Modelling the spread of the noctuid stemborer in smallholder maize farms

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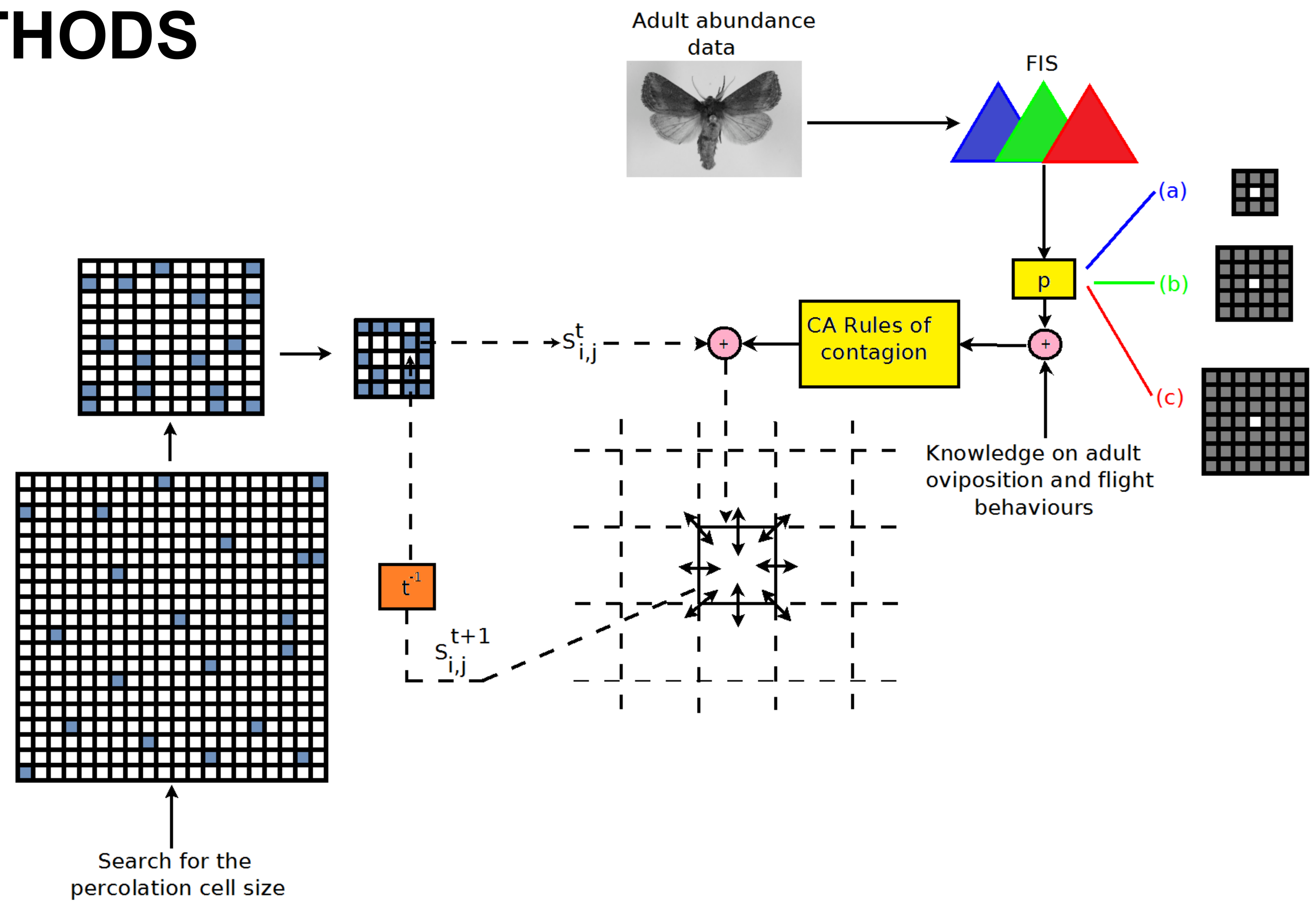
INTRODUCTION

The noctuid *Busseola fusca* (Fuller) is one of the most damaging insect pests of maize in Kenya with reported yield losses greater than 50%. The integrated pest management (IPM) strategies toward this pest fail to take into account the spatial and temporal dispersal of damage. Modelling the spread of *Busseola fusca* damage in maize farms is important, as it enhances the development of appropriate control measures for minimising the negative impact of the pest on maize crops (Gardner et al., 1989; Li, 2000; Piexoto, et al. 2008).

