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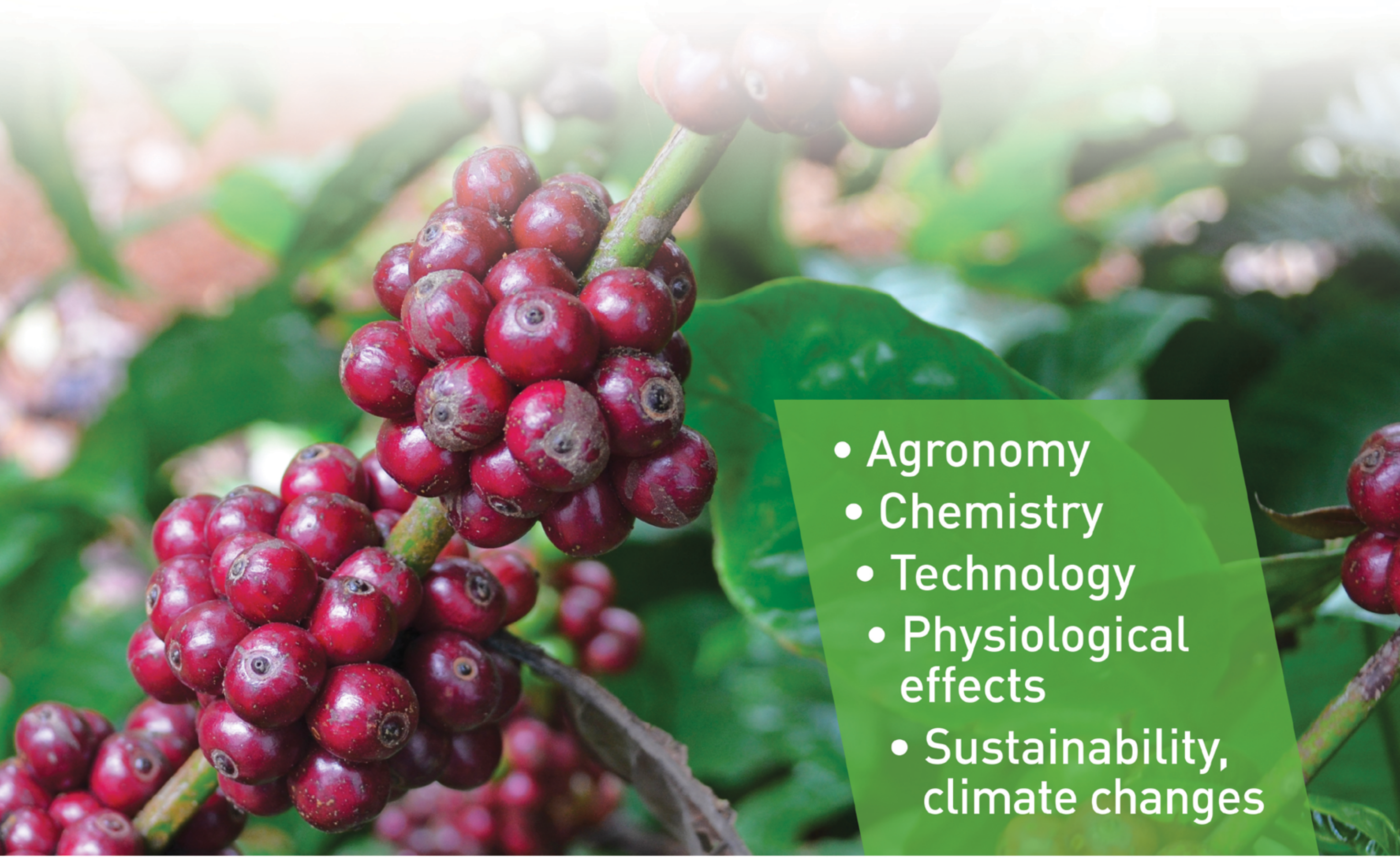
BOOK OF ABSTRACTS



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Detection and counting of coffee berry borer (*Hypothenemus hampei*) using computer vision algorithm.

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RATIONALE

Counting coffee berry borer (CBB) from field traps is a tedious process due to the number of traps (BROCAP®) that may be operating, the important number of individuals that can be captured in each trap, and the litter remains (moss, insects, leaves, etc.) found within the traps. The sample processing time to identify and count CBB can be reduced with the use of photographs and computer vision algorithms.

METHODS

We trained Corigan, a pipeline developed for small object detection with high resolution images that uses yolo3 engineering as the object detection core. The photos used to train Corigan came from a study to assess the effects of adjacent land uses on CBB dispersion, which is currently in the field phase. We used photographs with a resolution of 4000 x 2672 pixels of 180 dpi and 24bit depth, taken with a Panasonic DMC-G2 camera with a light aperture of 3.5, exposure time of 1/125s and an ISO of 100 with a focal length of 14 mm. We used 318 photographs to train the model and 30 photographs to validate the efficiency of the model.

RESULTS

Out of a total of 897 CBB found in the 30 photographs, the model identified 851 CBB (true positives; recall = 95%), identifying 230 objects (false positive) that did not correspond to CBB (accuracy = 72%) and not recognizing 53 CBB samples (5% of false negatives). The model mean average precision (mAP) was 74%.

CONCLUSIONS & PERSPECTIVES

The use of the pipeline detection reduces processing time considerably. Litter remains difficulted detection of CBB by the pipeline. Therefore, we suggest the use of at least three different photographs of the same sample each one taken after stirring the sampling material, and the use of the average detected CBB from these three counts for subsequent analysis. We believe that the use of detection averages will reduce the error caused by false positive detection. We will continue to improve the accuracy of the algorithm to reduce false positives, and work to improve the pipeline to detect CBB different stages (egg, larva, pupa, adult).

References:

- Tresson et al. 2019 Methods in Ecology and Evolution. 10. 11: 1888-1893. https://doi.org/10.1111/2041-210X.13281
- Redmon and Farhadi. 2018. YOLOv3: An incremental improvement. p. 6, ArXiv e-prints. Google Scholar