WHAT SHOULD I GROW TODAY SO I MAKE MONEY TOMORROW? SUPPORTING SMALL FARMERS' CROP PLANNING WITH SOCIAL, ENVIRONMENTAL, AND MARKET DATA

Aviva Prins, Christine Herlihy, & John P. Dickerson
Department of Computer Science, University of Maryland, College Park
{aviva, cherlihy, john}@cs.umd.edu

ABSTRACT

In India, the majority of farmers are classified as small or marginal, and their livelihoods are vulnerable to climate risk. One approach to mitigating this problem is via drip-irrigated greenhouses. We aim to build an optimization-based decision support tool that provides crop planning advice to farmers in conjunction with a nonprofit in India. We propose a Markov decision process approach for this low-resource sector, and discuss key evaluation metrics for the design and implementation phases of our project.

1 INTRODUCTION

In India, five out of six farmers are classified as small or marginal, with two or fewer hectares of arable land (FAO, 2022). In 2013, the National Sample Survey Office (NSSO)'s survey of India's agricultural households reported two-thirds of the one hundred million small farmers in India *lose* money on average from agriculture alone (NSSO, 2013).

A large reason for that is climate risk, made worse by climate change. Recently, India has experienced a rise in average temperatures, a decrease in monsoon precipitation, a rise in extreme temperature, rainfall and drought events, an increase in intensity of severe cyclones and other changes in the monsoon system (Krishnan et al., 2020). *Kharif* crops are cultivated and harvested during the Indian subcontinent's monsoon season. These crops are most affected by rainfall variance, while winter-planted *rabi* crops face challenges in higher minimum temperatures. Winter *rabi* crops require significant irrigation (Rosmann & Singh, 2021). Unfortunately, resource-poor farmers have a limited ability to adopt sustainable resource technologies.

One approach to mitigating this problem is via a "greenhouse-in-a-box" that is highly affordable (Peters, 2017). These greenhouses are equipped with a low-cost drip irrigation system that reduces water use (Polak et al., 1997). Another benefit of protected cropping is the ability to maintain a controlled growing environment in warm climates, reducing vulnerability to seasonal temperatures and humidity (Rabbi et al., 2019).

Still, greenhouse hardware alone is not enough because farmers lack the ecosystem to make that hardware work. Specifically, giving farmers help in planning their crops *well* can make a huge difference (Vinaya Kumar et al., 2017). Currently, farmers do not follow scientific, data-backed approaches when making their crop planting choices and cycles, nor do they necessarily aim to maximize utility (Sanga et al., 2021; Waldman et al., 2020). Rather, farmers rely on heuristic shortcuts and social norms when facing uncertainty. Heuristics such as timing the sowing of rice crops according to the onset of monsoon season are particularly valuable for marginal farmers, for whom alternative strategies such as increased irrigation are unobtainable (Jain et al., 2015). The role of social interactions is pervasive in the region, for example, Mittal & Mehar (2013) find that an overwhelming 90% of North Indian farmers rely on information provided by neighboring farmers (Munshi, 2004; Mittal & Mehar, 2013; Bhatta et al., 2017). However, if farmers choose to emulate their successful peers in making crop choices, the local markets may be flooded with a fairly homogeneous mix of in-season vegetables and fruits, creating a glut and depressing prices.

In collaboration with a nonprofit in India, we aim to build optimization-driven decision support tools to enable that ecosystem for small farmers. We are in a unique position to provide lightweight coordination across small farmers, in the process providing concrete planting advice to individual farmers based on local market data as well as farmer-level constraints such as budget, behavioral preferences, and appetite for risk–thus helping individual farmers and the broader local economy.

2 Problem Statement

We aim to create an optimization-based decision support tool that provides crop planning recommendations to farmers based on market price data, factoring in long-term soil fertility and farmers' skill levels, and other application-specific constraints. Specifically, we will define a crop portfolio optimization problem that takes as input heterogeneous data (social/historical related to a farmer and their community; environmental and ecological; and financial, including historical local market prices) and provides as output a slate of crops to plant over time. Leaning on the sequential decision making under uncertainty literature, our approach will be amenable to user-specific objective functions (e.g., maximize expected profit, maximize expected profit subject to a particular appetite for risk, etc.) as well as various application-specific constraints (e.g., budget constraints, farm sizing and number of crops). One key constraint is maintaining soil fertility–the same type of crop should not be planted sequentially to preserve the nutrients in the soil.

