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Research Article

Keywords:

Posted Date: June 25th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10012041/v1>

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Additional Declarations: No competing interests reported.

Spatiotemporal Canopy Temperature Forecasting for Precision Irrigation Management

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Abstract

Canopy temperature (T_c) is a critical physiological indicator of water and heat stress in cotton. Although weather-driven T_c forecasting is used by 60% of Australian cotton growers for irrigation scheduling, current methods typically rely on a single in-situ sensor to represent an entire management area. This uniform assumption overlooks substantial spatial variability in T_c and can lead to suboptimal water application. We propose UAV-linear, a novel spatio-temporal forecasting model that integrates high-accuracy in-situ sensors with weekly Unmanned Aerial Vehicle (UAV) thermal imagery to generate high-resolution hourly spatial T_c forecasts. Experimental results show that UAV-linear forecast stress conditions at unmeasured locations as effectively as models trained on exhaustive historical data, achieving a 25-35% improvement over the standard uniform-forecast assumption. Furthermore, in a large-scale validation across 25 50,000 hectares of commercially active farms (practical dataset), UAV-linear

30 improved stress-hour prediction by 22% relative to the uniform assumption while
maintaining accuracy comparable to historical benchmarks. These findings show
that the proposed spatio-temporal framework provides the spatial detail needed
for differentiated precision management, with potential to improve crop yield
and water-use efficiency.

35 **Impact:** This paper develops a spatio-temporal forecasting model combining in-situ
 T_c sensors and remote-sensing for canopy temperature. This advancement enables
look-ahead canopy temperature-based irrigation management, previously applied
using point measurements, to be extended to variable-rate and whole-farm irrigation
decision-making.

40 Funding Declarations

The authors have no funding declarations to disclose.

1 Introduction

Rising global emissions of greenhouse gases are driving climate change and intensifying water scarcity among some of the world’s most vulnerable communities ([UN-Water Expert Group on Water and Climate Change et al. 2019](#)). Increasing water scarcity creates an urgent need for cost-effective water-saving interventions. One such approach is precision agriculture, which employs detailed crop monitoring to enable timely, data-driven management decisions. One widely applied method of irrigation signalling is the T_c management approach, which forecasts canopy temperature to determine future water stress ([Petrusa et al. 2021](#)). This methodology is widely used for its effectiveness and low cost. It is currently applied to aid irrigation decisions for 60% of cotton farmers in Australia, as well as growers across 10 cotton belts in the USA ([Petrusa et al. 2021](#)). Precision irrigation for cotton is crucial as it is an increasingly important component of Australian agriculture, generating \$2.7 billion in gross revenue in 2024 and accounting for 4% of agricultural output ([Department of Agriculture and Forestry 2024](#)).

Canopy temperature is an indirect measure of transpirational and metabolic activity, both of which are important indicators of water availability ([Moore et al. 2021](#); [Burke and Oliver 1993](#)). There is often observed a crop-specific optimal T_c at which crop activity and yield are maximised ([Hatfield et al. 2011](#); [Hatfield and Prueger 2015](#)). Using cotton’s optimal T_c of $28^\circ C$, the forecast of T_c can be converted to ‘stress-hours’, defined as the number of hours the canopy spends above the optimal temperature ($T_c > 28^\circ C$) for cotton ([Conaty et al. 2012](#)). Stress-hours offer several advantages as a measure of water stress. Unlike point-based metrics like the Crop

65 Water Stress Index (CWSI), stress-hours as a cumulative measure is more resilient to
cloud cover and weather fluctuations, providing a continuous aggregate of heat stress
(Raper et al. 2016; Maes and Steppe 2012; Jackson et al. 1981; DeJonge et al. 2015;
Morales-Santos and Nolz 2023). Stress-hours have a strong biological relationship with
plant water use, evapotranspiration, stomatal conductance, and canopy temperature
70 (Maes and Steppe 2012; Conaty et al. 2012). Forecasting T_c and converting it to stress-
hours allows water stress to be identified and prevented before it occurs. In practice,
 T_c forecasting for irrigation management using stress-hours has delivered measurable
benefits, improving water use efficiency by 10% (Conaty et al. 2012; Wanjura et al.
2002; Petrusa et al. 2021).

75 Stress-hour forecasting management is currently utilised throughout Australia and
the USA, the forecasting method for farms relies on the data from a single in-situ
 T_c sensor. The use of a single sensor is operationally useful but spatially inadequate,
as it assumes the sensor is representative of the farm’s needs as a whole, ignoring
spatial variation in water stress. By adapting the forecast spatially, spatial water-stress
80 estimates can be obtained, enabling more accurate irrigation decisions. In particular,
the focus is on Australia’s dominant furrow-irrigated farms, which require a forecast
7 days in advance to plan irrigation and deliver water (Petrusa et al. 2021).

