Design Project – SIE 2022

SBB CFF FFS

Land Cover Prediction and Uncertainty using Deep Learning

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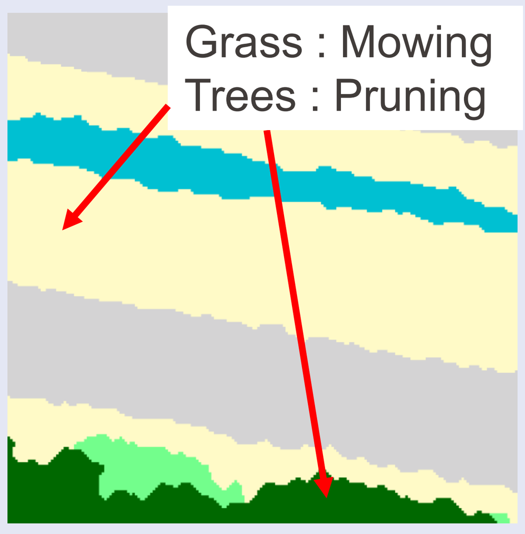
Objectives



Segmentation task example

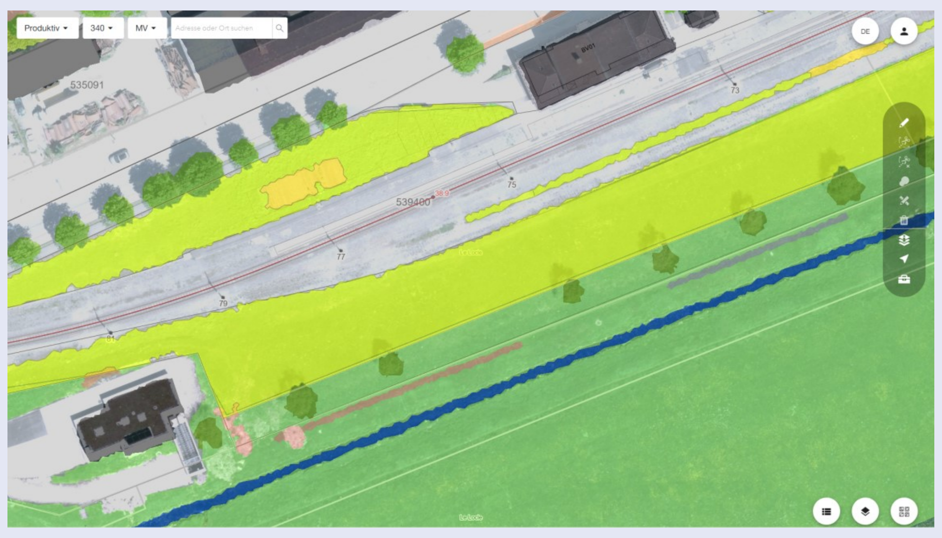
The SBB land cover classification (BBK) is included in the IVEG platform used for planning and execution of the vegetation maintenance around railways. With approximately 3000 km of tracks, the classification and updating of land cover maps is a considerable manual task. The use of deep learning segmentation networks can help alleviate this work by automating it.

Even when well trained, a deep learning model is likely to make prediction errors. The notion of uncertainty in predictions could thus provide information on the location of potential errors and facilitate the verification and correction of the classified maps.