3 A Mathematical Approach

We will begin by formulating the problem as a Markov decision process (MDP) (Bertsekas, 2012). Many optimal control problems in agriculture have been considered with this model, for example in disease control (Viet et al., 2018) and rainfall-based irrigation (Huong et al., 2018; Whan et al., 1976; Admasu et al., 2014). Here, states represent current circumstances. At a given timestep the agent takes an action. This action causes some changes in the environment and, depending on the changes that take place, gives some reward. Given the new state, the agent takes an action at the next timestep, repeating the process over and over again. By formulating the problem in this way, we can mathematically solve for the most optimal action at each timestep.

In the example shown in Figure 1, the current state is an empty greenhouse. We, the agent, have many options for actions, such as planting tomatoes, potatoes, or corn. Let us suppose we plant potatoes. The state becomes: a greenhouse with 10 unripe potatoes in the current season. While the potatoes grow, no profit is earned (in fact, we may incur some small costs). It is probably unwise to harvest the potatoes before they are mature, so in this example, the agent waits. After some time, the potatoes are mature and we harvest them. Selling the potatoes yields a profit of one thousand rupees. Now, we once again have an empty field and we need to decide what to plant. However, to maintain soil fertility, we will not plant potatoes.

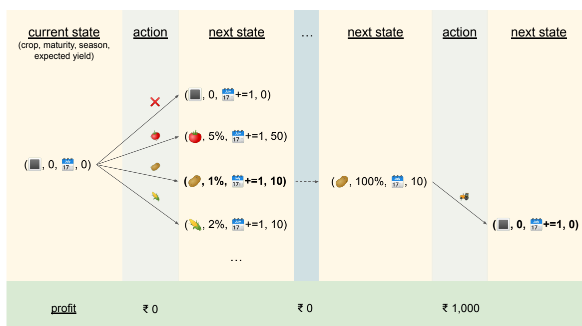

Figure 1: Example MDP for crop planting decision support.

We have to be careful that the number of combinations is not intractably large. Even though there are many possible situations, the sequential progression of the environment over time is often predictable. A key part of our plans is to address the efficiency and frequency of computing optimal actions using this model, and adapting our solution to emergent information such as changes in crop price. Depending on the availability of data and the results of preliminary evaluation, a reinforcement learning approach may be appropriate (Sutton & Barto, 2018).

4 Evaluation & Future Directions

In the short-term, we aim to develop a minimum viable product under close collaboration with our partners in India. Since the lifecycle of crops is between 70 and 200 days, we plan to incorporate interviews with stakeholders (i.e., small farmers who are part of the nonprofit's ecosystem already) in the early stages of development. Additionally, long-term success can be measured in multiple ways including, ordered by length of time: (1) calculating the increases in farmer incomes; (2) over multiple crop cycles, calculating differences in soil fertility based on pH levels; and (3) conducting a proper randomized control trial (RCT). First, we will identify comparable farmers growing similar crops in their greenhouses, and will offer them the proposed additional advisory on crop planning. At the end of the first season, we would be able to see the difference in incomes between the two farmer groups. Then, we can compare open air farming, greenhouse farmers without the proposed decision support tool, and greenhouse farmers with the proposed tool over several seasons.

Acknowledgements

We thank the team at Kheyti for partnership and frequent feedback on project scoping and the model, and a generous gift from Google's AI for Social Good program.

References

Wubengeda Admasu, Kassu Tadesse, Fitsume Yemenu, and Birhan Abdulkadir. Markov chain analysis of dry, wet weeks and statistical analysis of weekly rainfall for agricultural planning at dhera, central rift valley region of ethiopia. *African Journal of Agricultural Research*, 9(29):2205–2213, 2014.

Dimitri Bertsekas. *Dynamic programming and optimal control: Volume I*, volume 1. Athena scientific, 2012.

Gopal Datt Bhatta, Hemant Raj Ojha, Pramod Kumar Aggarwal, V Rasheed Sulaiman, Parvin Sultana, Dhanej Thapa, Nimisha Mittal, Khemraj Dahal, Paul Thomson, and Laxman Ghimire. Agricultural innovation and adaptation to climate change: empirical evidence from diverse agroecologies in south asia. *Environment, Development and Sustainability*, 19(2):497–525, 2017.

