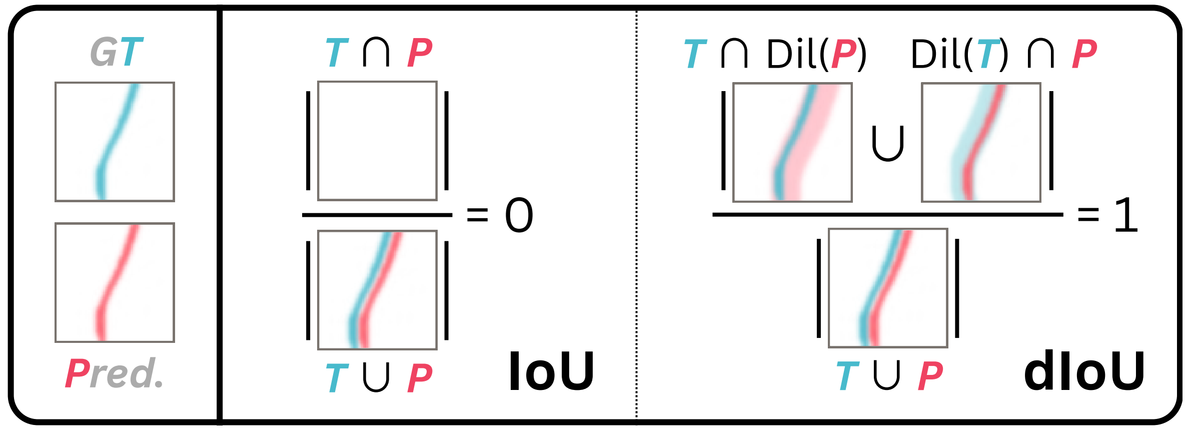

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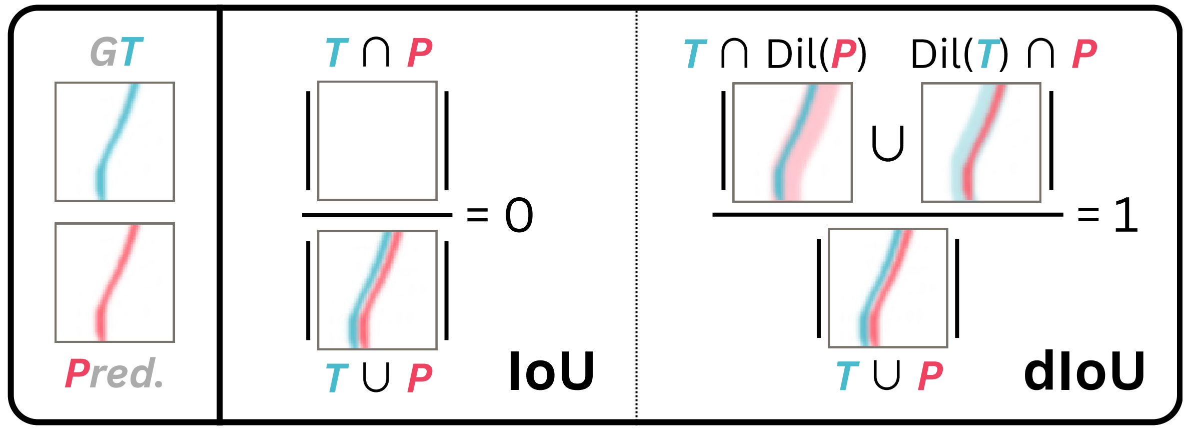

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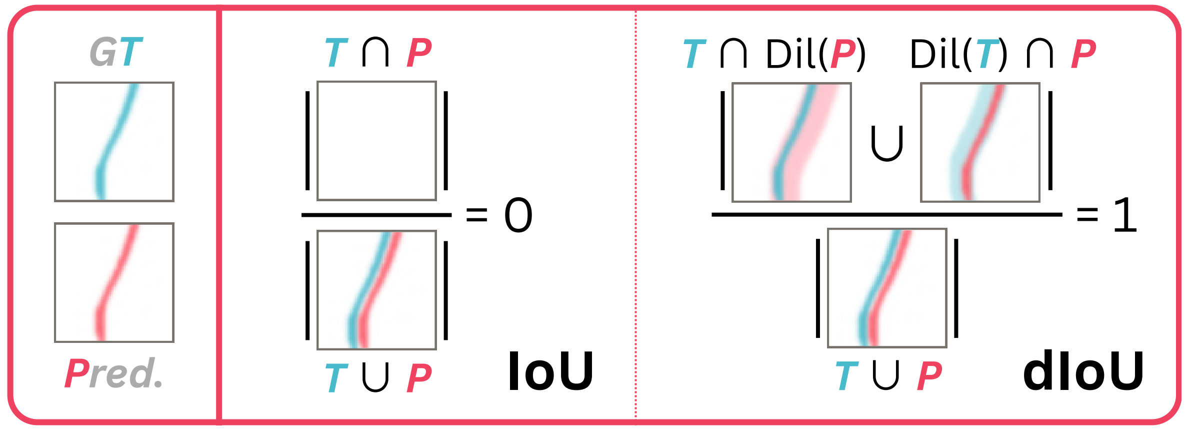