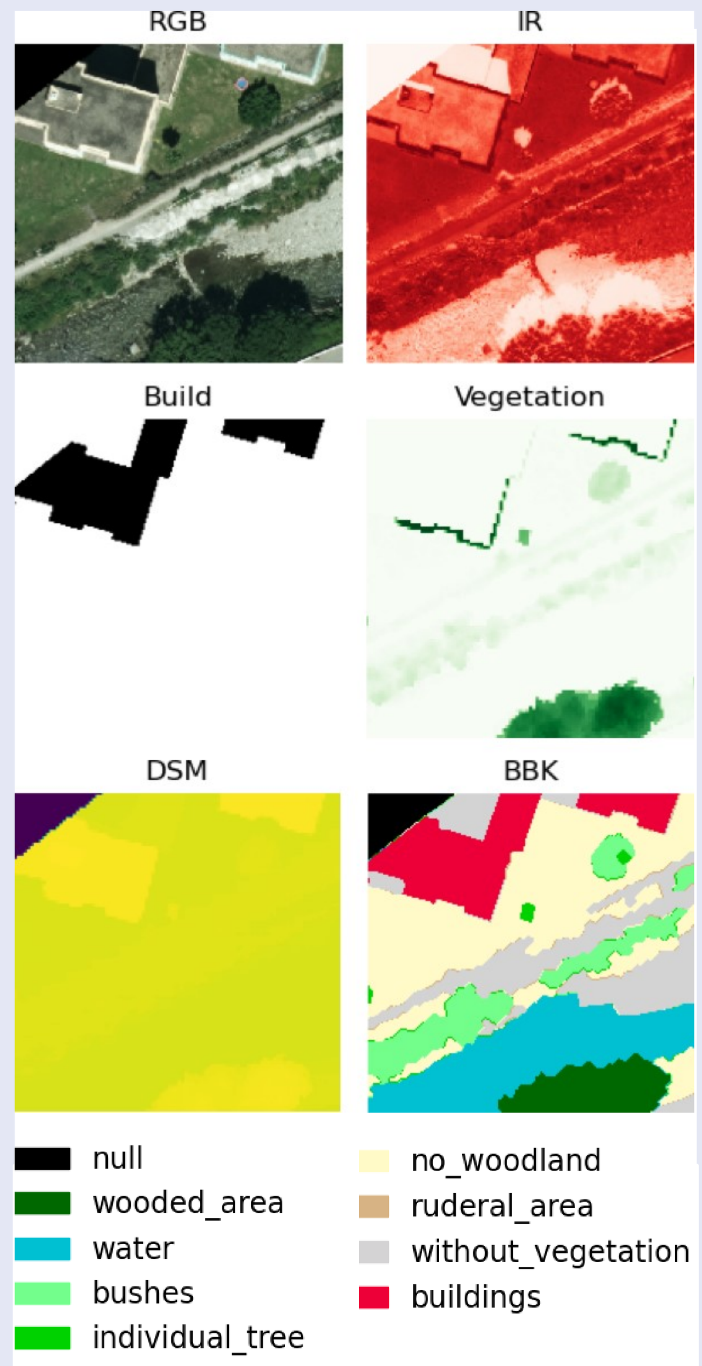
Data

The SBB dataset is made of 12069 tiles of 50 m x 50 m from various places in Switzerland. They contain :

- Aerial images with **RGB** and **IR** bands
- Digital surface models (**DSM**)
- Swisstopo building binary map (**Build**)
- Vegetation height data made by the SBB (**Vegetation**)
- Land cover classification (**BBK**)



IVEG platform

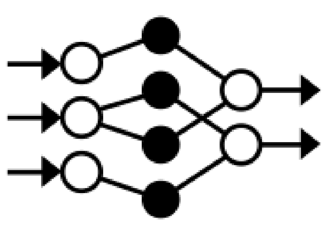


Data and legend

What does uncertainty in semantic segmentation mean ?

Data

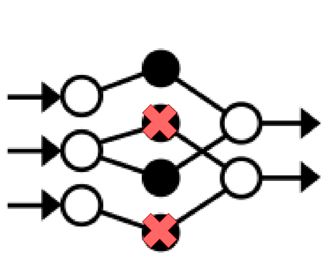
UNet model

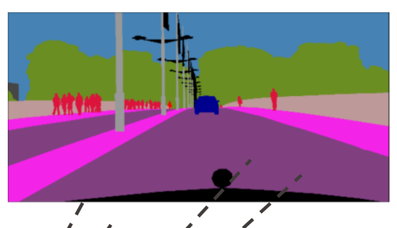


Predictions

But how sure are we of these predictions?

Bayesian UNet model with Monte-Carlo Dropout





Predictions

and

Uncertainty score for each pixel

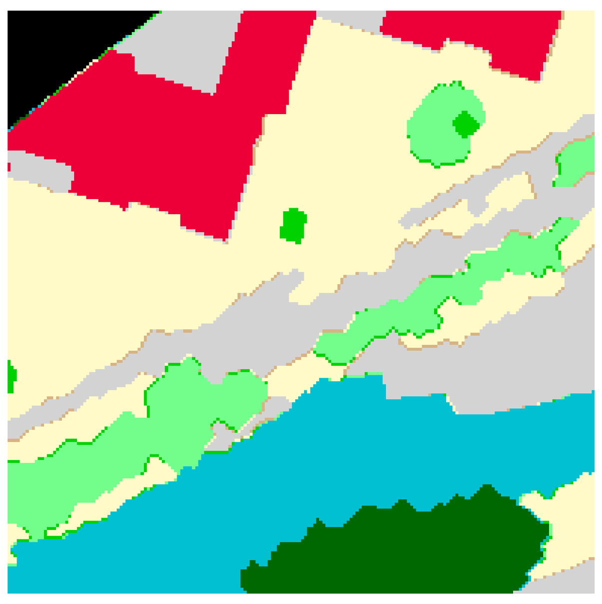
Predictive entropy :

$$\hat{\mathbb{H}}\left[y \mid \mathbf{x}, \mathcal{D}_{\text{train}}\right] = -\sum_{c}\left(\frac{1}{T}\sum_{t} p\left(y=c \mid \mathbf{x}, \hat{w}_t\right)\right)\log\left(\frac{1}{T}\sum_{t} p\left(y=c \mid \mathbf{x}, \hat{w}_t\right)\right)$$