METHODS



The approach for modelling leaf damage caused by *Busseola fusca* larvae under field conditions, using percolation theory, cellular automata, and fuzzy logic.

CONCLUSIONS

- *Busseola fusca* infestation can obey a cellular automata law during propagation.
- Integrated pest management practitioners could design efficient timing strategy based on the expected pattern of farm infestation week after week.

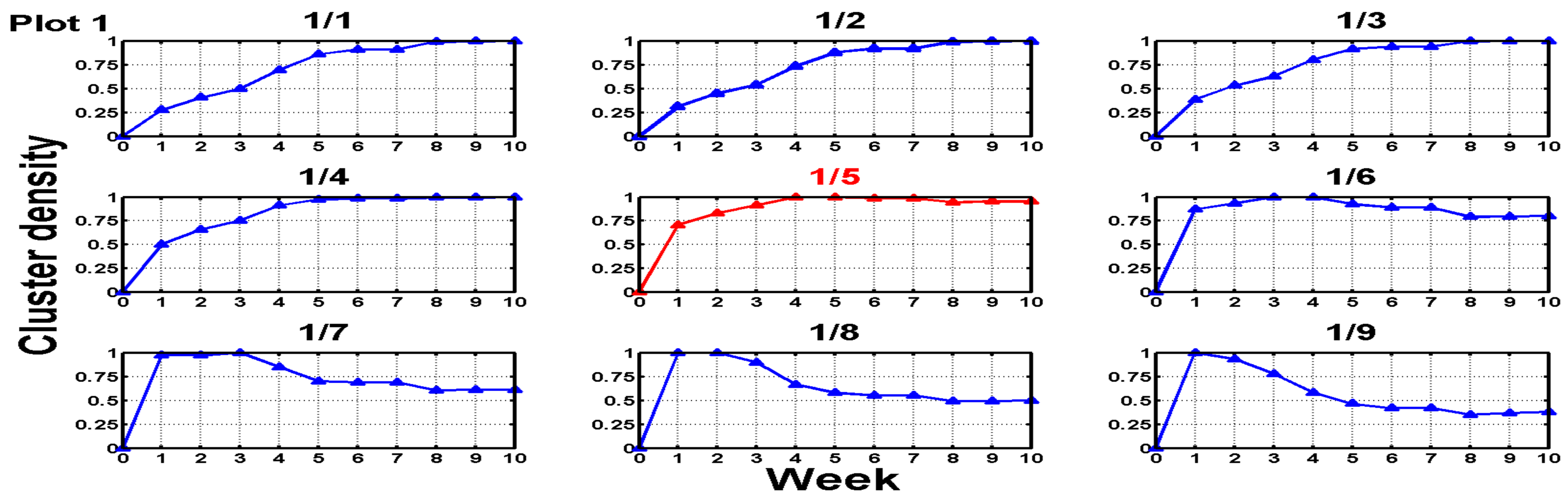
IMPACTS

- Instead of conducting systematic sampling within the entire field/farm, it may be adequate to conduct sampling at defined unit capable of showing the likely spread of infestations.
- Integrated pest management specialists could use the outcomes of the current study to design and develop efficient and more effective timing strategies to control stemborers in maize farms.