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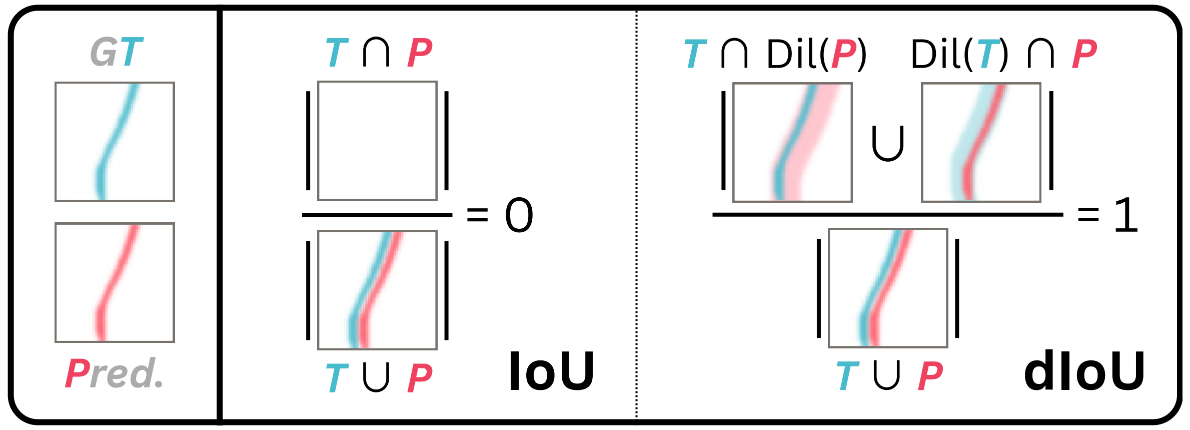

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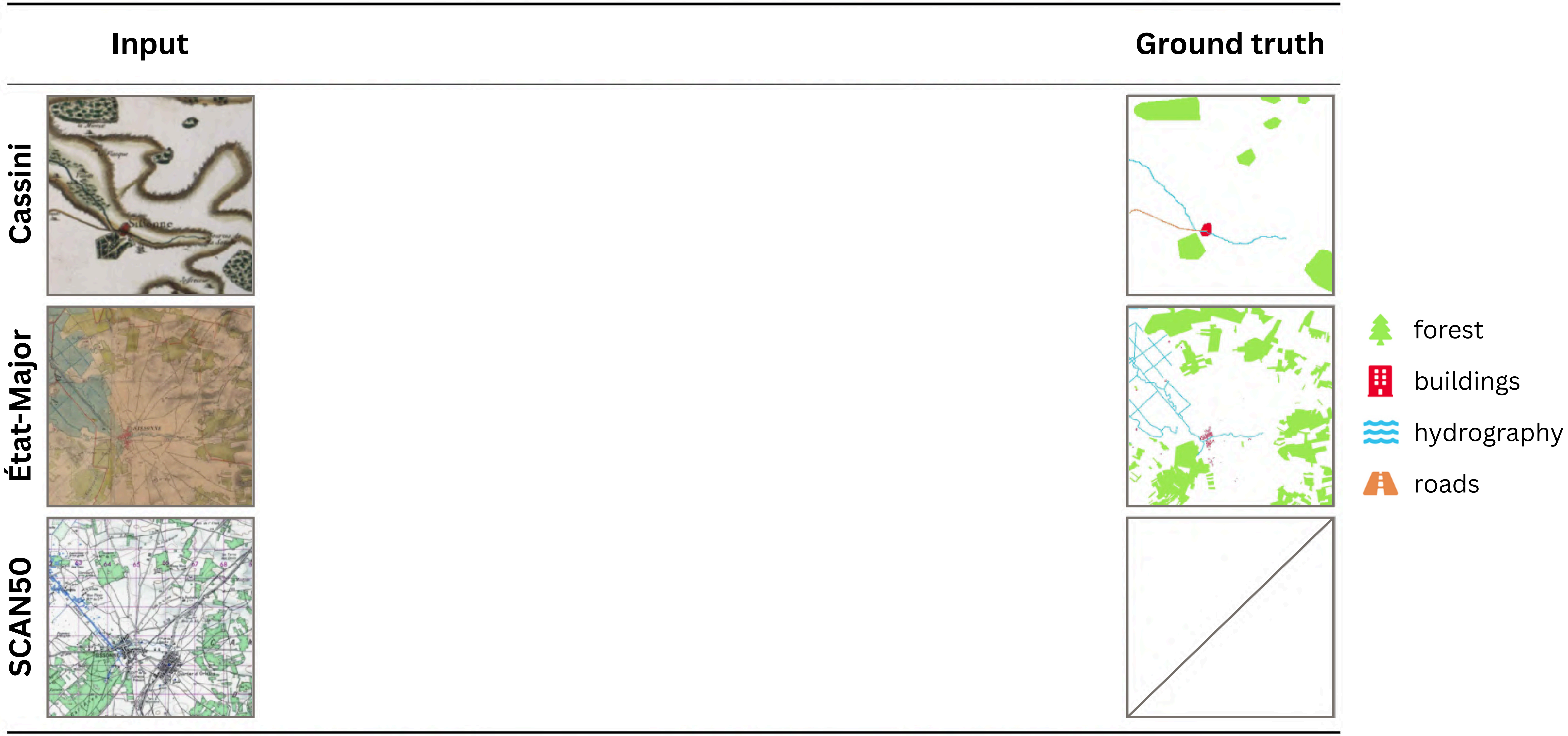