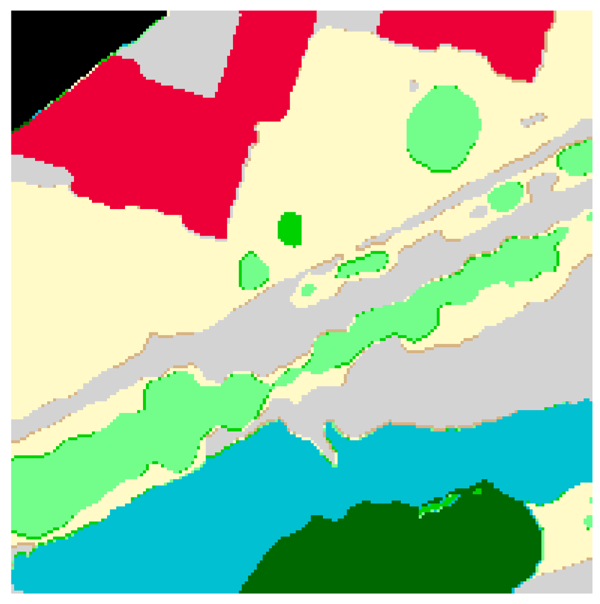
Mutual information :

$$\hat{\mathbb{I}}\left[y, w \mid \mathbf{x}, \mathcal{D}_{\text{train}}\right] = \hat{\mathbb{H}}\left[y \mid \mathbf{x}, \mathcal{D}_{\text{train}}\right] + \frac{1}{T}\sum_{c,t} p\left(y=c \mid \mathbf{x}, \hat{w}_t\right)\log p\left(y=c \mid \mathbf{x}, \hat{w}_t\right)$$

