Towards an automatic detection of charcoal production platforms in airborne LiDAR images

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Introduction

Charcoal produced from woodland exploitation was a key source of energy for the (proto-) industrial development from the Middle-Ages to the emergence of fossil energy sources during the 19th century. Charcoal production platforms (or kilns) are some evidences of these activities and they are spread and preserved, at some extent, in forest areas. These structures with a characteristic circular to oval shape (Fig. 1) are recognizable in airborne images such as LiDAR (Light Detection and Ranging). Frequently, the density of these kilns in woodlands is so high that the visual inspection is insufficient. Methods of automatic detection based on machine learning for image analysis are being implemented to detect and quantify these structures, remaining traces of ancient forest exploitation.

Fig. 1 | Examples of charcoal kilns in southern Meuse with the aspect on LiDAR-derived slope images.

Objectives

Development of an **expedite** and **reliable** methodology to routinely perform analysis in airborne images to increment the **detection** and quantification of kilns in order to better understand the history and evolution of forest resources' exploitation.

Study area

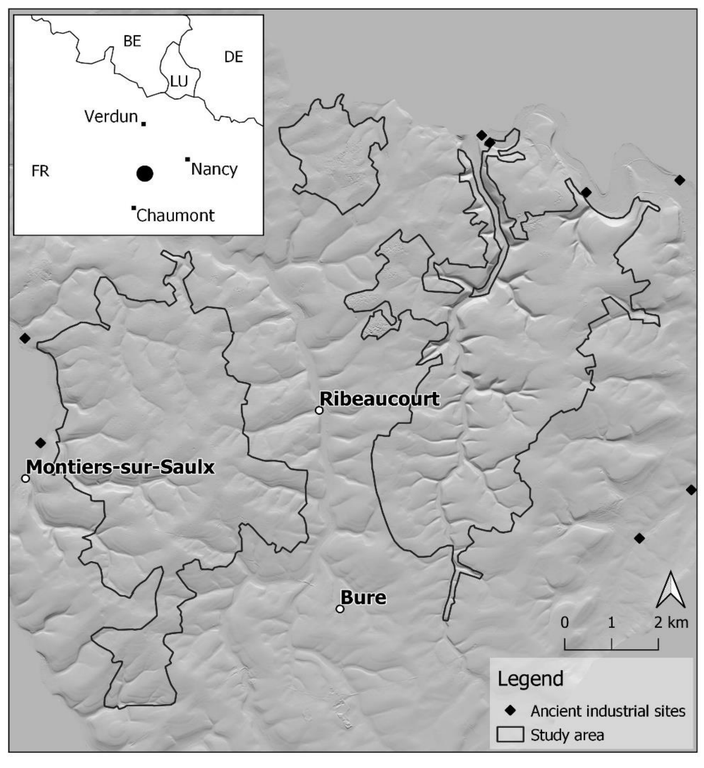


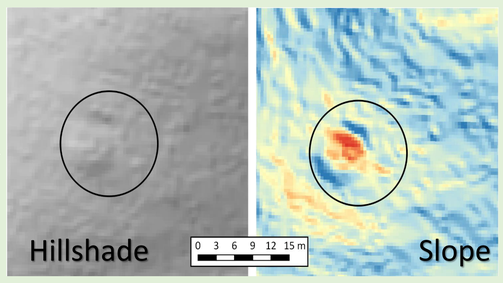
Fig. 2 | Study area in southern Meuse (NE France). The forest patches (black contour, 57.3km²) and ancient industrial activities (smithies) displayed in the LiDAR-derived Digital Elevation Model.

Methods

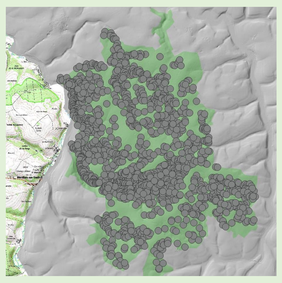
- **charcoal kilns' detection by visual inspection of images (1) and fieldwork (2)**

(1)

Visual inspection of **hillshade** and **slope** images

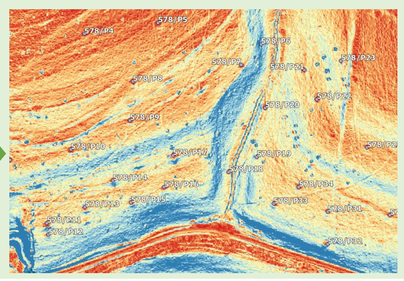


Coordinates of the potential kilns (eg: for fieldwork or quantification)