SAM: Kirillov, A. et al.: *Segment anything*. IEEE/CVF ICCV (2023)

Results - Segmentation

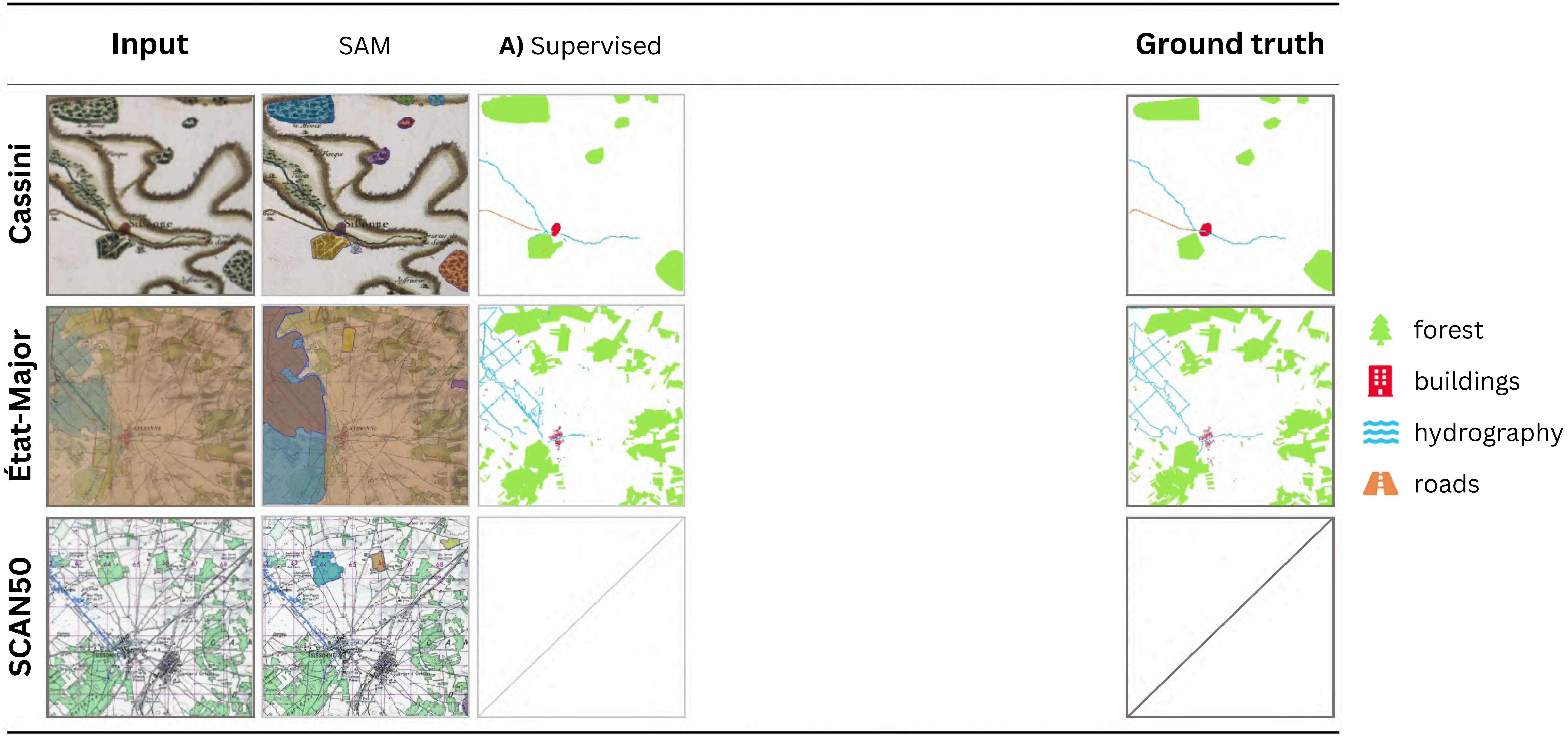
General-purpose models are not suitable for the task

- forest
- buildings
- hydrography
- roads

SAM: Kirillov, A. et al.: *Segment anything*. IEEE/CVF ICCV (2023)

