Urban Agriculture

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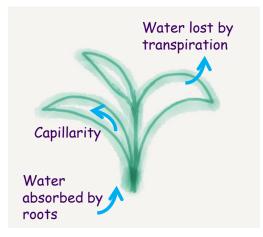
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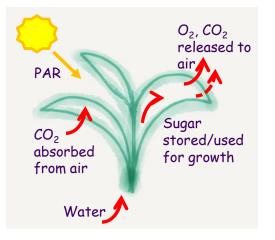


Why Urban Agriculture?

transpiration



photosynthesis

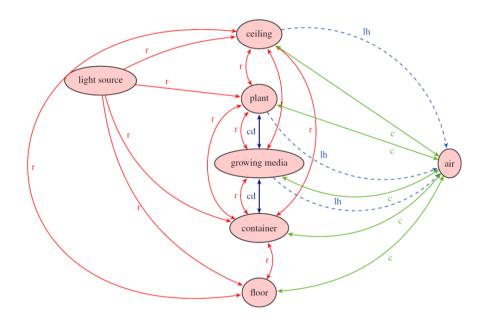


impact: cooling, increase in moisture content of air impact: net removal of CO_{2} , addition of O_{2}



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Research Challenges



- models of heat & mass exchange and plant growth. Largely empirical and limited to specific crops
- No models that couple greenhouse environment with standard buildings
- Monitoring difficult as environments are often bespoke



Growing Underground: our poster child...





Derelict Tunnels



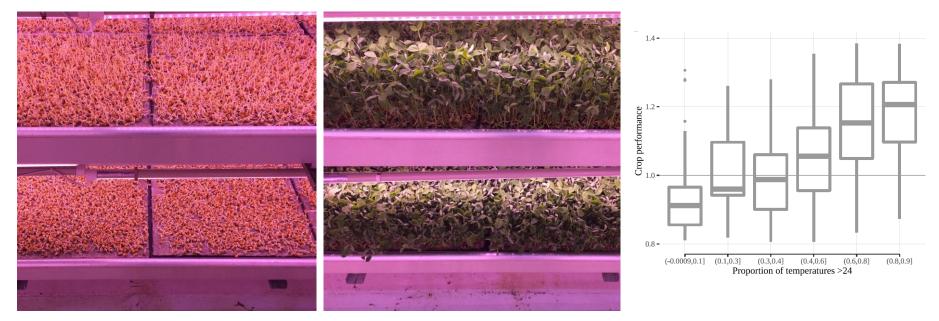
Initial Farm Trials



Commercial Farm (2015-)