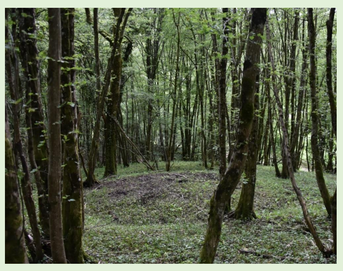


(2)

Coordinates of the potential kilns



Validation (confirmation of the visual detection) and **prospection** in the field



- **charcoal kilns' detection using deep learning techniques**

Training the charcoal kiln detector

Digital Elevation Model

2828 RGB images **300x300** pixels obtained with a **100** pixels stride

2641 points in geographic coordinates

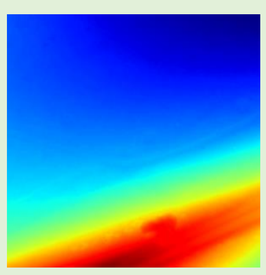
Labels associated to the images: **5824** bounding boxes

TensorFlow Object Detection API

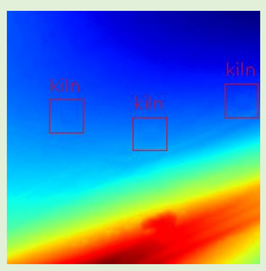
network: Faster R-CNN with Resnet-50

Charcoal kiln detector

Using the charcoal kiln detector



Charcoal kiln detector



Detected points in geographic coordinates

Results

Visual inspection of images	**Field validation and prospection**
2641 potential charcoal kilns detected	**288** kilns detected (128) and validated (160)

Preliminary results of charcoal kiln detection using deep learning techniques

tp: true positive; **fn**: false negative; **fp**: false positive

Recall → tp/(tp+fn) = 65%

False Discovery Rate FDR → fp/(fp+tp) = 38%

The **high** FDR makes us look at the detections: are all **false positive** really **false**?

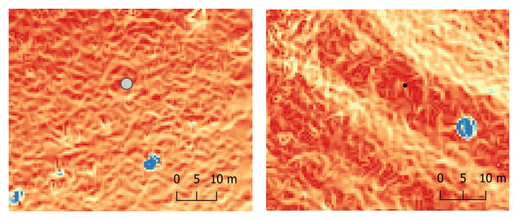


Fig. 3| Detail of a potential kiln exclusively detected by visual inspection (left) and an example of a kiln only detected by the Charcoal kiln detector (right).

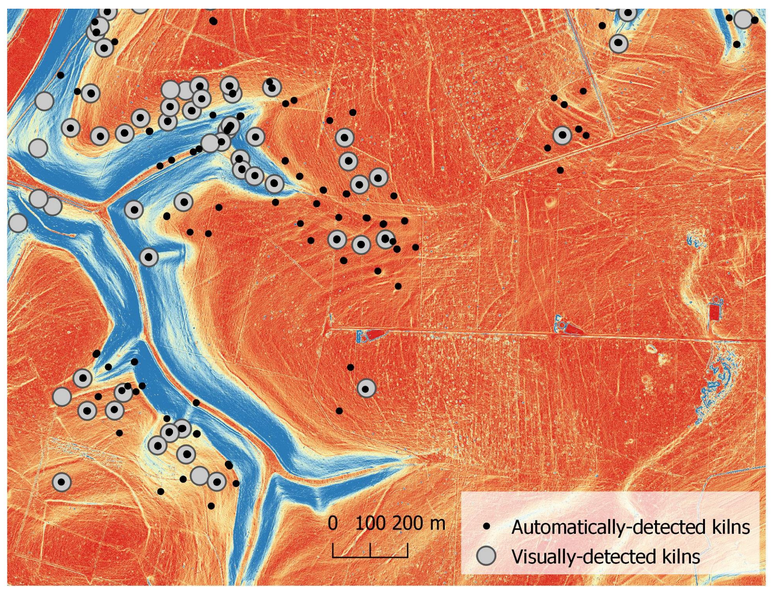


Fig. 4| Results of the visual and automatically-detected kilns in a selected area.

Perspectives

Future work will focus on (1) **assessing** of detection in the field (planned for mid-November 2020), (2) **improving** the charcoal kiln detector and, with the feedback of the fieldwork, fine-tune our model and (3) **using** our charcoal kiln detector in a new unstudied area.