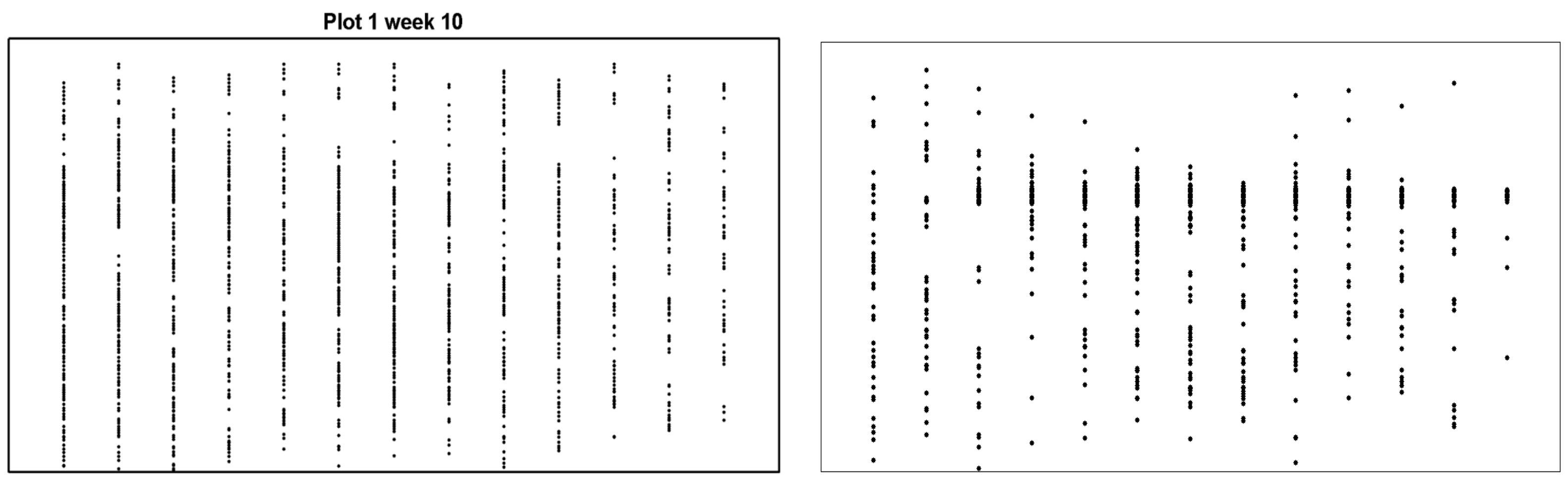
OBJECTIVES

- To estimate the spatial threshold for assessing the spread pattern of *B. fusca* infestation.
- To predict positions of the plants that the pest will infest.

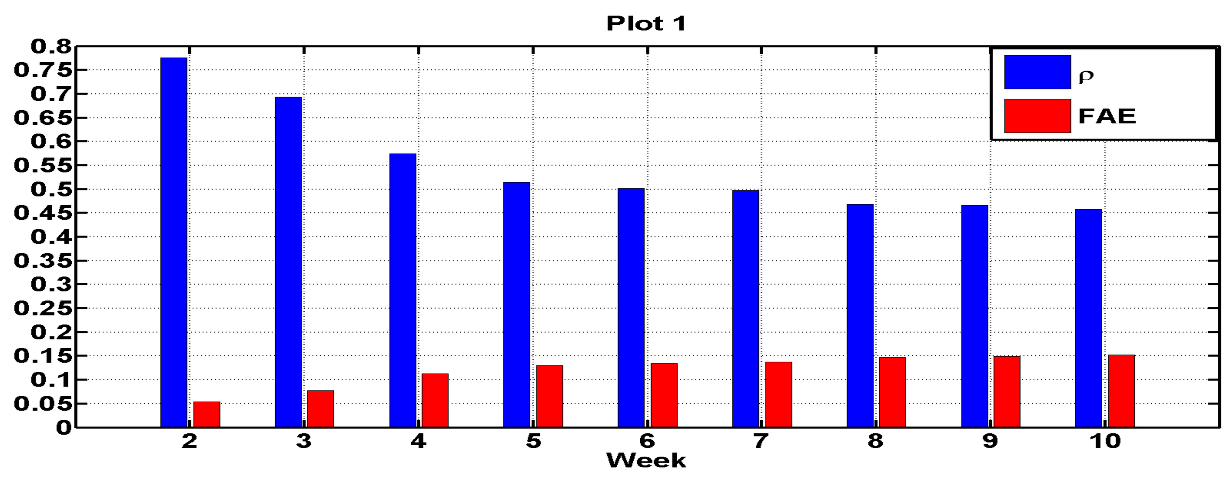
RESULTS



Estimation of the percolation scale in Plot 1. The cluster density represents the number of infested cells week after week. This number was normalised between 0 and 1. The fraction above each sub-figure represents the scale of observation.



Representation of the spatial and temporal evolution of infested cells in Plot 1. On the left are the observed data and on the right the simulated infestations. The black dots represent the infested cells and the white cells the non-infested cells.



Assessment of the model uncertainty at each iteration. The blue bars represent the correlation coefficient (rho) between the observed and the simulated results. The red bars represent the fractal average error (FAE) between the spatial distribution of infested cells in the observed and the predicted results.

REFERENCES

Gardner R.H., O'Neil R.V., Turner M.G. and Dale V.H. (1989) Quantifying scale dependent effects of movements with simple percolation models. *Landscape Ecology* 3, 217-227.

Li B.L. (2000) Fractal geometry applications in description and analysis of patch patterns and patch dynamics. *Ecological Modelling* 132, 35-50.

Piexoto M.S., Carvalho de Barros L.and Bassanezi R.C.(2008) A model of cellular automata for the spatial and temporal analysis of citrus sudden death with fuzzy parameter. *Ecological Modelling* 214, 45-52.