Climate Change and Vineyard Farmers' Decision

Lixuan Jian*
*Dyson School of Applied Economics and Management, Cornell University, Ithaca, NY 14850 USA

***Abstract*—This project aims to find out the optimal choice for vineyard farmers who grow Pinot Grins when the temperature is 60 - 70 °F using Q-learning. We will first specify all the vectors, build the grid world for this problem, and then have a simulation. According to the result of the model we built, the optimal strategy for vineyard farmer is to adjust harvest date.**

***Index Terms*—Reinforcement learning, Q-learning**

I. Introduction

Wine industry is highly sensitive to the nuances of climate and terrior, is facing unprecedented challenges due to climate change. And climate change will affect vineyards production through shifts in temperature and precipitation patterns.

One response to the climatic shift is "migration" – relocate to a more climatically suitable area. But this strategy might incur a potential loss of location-specific premium associated with established wine-producing regions.

Another possible strategy is "adaptation". This includes adjust harvest dates, introducing new grape varieties, using full-capacity watering, improving canopy management, changing vineyard row orientations, etc[1]. And introducing these strategies will increase the cost of production.

We aim to employ a reinforcement learning model to optimize strategies for vineyards in the context of temperature rise. And the result shows that the optimal reaction for vineyard farmers when temperature increases to 60-70 °F is to adjusting harvest date.

II. Results

In the first task, we successfully specified the key vectors required for our model. This included defining the state space, action space, and the initial Q-values for our Q-learning algorithm. The state space was determined based on the relevant environmental factors for vineyards - temperature ranges. The action space encompassed possible vineyard management strategies like irrigation, canopy management, and harvest time adjustments. The initialization of the Q-table was an essential step, setting the groundwork for the learning process of the agent.

The second task involved constructing a grid world model that represented our vineyard environment. This model was crucial in simulating the various states our agent could encounter. We created a Q-learning agent with the capability to navigate this grid world. This agent was programmed to learn from its interactions with the environment, updating its policy based on the rewards associated with its actions. The grid world and the agent were integrated to function cohesively, with the agent's actions influencing its movement and experiences within the grid world.

Corresponding author: Lixuan Jian (email:lj288@cornell.edu).

Strategy	Cost	Temperature Offset
Adjust harvest date	0	1
Change vine type	824.6	9
Full-capacity watering	750	3
Canopy manipulation	550	2
Changing row orientation	7500	3
Northward migration	6930[2]	Will be optimal temperature

TABLE I
COSTS AND TEMPERATURE OFFSETS OF DIFFERENT STRATEGIES

In the final task, we conducted simulations using our Q-learning agent within the grid world. The agent explored different states, made decisions, and learned from the outcomes of these decisions. Throughout the simulation, the Q-values in the agent's Q-table were updated, reflecting the agent's learning and adaptation over time. The simulation results showed that the optimal response for farmers in the stated situation is to adjust harvest date.

III. Discussion

The project results indicate that reinforcement learning can be a powerful tool in precision agriculture, aiding in decision-making and adaptive management strategies in the context of changing environmental conditions. It opens up possibilities for further research and application in other areas of environmental management and sustainability.

However, the limitation of this project is that, we only study Pinot Grins farmers' situation, and when the temperature increases to 60-70 Fahrenheit. Future work could focus on integrating more complex environmental factors (different temperatures, and including factors like moisture) and other cultivars.

IV. Materials and Methods

A. Strategy Specification

The first task involved specifying critical vectors in the model. The optimal temperature range for the growth of Pinot Grins, a chosen baseline for this study, is identified as 56-59 °F. In our scenario, we assume the current temperature range to be 60-70 °F. The estimated costs and potential temperature offsets for various vineyard management strategies are detailed in Table 1.

B. Grid World Model and Q-Learning Agent Construction

The second task focuses on building the grid world model and the Q-learning agent. The grid world in this study is triangular, with the horizontal axis representing the minimum temperature and the vertical axis representing the maximum temperature. Each state or coordinate in the grid world is associated with a set of potential actions or strategies, each yielding a corresponding reward and movement to a subsequent state. The reward system is twofold: a base reward and a cost component. The base reward is set at 10,000 for states within the optimal temperature range and -500 for states outside this range. The costs vary depending on the chosen action, as detailed in Table 1.

C. Simulation Process

The third task involves conducting simulations using the developed model. The simulation's objective is to observe and analyze the agent's learning process and strategy adaptation in response to varying environmental conditions. Through iterative episodes, the agent explores different states, actions, and their consequences, leading to an evolved policy guided by the Q-learning algorithm. This process aids in understanding the efficacy and adaptability of different management strategies under simulated climatic conditions.

V. Data and Model Availability

The model equations were implemented in Julia (v.1.9.3) [3]. The model code is available at https://github.com/jianlixuan1999/CHEME5760-finalproject.git

References

1. Ashenfelter, O. & Storchmann, K. Climate change and wine: A review of the economic implications. *Journal of Wine Economics* **11**, 105–138 (2016).
2. Cross, R., Plantinga, A. J. & Stavins, R. N. The value of terroir: Hedonic estimation of vineyard sale prices. *Journal of Wine Economics* **6**, 1–14 (2011).
3. Bezanson, J., Edelman, A., Karpinski, S. & Shah, V. B. Julia: A fresh approach to numerical computing (2014). arXiv:1411.1607.