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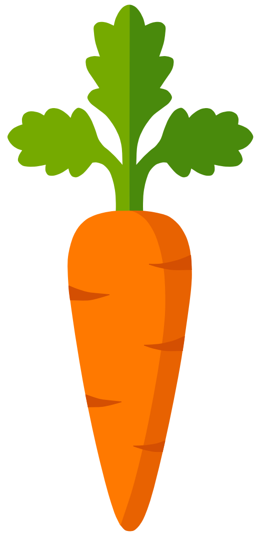
# Reinforcement Learning Final Project



## CropGym Intercropping Extension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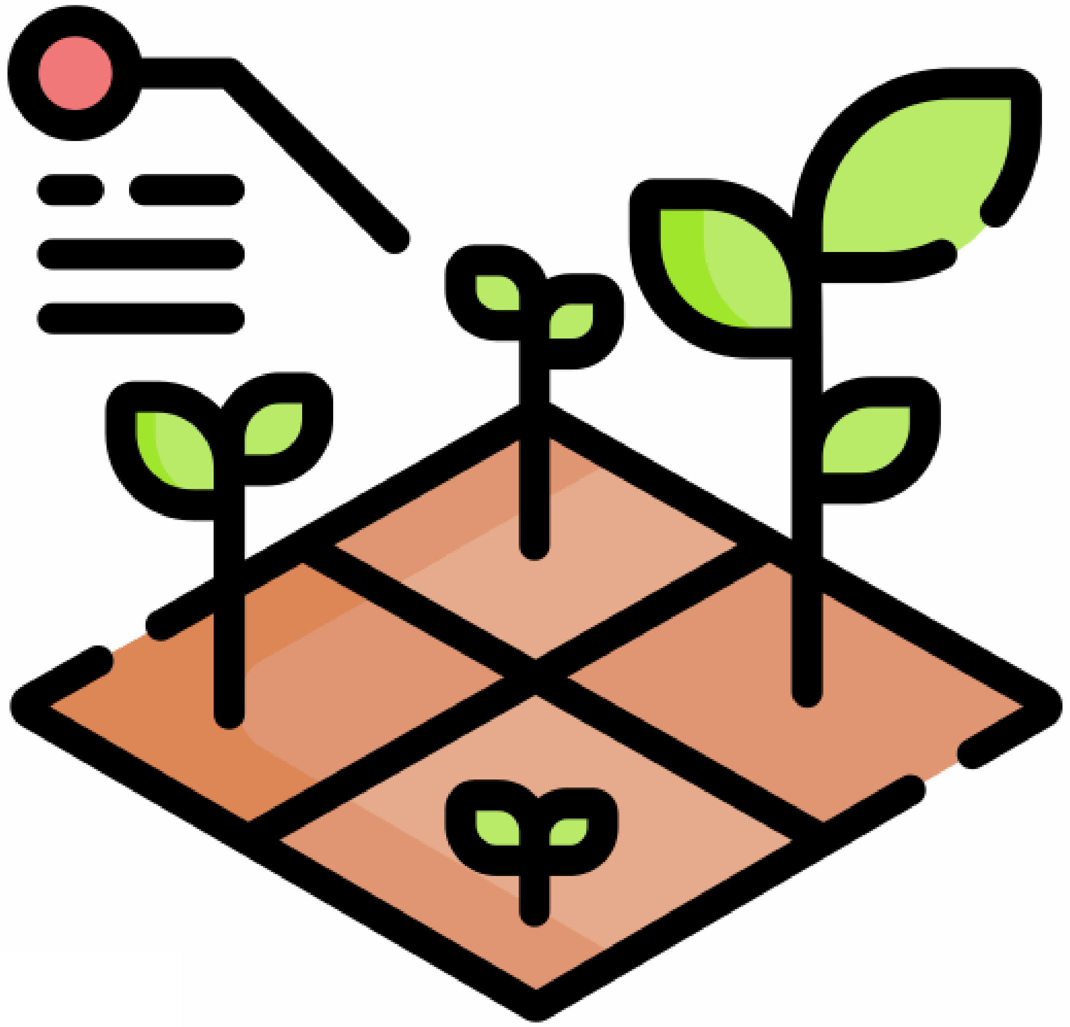
# Introduction



### Inter-cropping:

Growing multiple crops together, improving sustainability through better resource use and biodiversity.