Increase yield and minimise energy



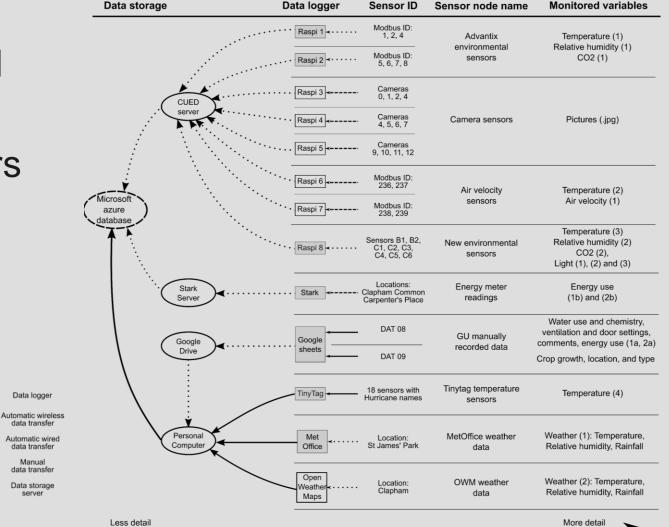
Peashoots: 5 days

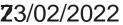
10 days

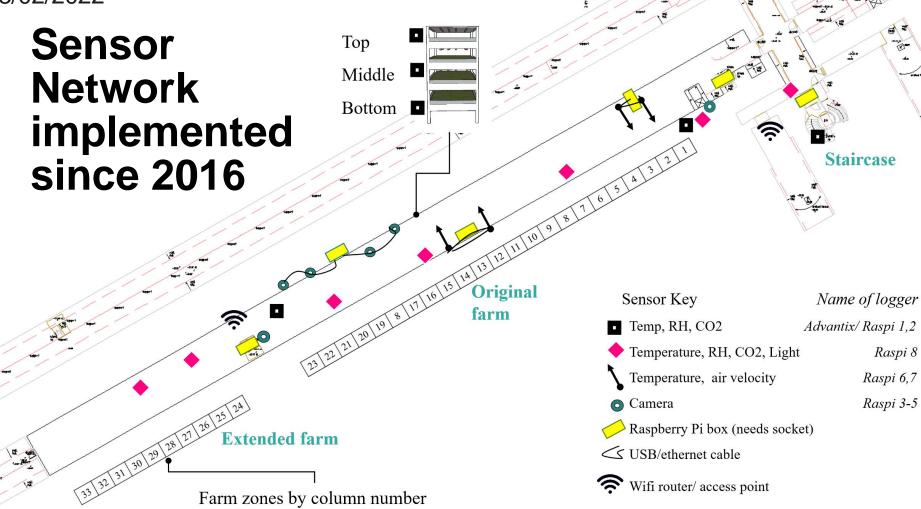
Performance with temperature

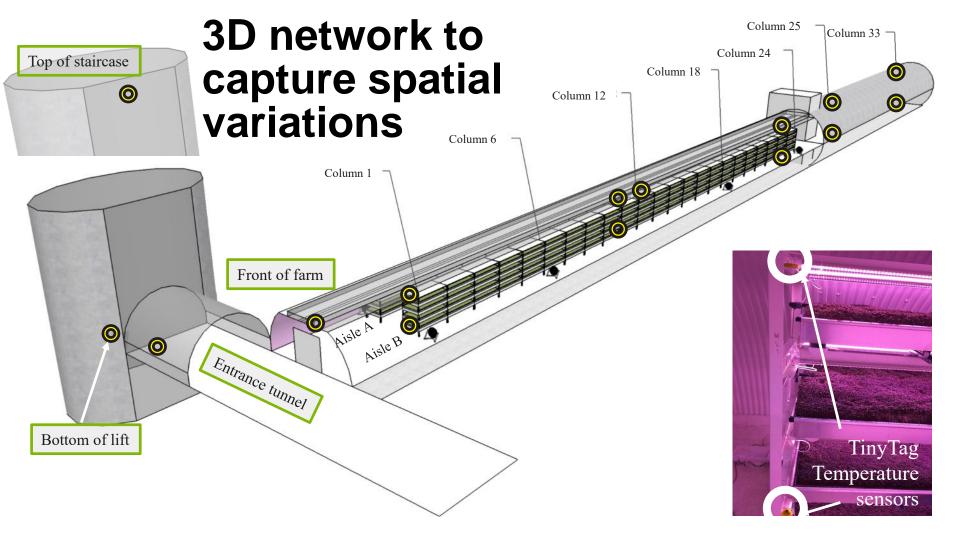
- 89 monitored variables
- 8 data loggers
 2 APIs
- Manual data collection