Ground Truth



Predictions

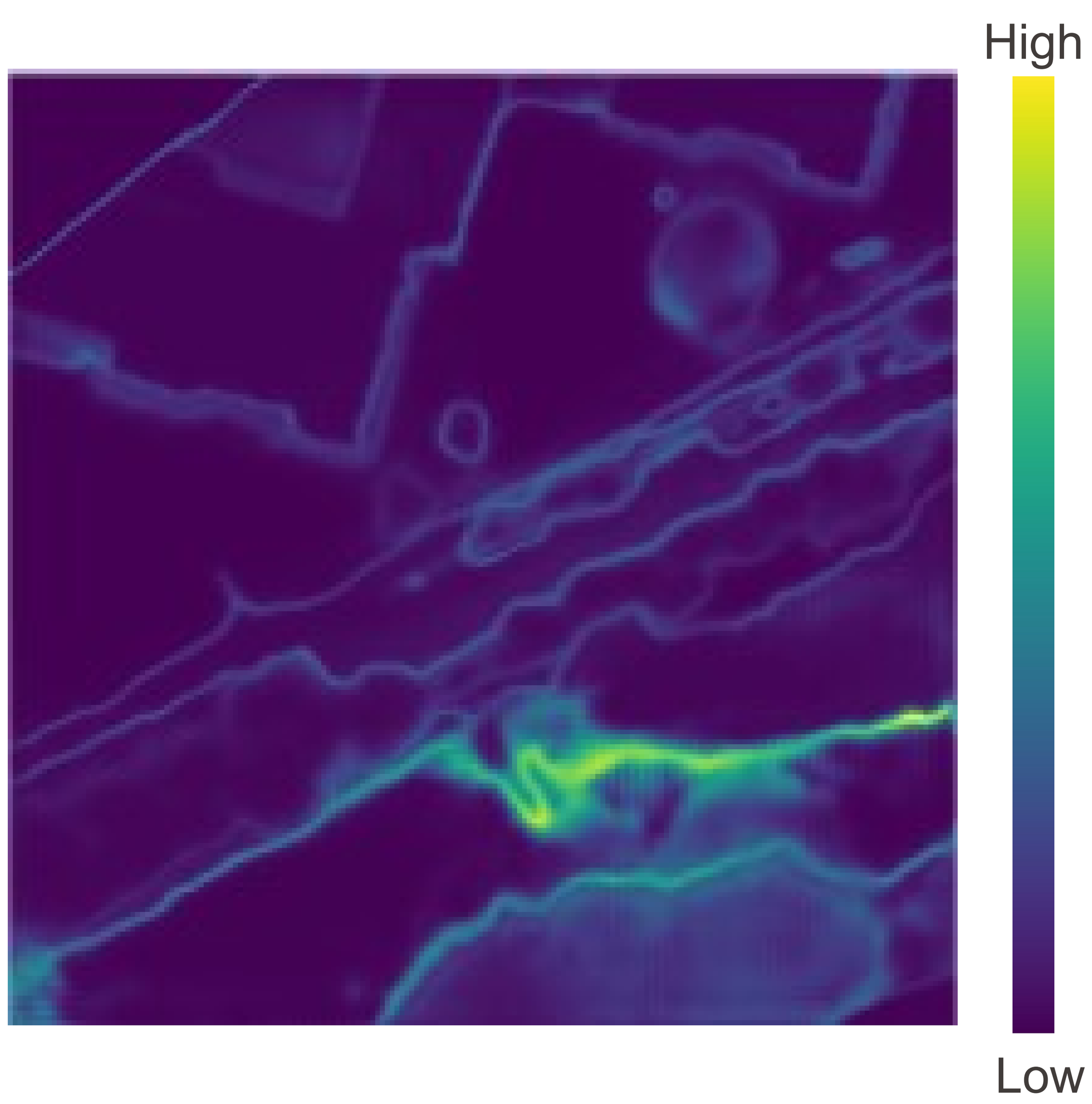


Performance metrics of the Bayesian model

Class	Accuracy [%]	IOU score [%]
null	99.9	99.7
wooded_area	92.7	86.4
water	94.4	90.7
bushes	68.1	52.4
indivual_tree	74.1	57.4
no_woodland	94.5	87.5
ruderal_area	15.3	13.0
without_vegetation	95.1	90.7
buildings	92.3	86.3

80.2 %
Overall accuracy score

Uncertainty prediction: mutual information



Evaluation metrics for uncertainty :

$$PAvPU = \frac{(n_{ac} + n_{iu})}{(n_{ac} + n_{ac} + n_{ic} + n_{iu})}$$

$\boldsymbol{n = number\ of\ pixels}$:

n_{ac}: *accuracte and certain*

n_{au}: *accurate and uncertain*

n_{iu}: *inaccurate and uncertain*

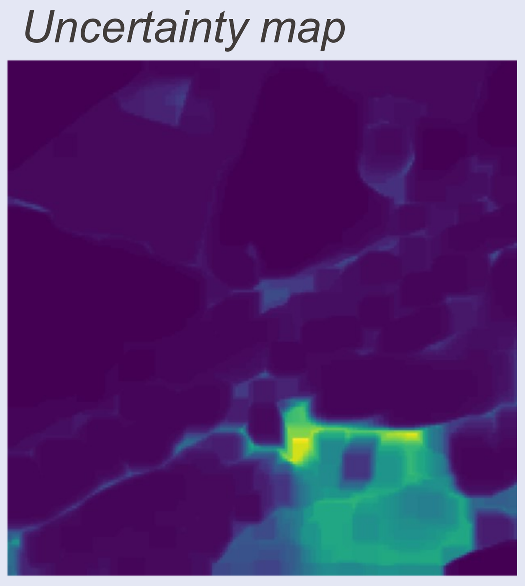
n_{ic}: *inaccurate and certain*

90.3 %
PavPu score

Turnkey product for end users

Interpreting uncertainty maps can be a difficult task. In general, predictions at the boundary between two patches are highly uncertain. Therefore, some processing on the output maps is necessary to create a final product that can be used by any field worker, and whose interpretation will not interfere with their work.

Eroded Uncertainty map



Thresholding on the eroded map

Conclusion

Determining the uncertainty of segmentation model is achievable relatively simply by adapting a pre-existing model to perform Monte-Carlo dropout. It provides significant results that could help in mapping control and correction. This opens up a possible new direction for the development of deep learning semantic segmentation models within the SBB.

References

MUKHOTI, Jishnu et GAL, Yarin. Evaluating bayesian deep learning methods for semantic segmentation. *arXiv preprint arXiv:1811.12709*, 2018

GAL, Yarin et GHAHRAMANI, Zoubin. Dropout as a bayesian approximation: Representing model uncertainty in deep learning. In : *international conference on machine learning*. PMLR, 2016. p. 1050-1059.

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