# Introduction

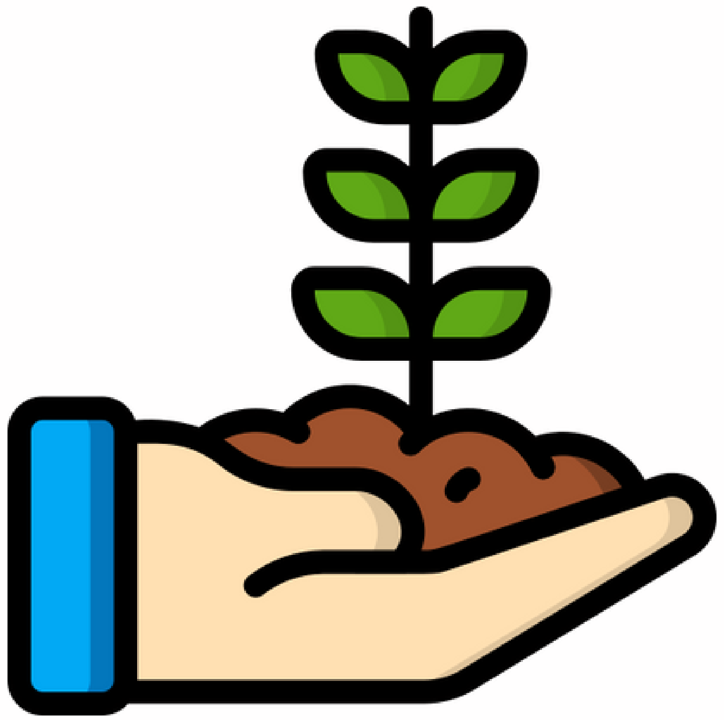
**Aim:**

Contributing in AI application on sustainable farming practices

**Idea:**

Building from scratch an extension of a pre-existing environment in order to provide to future researchers a tool for simulating inter-cropping techniques

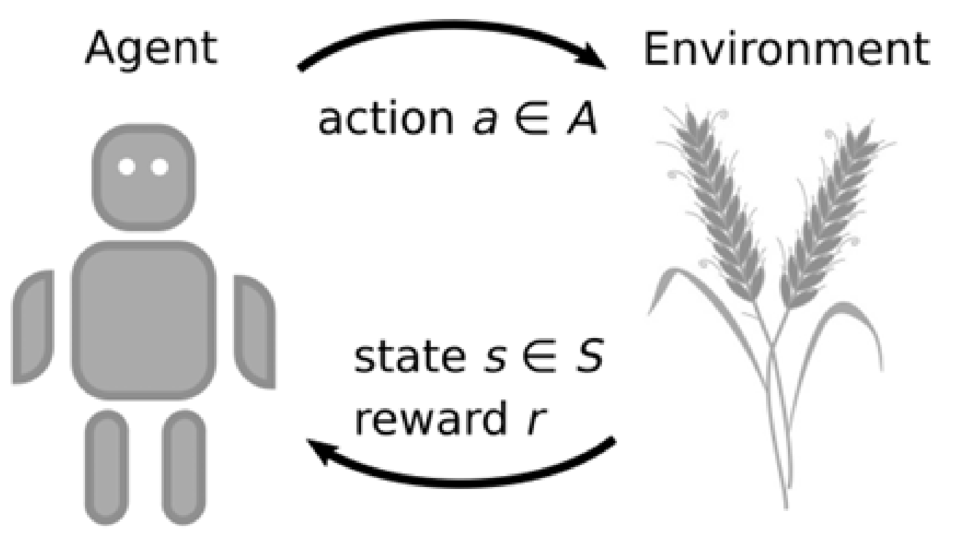
# Environment



**CropGym:**

RL environment based on the Lintul3 engine for fertilizer optimization on a nitrogen-limited environment.
Used as a base for custom environment.

# Environment




## CropGym:

- Action space: quantity of fertilizer to use every 7 days
- Reward: tradeoff between account fertilizer used and crop growth compared to a baseline
- Observation space: crop, soil and weather variables.