Key











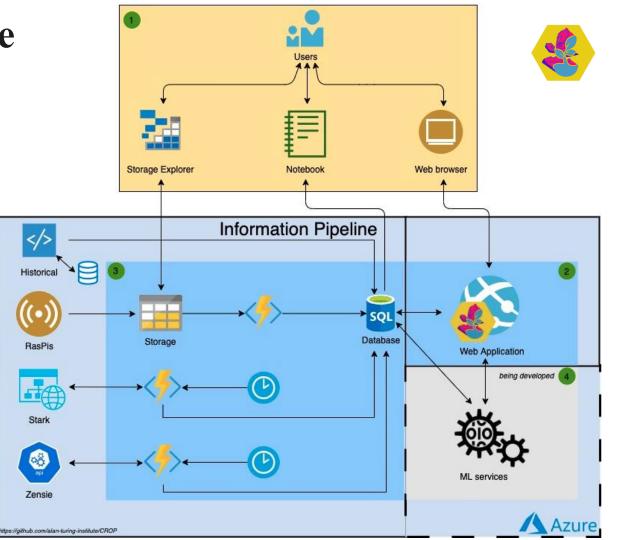
CROP Architecture

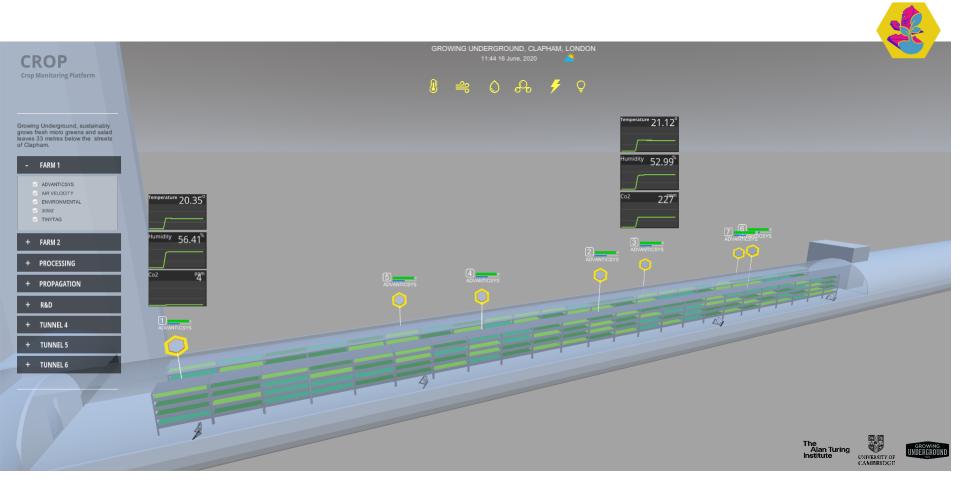
1 Users can **access** the CROP platform and database using multiple ways.

2 CROP **web application** is the main interface for the digital twin. Users can explore collected heterogeneous IoT sensor data, analyse farm conditions at various points in time, use the developed 3D visualisation tools.

3 CROP **database** is constantly updated from multiple streams of data: Zensie API, Stark energy usage platform, custom made (Raspberry Pi) sensors, and others.

4 CROP machine learning services integrate automated prediction and calibration models into the platform.

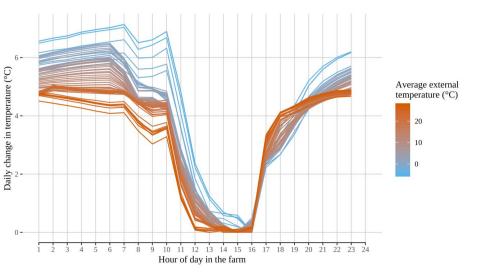








Temperature forecasting: too hot to grow?



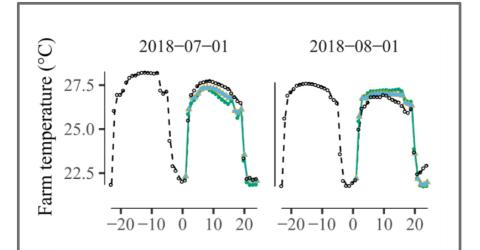
- Temperatures have changing mean, and an irregular, changing daily shape
- Energy readings are used to infer the lighting schedule as this is the main process behind the temperature changes
- Bayesian dynamic linear model with data-driven seasonal component handles typical and atypical forecasts, important for optimising yield
- Flexible to new data streams

Digital twin: use model to suggest operational changes and feedback to improve model

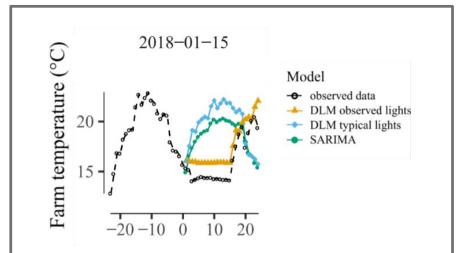


Temperature forecasting





Typical lighting days: bespoke and traditional forecasts are similar



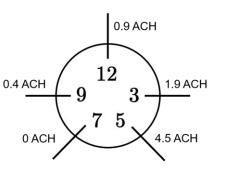
Atypical lighting days: data-driven method can forecast the effect on temperature by utilising the unique lighting pattern (lights switched on much later than usual)