Significant spatial differences can arise on furrow irrigated farms from non-uniform
water distribution, rooting and stomatal characteristics, soil type/density variation,
85 canopy microclimates, all of which are exacerbated under water stress, these cause
non-linear and local variations (Aleman et al. 2011; Liu et al. 2020; Pinter et al.
1990; Wanjura et al. 2004; González-Dugo et al. 2006; Choudhury 1983; Wang and

Juang 2024; Liu et al. 2020). Under water stress, these effectors mean even two close cotton crops T_c often differ by $2 - 3^\circ C$ in T_c during the day, which leads to large differences in stress-hours and water needs (Wanjura et al. 2004; Conaty 2010; Maes and Steppe 2012) (Table 1). Table 1 shows large differences in nearby T_c monitored crops, with a low-irrigated farm causing over $2^\circ C$ difference from elevated ($T_c > 28^\circ C$). Additionally, for a well-irrigated farm, there was an average difference in 2 irrigations decided (using stress-hours) over the season (average of 5), which would lead to drastically differing water costs and yield results (Table 1). As a result, the widely used point T_c stress-hour forecasting method can yield poor and variable outcomes depending on sensor placement, prompting consideration of spatial variation (Wanjura et al. 2004; Peters and Evett 2004a). To address this, the study focuses on developing and evaluating a spatio-temporal T_c forecast method for spatial precision irrigation.

Spatial T_c sensing is well-suited to spatial irrigation management because it can be captured using emerging thermal-imaging methods from UAVs and satellites, unlike the other main indicator of water stress, soil moisture (Conaty 2010; Durigon and de Jong van Lier 2013). T_c spatial precision irrigation management has only been applied retroactively, limiting its use for Australia’s furrow irrigated cotton. Peters and Evett (2008) applied T_c diurnal modelling methods to T_c sensors to spatially irrigate with accuracy equivalent to utilising spatial soil measurements. Ben-Gal et al. (2025) improved on this, incorporating weekly thermal UAV images to derive CWSI and perform spatial irrigation (Jackson et al. 1981). Ben-Gal et al. (2025) method improved water efficiency in cotton by 19% relative to uniform irrigation. Both methods were deemed uneconomical due to the cost-benefit of imaging and spatial irrigation relative

to WUE benefits (Ben-Gal et al. 2025; Peters and Evett 2008). By creating a spatio-temporal (ST) forecasting method, irrigation can be applied before stress occurs and to larger furrow-irrigated farms, which often require water delivery and may yield higher benefits relative to costs (Smith et al. 2009).

115 Applying an ST forecast method requires assessing the data available for modelling. Australia furrow irrigated cotton farms often have one or a few in-situ T_c sensors, and current UAV or satellite TIR data at farm-scale ($\sim 30m$) can only reasonably be acquired every 4 days to a week (Allu and Mesapam 2025; Xue et al. 2022; Cawse-Nicholson and Anderson 2021; Bahi et al. 2025; Meng et al. 2025; Petrusa et al. 2021).

120 Besides T_c , other spatial information that could be utilised is often either shared, such as management, cultivar, genotype or more dynamic factors, such as soil moisture, which require additional sensors (Petrusa et al. 2021). To maintain practical relevance, this study focuses on producing a spatio-temporal forecasting from one or a few currently utilised T_c sensors, emerging a weekly T_c image and an input weather
125 forecast.

The only current spatio-temporal forecasting model requires a significant amount of data, which is usually unavailable. Andrade et al. (2023) used an artificial neural network (ANN) to generate spatio-temporal forecasts from a sequence of pivot-mounted thermal 7-day T_c observations. Training of this ANN relied on continuous spatio-
130 temporal T_c data acquired from a pivot-mounted thermal camera, with scans (images) taken at 1-minute intervals over 10-hour T_c periods, repeated across 3 separate days. Such high-resolution data are neither commonly available nor practically attainable for farms without centre-pivot systems.

Developing a spatio-temporal model requires considering how to capture both the
135 spatial and temporal behaviour of T_c . Time-series models have utilised continuous 15-minute T_c data along with weather data to accurately forecast T_c up to 7-days ahead (Shao et al. 2019; Rogers et al. 2026; Anon 2025; Shao et al. 2025). However, spatial modelling utilising T_c curves and spatial imagery has been studied to a lesser extent. Peters and Evett (2004b) modelled differences in T_c curves diurnally using a single
140 point T_c difference with the optional inclusion of dawn T_c . They found high accuracy of this method for daily interpolation for several crops across three irrigation treatments. The Peters and Evett (2004b) method could be extended to use remote sensing image data and 7-day forecast T_c curves to produce a 7-day forecast. This approach would utilise widely available T_c point sensors and increasingly accessible thermal infrared
145 (TIR) sensors, enabling spatial irrigation on furrow-irrigated farms, which represent a dominant irrigation practice globally (Smith et al. 2010). This model would solve both issues by providing a 7-day ST forecast, while using data which is practically feasible.