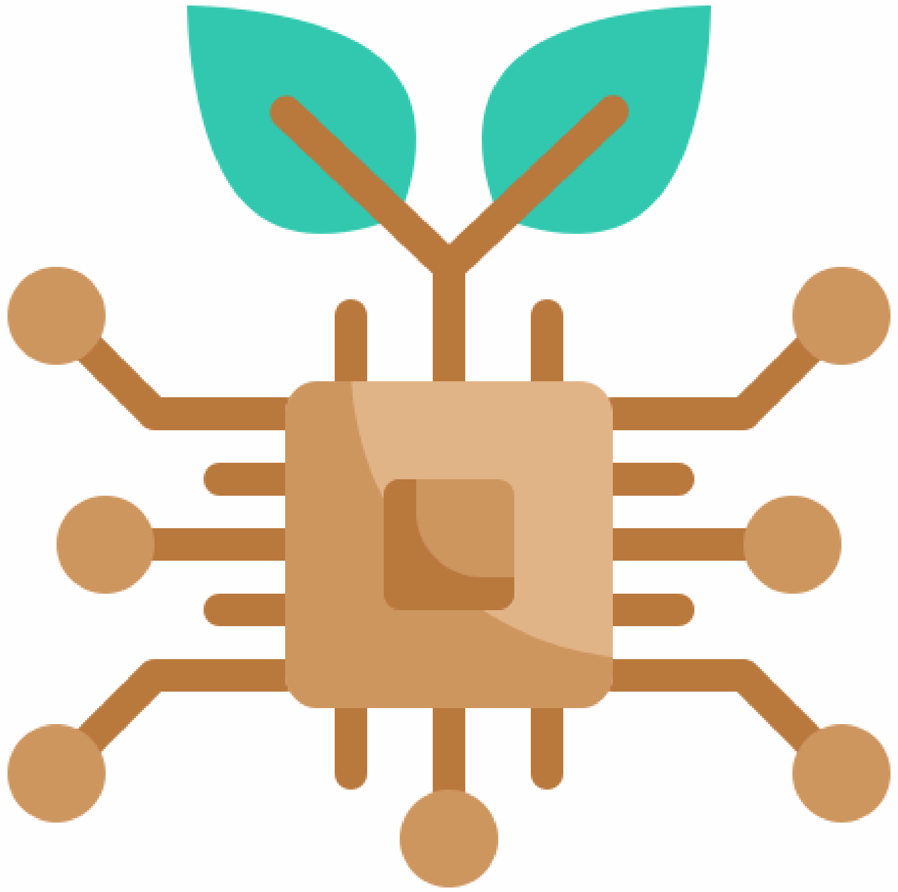
*Action Space* →

$$A = \{20k\frac{\text{kg}}{\text{ha}} \mid k \in \{0, 1, 2, ..., 6\}\}$$

*Reward Formula* →

$$r_t = m_{SO,t} - m_{SO,t-1} - (m^*_{SO,t} - m^*_{SO,t-1}) - \beta m_{fert,t}$$

# Environment



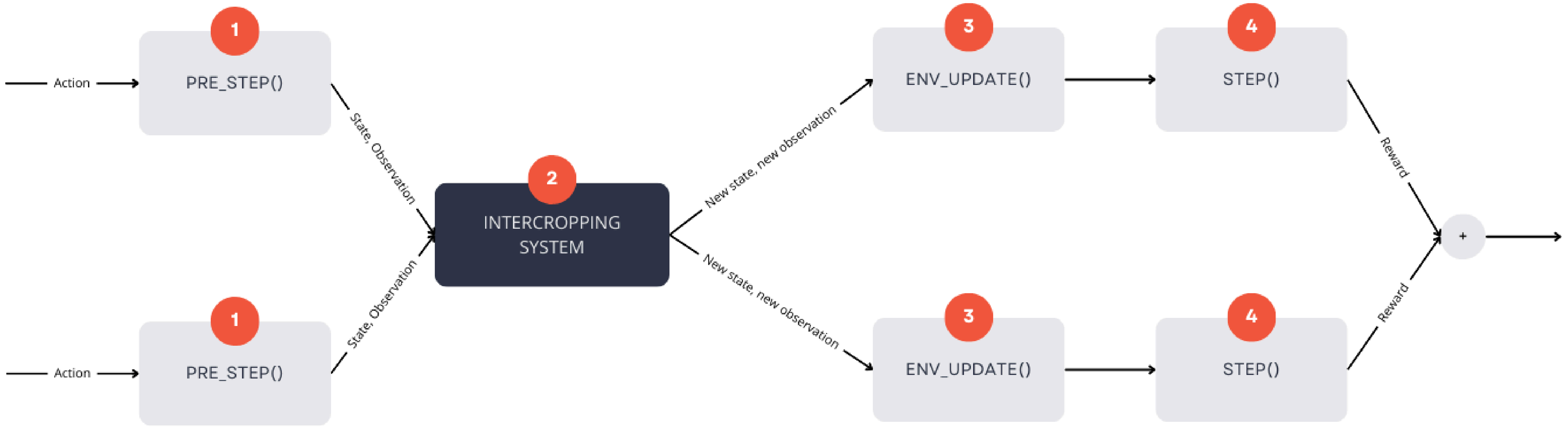
## Our extension:

InterCropGym combines two CropGym instances, applying intercropping techniques. The agent's nitrogen choice is used for both instances, and rewards are summed.

**Formulas and data used have not been validated by agronomists**

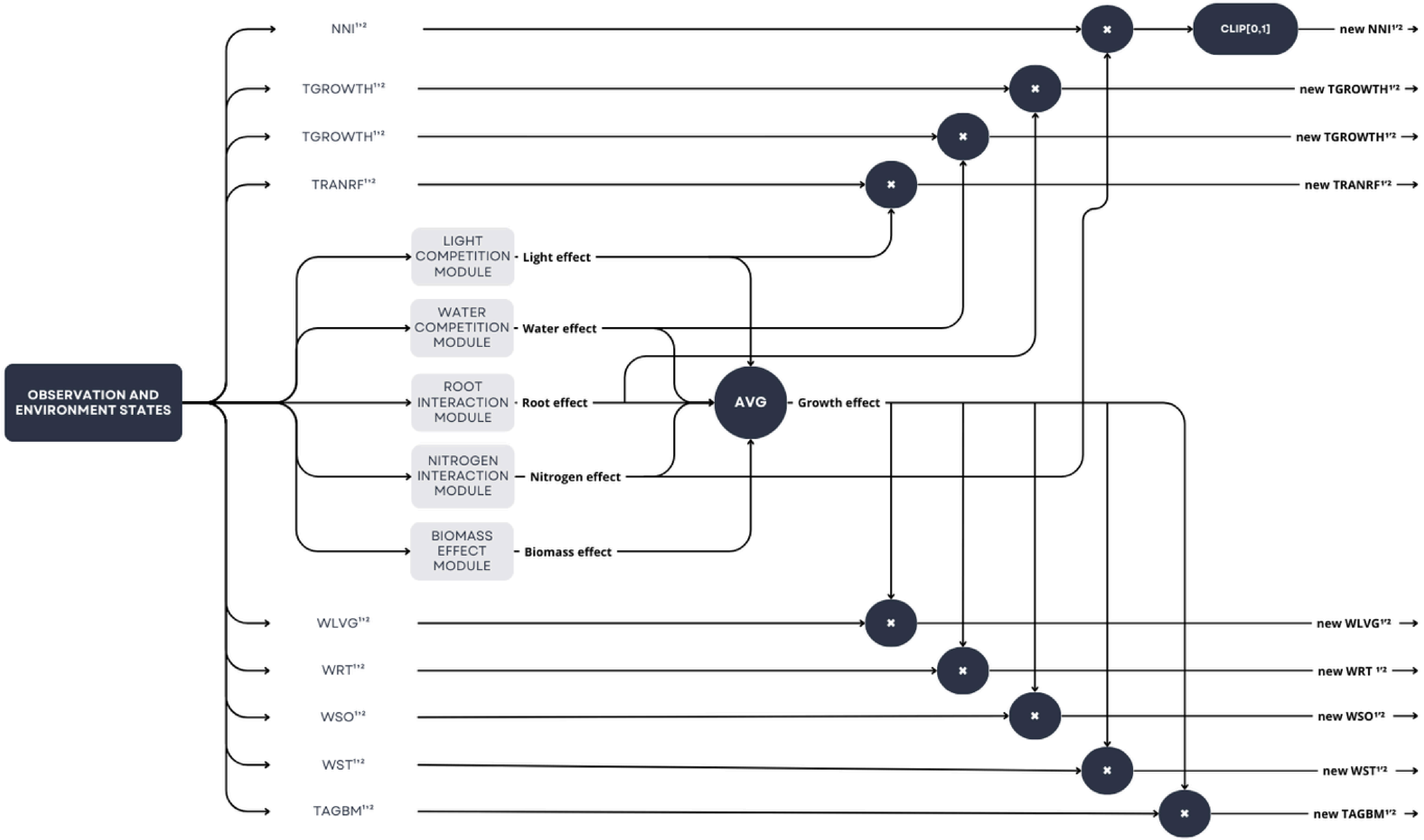
**Disclaimer**

# Environment



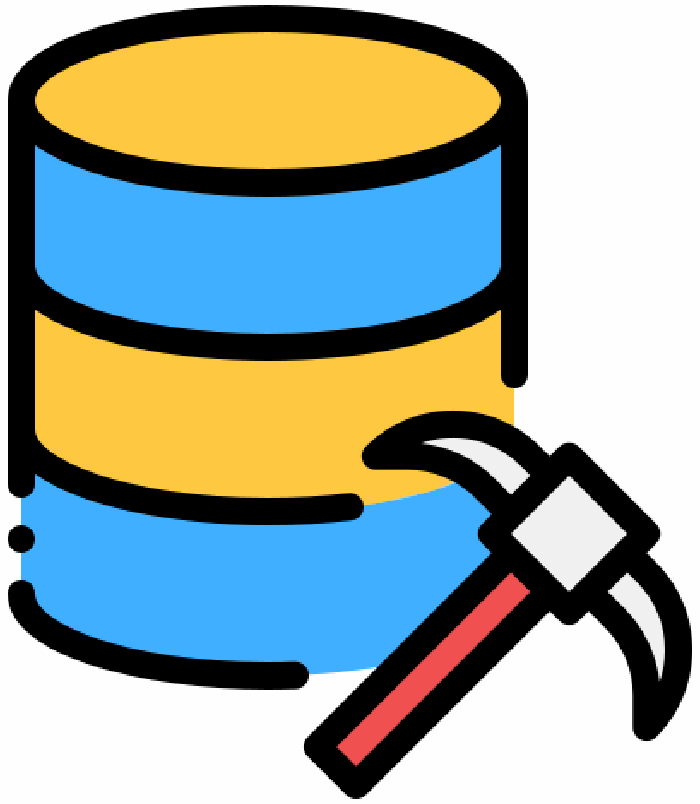

***InterGymCrop structure***

# Environment




*Intercropping System*

# Dataset



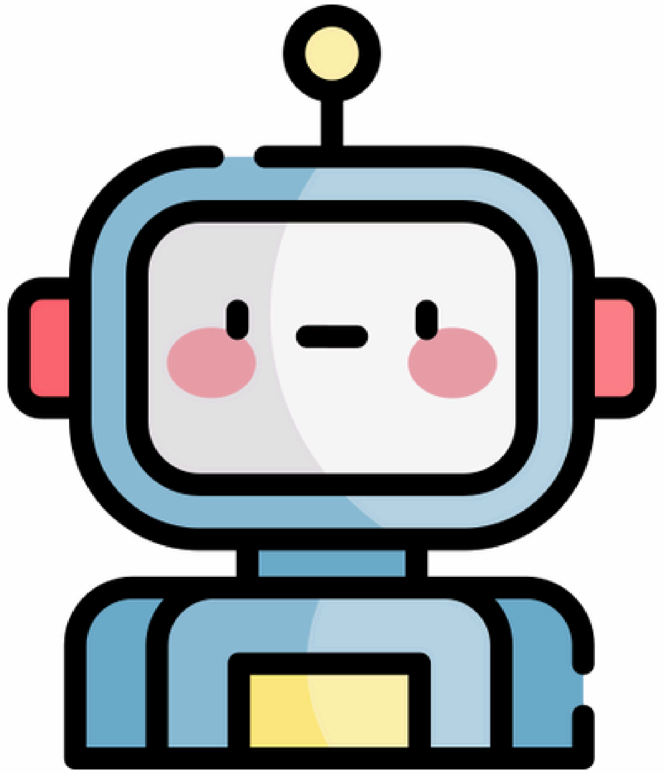
DSSAT / APSIM / WOFOST / PCSE

Concatenation & merging

Generation

# Agents

| Parameter | | Value |
|---|---|---|
| Optimizer | Learning Rate | 5e-4 |
| | Optimizer | Adam |
| | Max gradient norm | 0.5 |
| Network | Actor hidden sizes | [256, 256] |
| | Critic hidden sizes | [64, 64] |
| | Activation | ReLU |
| Algorithm | $\gamma$ | 0.99 |
| | GAE $\lambda$ | 0.95 |
| | Clip_range | 0.2 |
| | Entropy coefficient | 0.05 |
| | Value function coefficient | 0.5 |
| Training Process | Buffer size | 4096 |
| | Batch Size | 512 |
| | Epochs per update | 10 |
| | Eval Frequency | 25 |
| | Eval episodes | 80 |