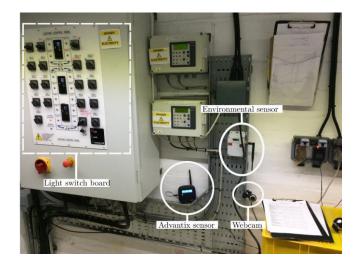




Meaningful bespoke outputs







Turn ventilation setting to 3 o'clock

Recommend to place peashoots in zone 6

Lights were on for 20 hours yesterday

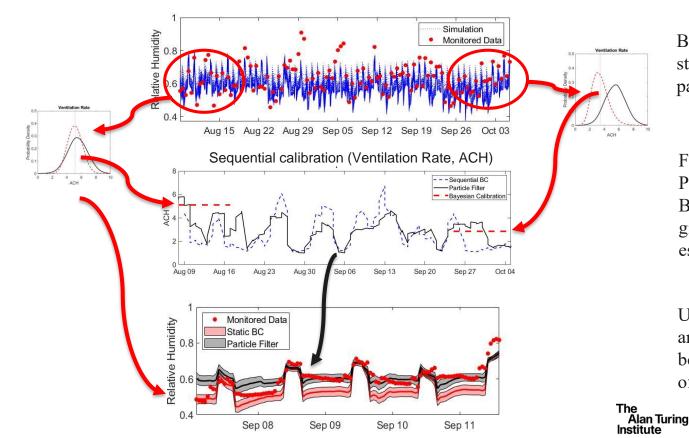
Continuous calibration of physics-based model



CAMBRIDGE

Department of Engineering

Physics-based model is used to simulate tunnel environment and to model future scenarios



Bayesian Calibration gives only static estimates of calibration parameters

For time-varying parameters a Particle Filter or sequential Bayesian Calibration approach gives continuously updated estimates of parameter values

Updated parameter estimates are used in simulation to give better estimates

of environmental conditions

Smart Infrastructure

Cambridge Centre for

& Construction

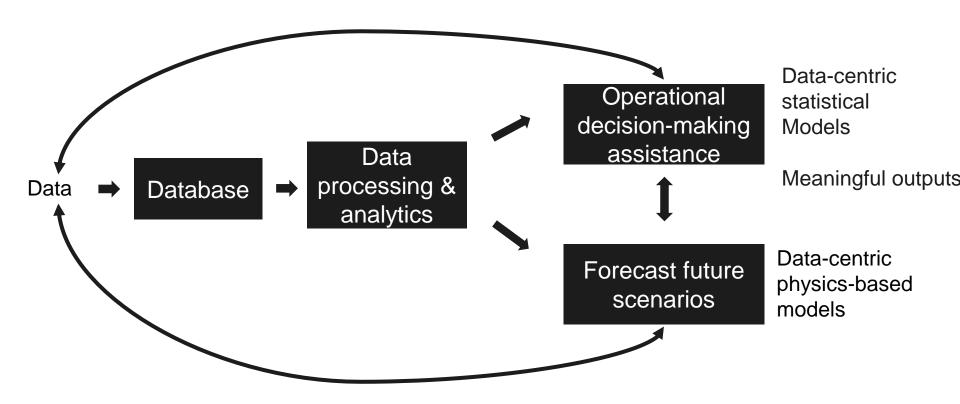
Benefits of the Digital Twin



- Continuously monitored data are uploaded to a central database for ease of access
- Data are extracted from the database for continuous calibration of the physics-based model
- The physics-based model with calibrated parameters is used to simulate potential scenarios for mitigation of undesirable environmental conditions
- Farm operators are alerted to potential problems and proposed remedial actions



Benefits of the digital twin



Questions?