Results - Segmentation

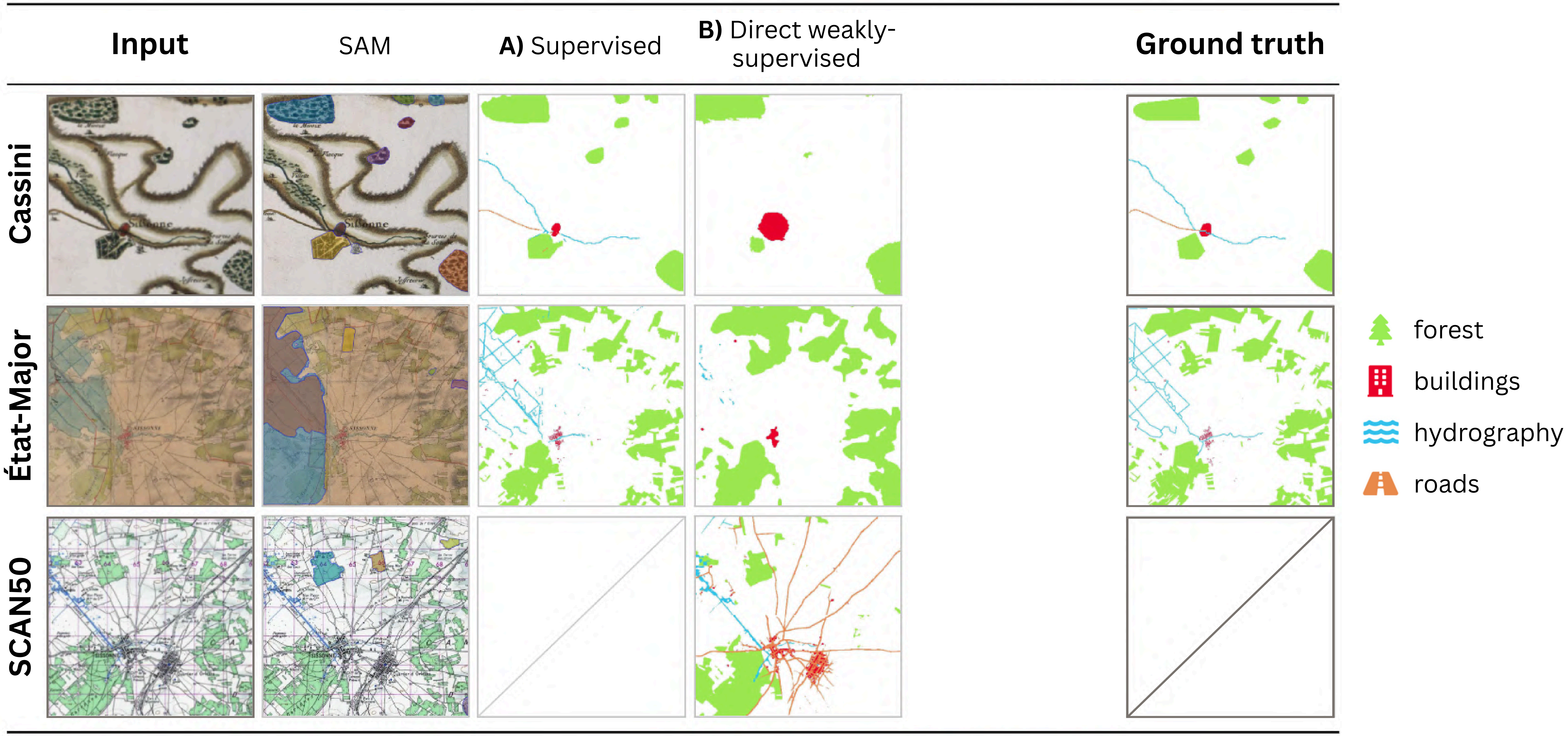
Strong supervision is the best, but annotation is **too costly**



SAM: Kirillov, A. et al.: *Segment anything*. IEEE/CVF ICCV (2023)