**PPO**

- Actor-Critic architecture
- Clipped Objective Function
- Generalized Advantage Estimation (GAE)

$$\theta_{t+1} = \theta_t + \alpha \nabla_\theta L^{CLIP}(\theta_t)$$

# Agents

| Parameter | | Value |
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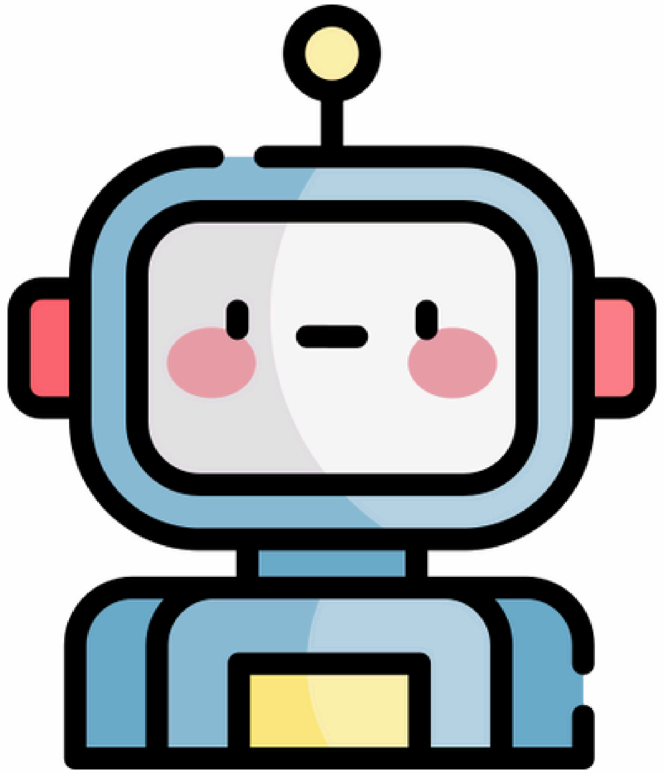


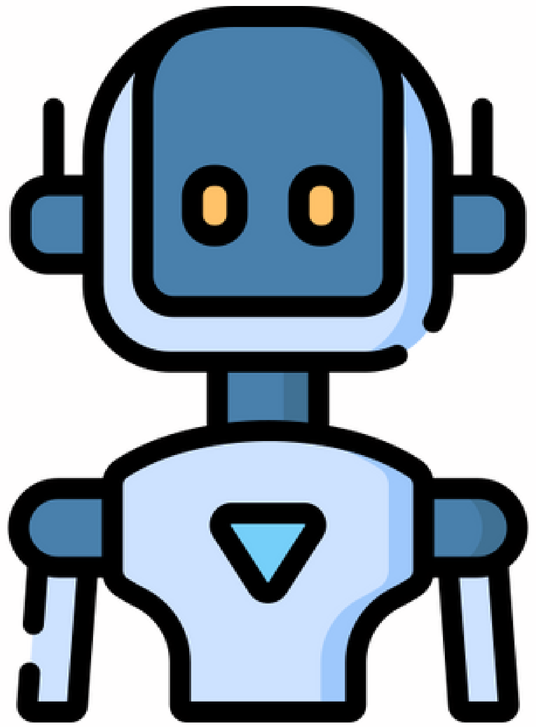
## PPO

Reaching stable convergence and consistent training required time and specific techniques:

- Value function clipping
- State normalization

# Agents

| Parameter | | Value |
|---|---|---|
| Optimizer | Learning Rate | 1e-4 |
| | Optimizer | Adam |
| | Max gradient norm | 20.0 |
| Training Process | Batch Size | 32 |
| | Epochs | 660 |
| | Eval Frequency | 25 |
| | Eval episodes | 80 |
| Algorithm | $\gamma$ | 0.99 |
| | $Q_t$ Update Frequency | 40 |
| Exploration | $\epsilon_0$ | 1.0 |
| | $\epsilon_f$ | 0.05 |
| | $decay\_rate$ | 0.9999 |
| Replay Buffer | Capacity | 5000 |



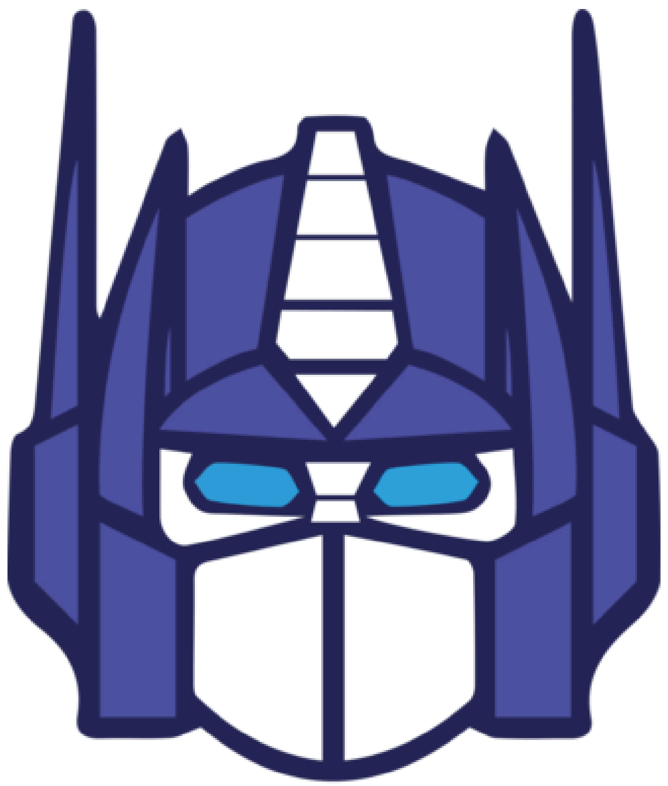
## Double Deep Q-Learning ( DDQN )

- Double Q-Learning
- Temportal Difference Learning
- Replay buffer
- Action selection with online Q-network

*Action Selection:* $a \leftarrow argmax_a(Q_o^\theta(s,a))$

# Agents

| Parameter | | Value |
|---|---|---|
| Optimizer | Learning Rate | 1e-3 |
| | Optimizer | Adam |
| | Max gradient norm | 10.0 |
| Training Process | Batch Size | 256 |
| | Epochs | 660 |
| | Eval Frequency | 25 |
| | Eval episodes | 80 |
| Algorithm | $\gamma$ | 0.99 |
| | $Q_t$ Update Frequency | 5 |
| | $\tau$ | 0.005 |
| Exploration | $\alpha$ | 0.2 |
| | $update\_frequency$ | 1 |
| Replay Buffer | Capacity | 5000 |



## Soft Actor Critic ( SAC )

- Double Q-Learning
- Entropy learning
- Replay buffer
- Actor-critic architecture
- Soft Updates for target Q-network

*TD error:* $\delta = r + \gamma Q_t^{\Theta}(S', A') - (Q_o^{\theta}(s, a) - \xi \log P(A'))$

*Soft Update:* $\Theta \leftarrow (1 - \tau)\Theta + \tau\theta$

# Experimental results

| | PPO | DDQN | SAC |
|---|---|---|---|
| *Reward* | **-657.94** | **-695.0** | **-372.29** |
| *Yield crop 1* | $20.64 \frac{g}{m^2}$ | $20.64 \frac{g}{m^2}$ | $20.64 \frac{g}{m^2}$ |
| *Yield crop 2* | $579.56 \frac{g}{m^2}$ | $579.56 \frac{g}{m^2}$ | $579.52 \frac{g}{m^2}$ |
| *Fertilizer used* | $60.76 \frac{kg}{ha}$ | $64.44 \frac{kg}{ha}$ | $33.04 \frac{kg}{ha}$ |

# Conclusion and future work

Our aim was to create a reference.
Future agronomists may review the work and adjust formulas and data to realistic applications.
Further experiments with model may be done in order to improve performance and obtain real-world approaches for sustainable agriculture.

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