FAO. India at a glance | fao in india | food and agriculture organization of the united nations, 2022. URL https://www.fao.org/india/fao-in-india/india-at-a-glance/en/.

Truong Thu Huong, Nguyen Huu Thanh, Nguyen Thi Van, Nguyen Tien Dat, Nguyen Van Long, and Alan Marshall. Water and energy-efficient irrigation based on markov decision model for precision agriculture. In *2018 IEEE Seventh International Conference on Communications and Electronics (ICCE)*, pp. 51–56. IEEE, 2018.

Meha Jain, Shahid Naeem, Ben Orlove, Vijay Modi, and Ruth S DeFries. Understanding the causes and consequences of differential decision-making in adaptation research: adapting to a delayed monsoon onset in gujarat, india. *Global Environmental Change*, 31:98–109, 2015.

R Krishnan, J Sanjay, Chellappan Gnanaseelan, Milind Mujumdar, Ashwini Kulkarni, and Supriyo Chakraborty. *Assessment of climate change over the Indian region: a report of the ministry of earth sciences (MOES), government of India*. Springer Nature, 2020. URL http://www.indiaenvironmentportal.org.in/files/file/Assessment-of-Climate-Change-over-the-Indian-Region.pdf.

Surabhi Mittal and Mamta Mehar. *Agricultural information networks, information needs and risk management strategies: a survey of farmers in Indo-Gangetic plains of India*, volume 10. CIMMYT, 2013.

Kaivan Munshi. Social learning in a heterogeneous population: technology diffusion in the indian green revolution. *Journal of development Economics*, 73(1):185–213, 2004.

NSSO. Situation assessment survey of agricultural households, january - december 2013. 2013. URL http://microdata.gov.in/nada43/index.php/catalog/133.

Adele Peters. This low-cost greenhouse is designed to help the poorest farmers, 2017. URL https://www.fastcompany.com/40405369/this-low-cost-greenhouse-is-designed-to-help-the-poorest-farmers.

Paul Polak, Bob Nanes, and Deepak Adhikari. A low cost drip irrigation system for small farmers in developing countries 1. *JAWRA Journal of the American Water Resources Association*, 33(1): 119–124, 1997.

Barkat Rabbi, Zhong-Hua Chen, and Subbu Sethuvenkatraman. Protected cropping in warm climates: A review of humidity control and cooling methods. *Energies*, 12(14):2737, 2019.

Mark Rosmann and Santosh K. Singh. Climate change - agriculture and policy in india. 2021. URL https://www.fas.usda.gov/data/india-climate-change-agriculture-and-policy-india.

Udita Sanga, Hogeun Park, Courtney Hammond Wagner, Sameer H Shah, and Arika Ligmann-Zielinska. How do farmers adapt to agricultural risks in northern india? an agent-based exploration of alternate theories of decision-making. *Journal of Environmental Management*, 298: 113353, 2021.

Richard S Sutton and Andrew G Barto. *Reinforcement learning: An introduction*. MIT press, 2018.

Anne-France Viet, Stéphane Krebs, Olivier Rat-Aspert, Laurent Jeanpierre, Catherine Belloc, and Pauline Ezanno. A modelling framework based on mdp to coordinate farmers' disease control decisions at a regional scale. *Plos one*, 13(6):e0197612, 2018.

HM Vinaya Kumar, M Shivamurthy, V Govinda Gowda, and GS Biradar. Assessing decision-making and economic performance of farmers to manage climate-induced crisis in coastal karnataka (india). *Climatic change*, 142(1):143–153, 2017.

Kurt B Waldman, Peter M Todd, Shahera Omar, Jordan P Blekking, Stacey A Giroux, Shahzeen Z Attari, Kathy Baylis, and Tom P Evans. Agricultural decision making and climate uncertainty in developing countries. *Environmental Research Letters*, 15(11):113004, 2020.

BM Whan, CH Scott, and TR Jefferson. Scheduling sugar cane plant and ratoon crops and a fallow—a constrained markov model. *Journal of agricultural engineering research*, 21(3):281–289, 1976.