Results - Segmentation

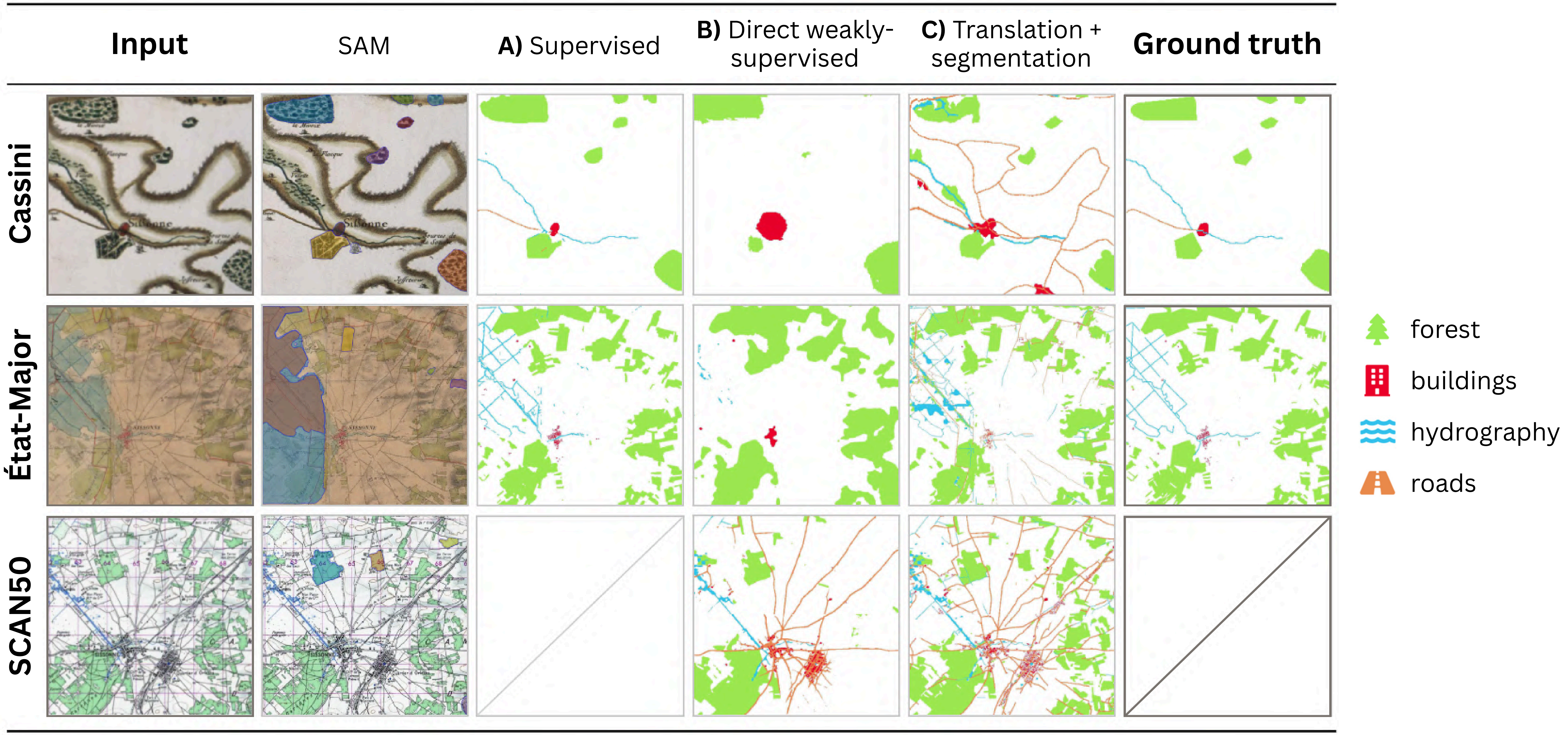
Weakly-supervised methods avoid manual annotation



SAM: Kirillov, A. et al.: *Segment anything*. IEEE/CVF ICCV (2023)

Results - Segmentation

Translation + segmentation baseline preserves details

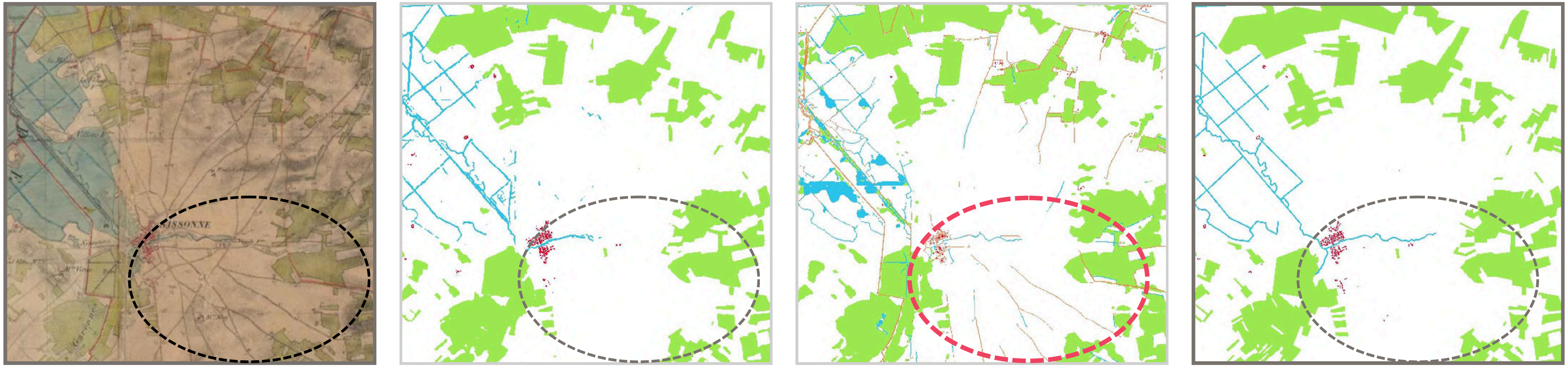


SAM: Kirillov, A. et al.: *Segment anything*. IEEE/CVF ICCV (2023)

