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PROXIMATE SENSING OF FOOD TYPES AND LAND USES IN THAILAND USING STREET-LEVEL PHOTOGRAPHY AND DEEP LEARNING

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ABSTRACT

High-resolution satellite images available in the last decade begin to make feasible the worldwide classification and monitoring of agricultural land use even by small-holder farmers whose fields are often smaller than 1 hectare. However, an even finer resolution is needed to accurately characterize farming practices of intensification and diversification, and cultivation of food for own consumption in the home gardens critical to ameliorating food insecurity in many regions. Home gardens, in particular, which are often heterogeneous at sub-meter scales, provide significant nutritional benefits and preserve genetic diversity of food plant species in many countries, but often are neglected in data collection efforts focusing on quantification of macro-economically important crop production. The literature reports that in Thailand, 22% of national caloric intake comes from sources other than food purchases or prepared meals, and includes significant amounts of home-grown food. In most rural areas this rises to 28%, and in the very rural northeast of the country this is as high as 41.8%. In addition to providing calories, producing food for personal consumption in home gardens can also affect food security and diet-related health outcomes by buffering small farmers against negative potential consequences of monocultural farming, such as crop failures and price fluctuations.

Reliable data on food production and agricultural practices is essential for understanding agricultural productivity and predicting food security. Using remote sensing to characterize food production that has the fine granularity and diversity of home gardens (20-40 species in a single garden is common in Thailand) would be extremely challenging even with the remarkable resolution provided by recently launched commercial satellites. A possible solution is “proximate” sensing, using computer analysis of images captured by cameras that are centimeters to tens of meters from their subjects. Indeed, the use of proximate sensing in agricultural applications is very rapidly expanding. It is used for automated plant identification from images of leaves or of full plants and aids in yield estimation, especially of fruit crops. It is fundamental to autonomous navigation in precision agriculture, to weed/crop differentiation for precision spraying or weeding and to the detection of fruits for robotic harvesting. A final significant agricultural challenge addressed through proximate sensing is the detection and characterization of pests and diseases.

This investigation develops tools to exploit street-level imagery to inventory land uses, crop types and food cultivation practices as a complement to remote sensing. Google Street View (GSV) is an enormous repository of such street-level imagery. In this paper, we explore the potential of using GSV imagery for

the characterization of food cultivation practices by training a deep convolutional neural network (CNN) to classify GSV images of rural Thailand.

We describe two tools for crop and land use classification using GSV imagery and a deep convolutional neural network (CNN). First, a multi-class classifier distinguishes six common regionally cultivated species, as well as three land uses (uncultivated land, built environment, and water). Second, a specialized detector recognizes the presence of a single species. These two classification tools were tested along roadside transects in two areas of Thailand, where roads are well covered by GSV.

On the entire test set, the overall accuracy of the multi-class classifier was 83.3%.
For several classes, (banana, built, cassava, maize, rice, and sugarcane), the producer's accuracy was over 90%, meaning that the classifier was infrequently making omission errors.
This performance is comparable to that of some remote-sensing classifiers, and ours does not require any additional site-visits for ground-truthing. The overall classifier accuracy on the 40% of images that it is most sure about is excellent: 99.0%. For the specialized detector, the area under the receiver operating characteristic curve was 0.9905, indicating excellent performance in detecting the presence of, in this case, banana plants. We believe improvements in training data organization and retraining additional layers of the pre-trained CNN will yield further accuracy improvements. A spot-check of the performance of the multi-class classifier suggests it generalizes outside of Thailand.

Based on this pilot study, our technique has potential for deployment over large areas to yield fine-grained food cultivation analysis. We are also developing the approach in this study further to provide fine scale information on food plant cultivation near homesteads. Detailed spatial information about the distribution of crops, especially in kitchen gardens, is important in order to understand precisely the intense and diverse ways in which agricultural and private residential land is used to produce food. This will supplement remote sensing data, leading to a deeper and more comprehensive understanding of local food cultivation practices. The impacts of these practices on food security and diet-related health outcomes are not well understood but are assumed by the project team to be significant and in need of further examination. In particular, the recognition of individual instances of plants in kitchen gardens, as our current approach is beginning to enable, will shed light on foods grown solely for personal consumption but missing from governmental crop surveys. While the remote sensing community is also working to provide better ways to produce more detailed and accurate crop type maps, these other efforts are not currently able to provide information at a very fine (eg household) scale. We believe our approach may be able to fill a gap, which can lead to much deeper understanding of food cultivation practices relating to diet, health and eventually food security.