État-Major

Translation + segmentation baseline preserves details

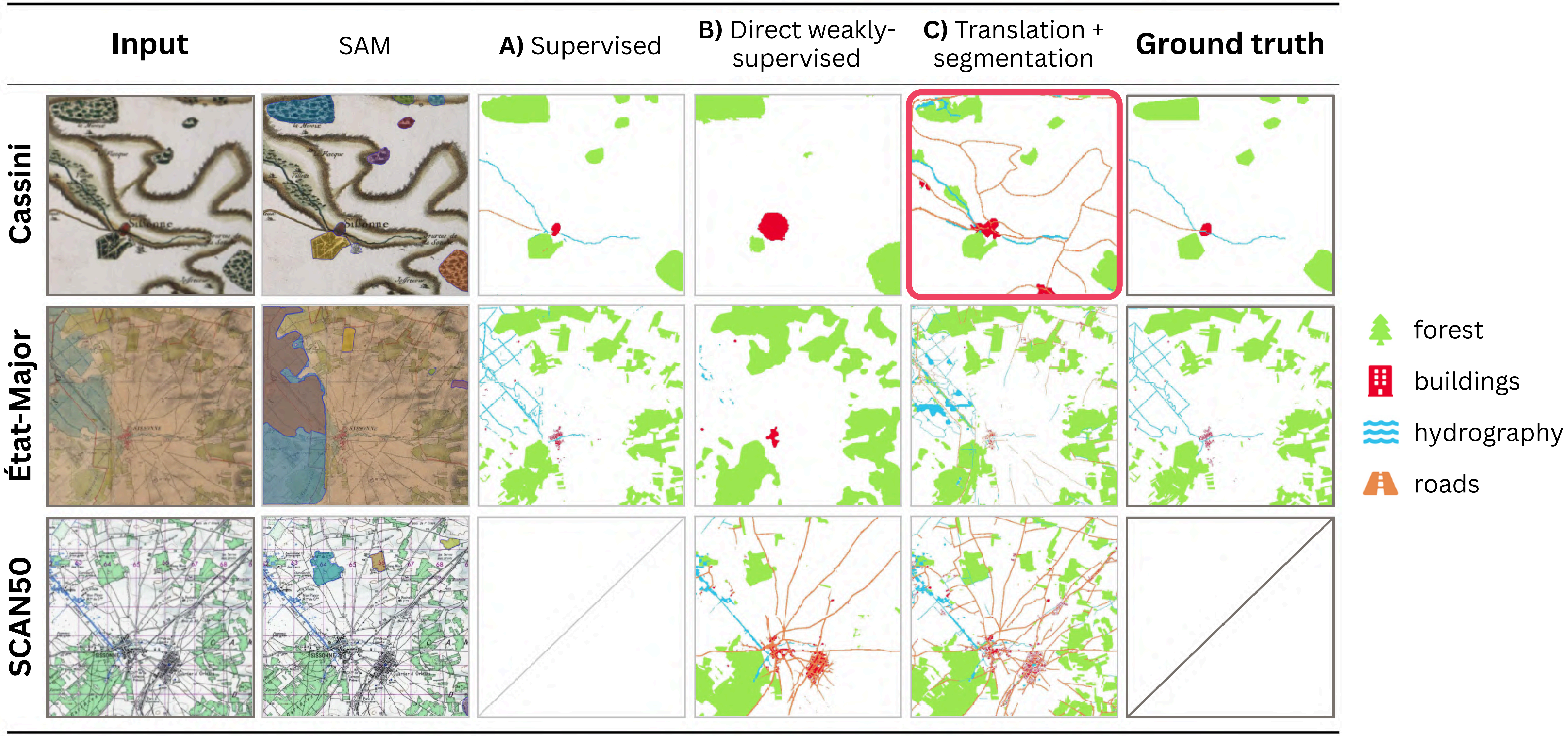
Input | **A)** Supervised | **C)** Translation + segmentation | **Ground truth**



forest buildings hydrography roads

Results - Segmentation

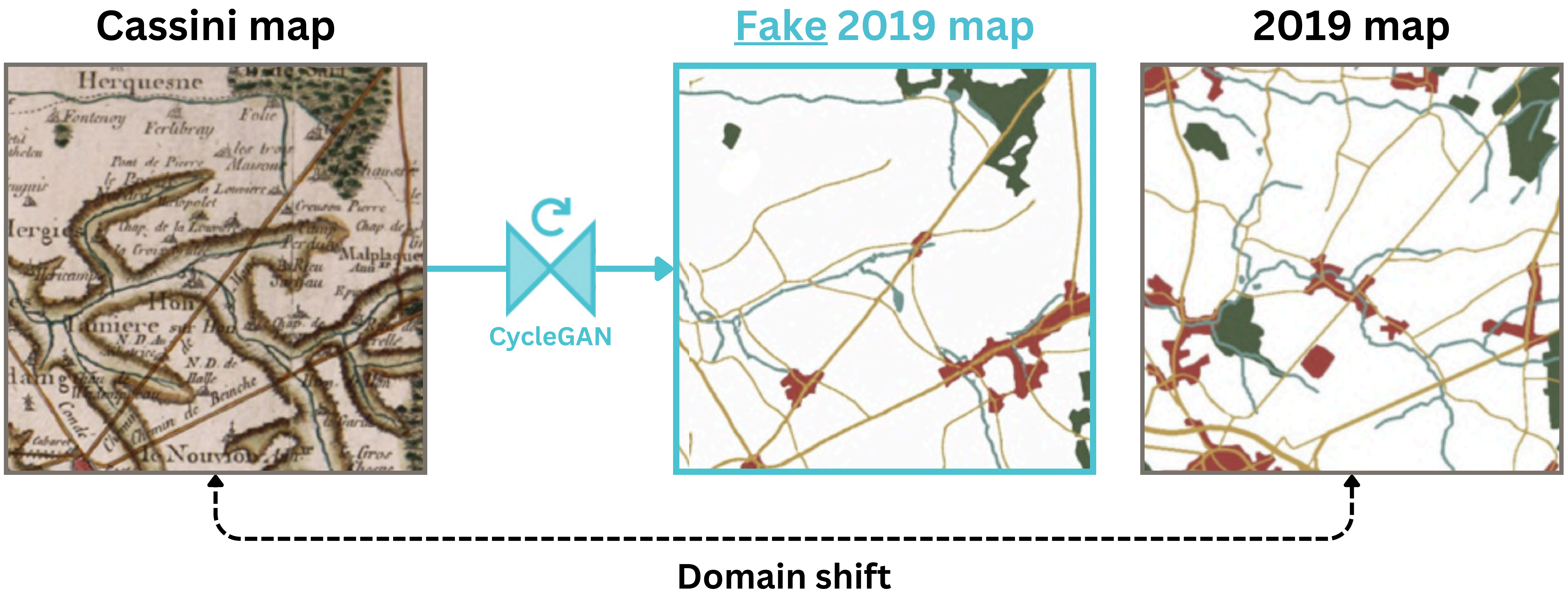
Translation + segmentation baseline hallucinates



SAM: Kirillov, A. et al.: *Segment anything*. IEEE/CVF ICCV (2023)

Cassini

Translation + segmentation baseline hallucinates

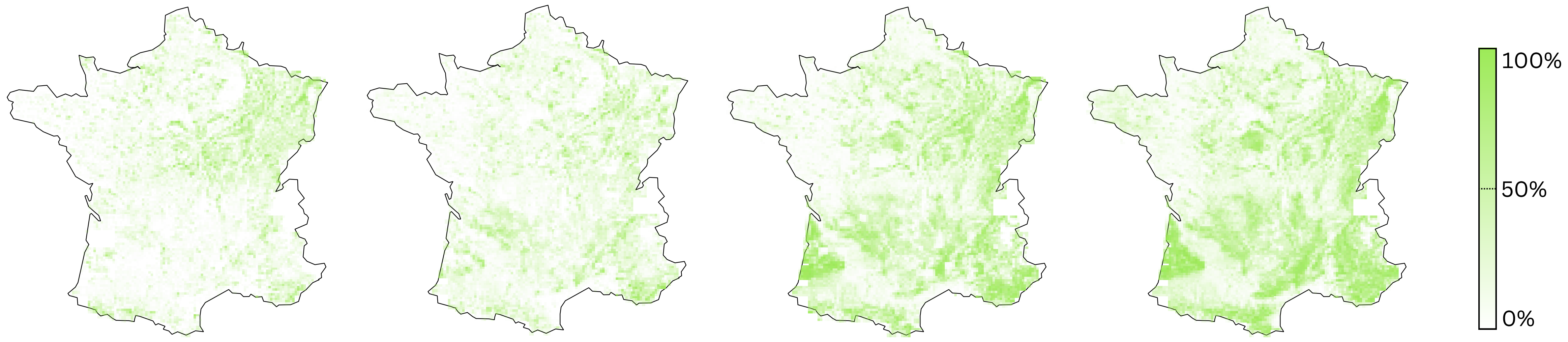


Application

Long-term forest monitoring

Forest density

Supervised	*Supervised*	*Translation + segmentation*	*2019 labels*



Cassini	**État-Major**	**SCAN50**	**Present**
1747-1815	1817-1866	1889-1922	2019

Historical trends

18th century
- Deforestation peak in 1789
- Forests in the northeast

19th century onwards
- Rise of fossil fuels
- Conservation efforts
  - Mountain areas
  - Marshlands

Scheifley, W.H.: *The depleted forests of France.* The North American Review 212(778) (1920)
Matteson, K.: *Forests in revolutionary France: Conservation, community, and conflict, 1669–1848*. Studies in Environment and History, Cambridge University Press (2015)
Ford, C.: *The environmental transformation of "empty space": From desert to forest in the Landes of southwestern France.* Comparative Studies in Society and History 65(2) (2023)

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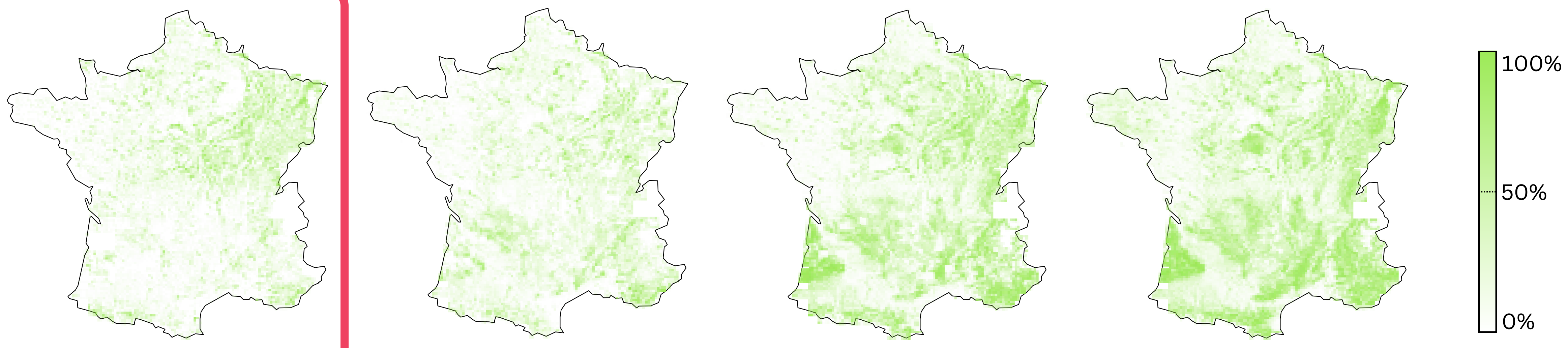

Cassini 1747-1815 | **État-Major** 1817-1866 | **SCAN50** 1889-1922 | **Present** 2019

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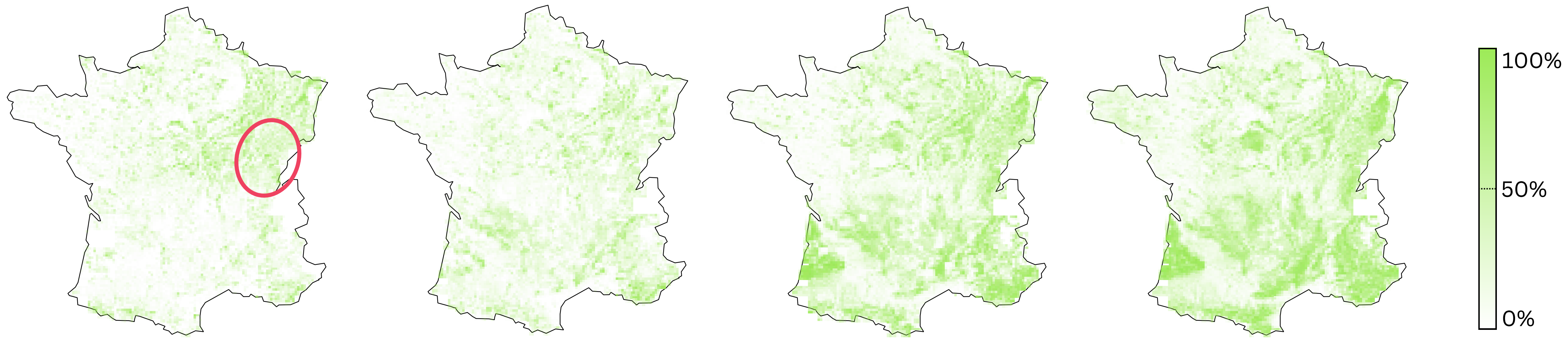

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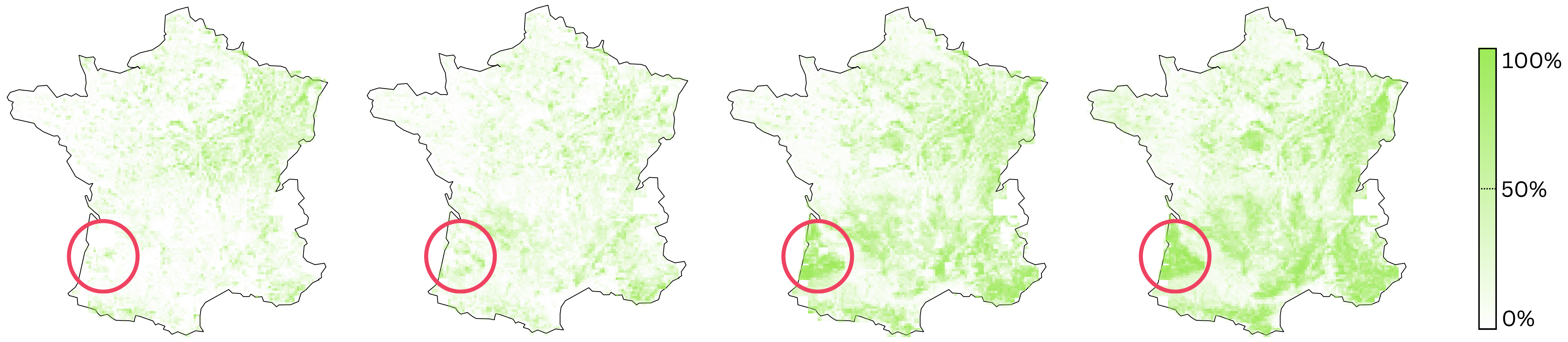

Cassini 1747-1815 | **État-Major** 1817-1866 | **SCAN50** 1889-1922 | **Present** 2019

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Summary

- Countrywide, multi-class historical map segmentation **dataset** spanning four centuries
- One supervised and two weakly-supervised segmentation **baselines**

We hope to inspire further research into **weakly-supervised** methods

github.com/Archiel19/FRAx4