The proposed method has shown strong modelling of T_c , however, it is relatively simple in terms of spatio-temporal modelling. ST modelling aims to capture spa-
150 tial, temporal and joint behaviour (Wikle et al. 2019). Complex ST models require high-resolution ST data to capture T_c behaviour, which is not available (Wikle and Zammit-Mangion 2023; Yin et al. 2021). For lower ST-resolution data, standard statistical covariance-structure ST methods are more appropriate; they will only outperform simpler interpolation methods (such as Peters and Evett (2004b)) when spatial auto-
155 correlation is strong or other spatial covariates are available (Wikle et al. 2019; Jin et al. 2021; Bakar et al. 2015). Application of either of these ST models without

additional spatial covariates requires high-density hourly T_c data, produced from numerous T_c sensors (> 10) or sub-weekly imagery and/or sufficiently strong spatial autocorrelation in T_c .

160 T_c spatial variation is largely driven by non-linear and local effects, which often causes weak spatial autocorrelation (Figure A.1). As a result, higher-resolution ST data from a few input sensors and images are necessary, requiring data fusion of the two sources. In agriculture, high-resolution spatial data is becoming more feasible with decreasing UAV cost, improving satellite thermal products and increasing the
165 number of T_c sensors (Sishodia et al. 2020; Allu and Mesapam 2025; Petrusa et al. 2021). Thermal satellite fusion products of Landsat, Sentinel-2, Ecstress, *etc.* can routinely obtain high resolution and accuracy of land surface temperature estimates at 4-days and 30m, providing repeated T_c images (Zoratipour et al. 2025; Bahi et al. 2025; Meng et al. 2025; Pu and Bonafoni 2023; Cawse-Nicholson and Anderson 2021;
170 Roy et al. 2014; Claverie et al. 2018; Stavros et al. 2017). TIR UAV images can also obtain similar resolution with a strong relation to T_c and crop water stress, however, they are more costly (Liu et al. 2024; Pei et al. 2024; Treier et al. 2024; Gerchow et al. 2025; Ben-Gal et al. 2025; Chandel et al. 2025).

Compared to in-situ sensors, UAV and aerial flights have exhibited significant
175 disagreements of $1.5^\circ C$ and $1.0^\circ C$ to T_c (Gadhwal et al. 2023; Sobrino et al. 2006) (Figure A.2). Inconsistent agreement between in-situ sensors and imaging limits their data fusion for ST T_c forecasting (Goebel et al. 2023; Wang et al. 2023). Disagreements between sources are caused by geometric, temporal and calibration errors, arising due to microclimate and soil impact, high fluctuation in cotton T_c over time ($2.8^\circ C/hr$

180 around midday) and different calibrations (Goebel et al. 2023; Wang et al. 2023; Elfarkh et al. 2023). While these issues have correction methods, they have not been sufficiently effective for fusing data from on-ground T_c sensors with remote imaging approaches (Zoratipour et al. 2025; Goebel et al. 2023; Gadhwal et al. 2023).

Poor data fusion does not limit either method’s ability to determine water stress. 185 Tattaris et al. (2016) showed that both TIR UAV images and proximal measures correlate well with important phenotypic traits, including T_c . Furthermore, reasonable agreement between T_c sources has been reached when converting to CWSI from satellite (Zoratipour et al. 2025) and UAV (Pei et al. 2024). Both image and in-situ sensors can provide accurate water stress information and have been effectively used together 190 for crop water stress analysis or for calibrating one another (Carella et al. 2024; Gerchow et al. 2025). Given that both are informative, combining them into a novel, cohesive spatio-temporal forecast of water stress is a practical and important step in the development of precision T_c irrigation for furrow-irrigated farms.

An effective spatio-temporal T_c forecasting method with practical data require- 195 ments enables precise, ahead-of-time spatial management decisions using the stress-hour approach, which is currently not possible under current T_c forecasting methods. This ST forecast can be applied to furrow irrigated farms to improve irrigation decisions, yield and WUE for 60% of Australian cotton farmers (Petrusa et al. 2021).

2 Materials and methods

200 Here describes the datasets which were used to evaluate the novel spatio-temporally model UAV-linear. Overall two single farms with known and shared irrigation and

> 12 in-situ sensors were used along with a practical dataset covering 22 locations with > 7 sensors across multiple farms, irrigation treatment and even crops were used to evaluate the ST model UAV-linear.

205 2.1 Single-Farm T_c sensors

The evaluation of the new spatio-temporal model centres on two datasets from a single farm, each featuring clearly specified irrigation treatments and in-field T_c sensors. The thermal sensors used are described in detail in [Deery et al. \(2019\)](#). T_c sensors are point thermal infrared (TIR) sensors (MLX90614-BCF from Melexis, Ypres, Belgium) with
210 resolution of $0.2^\circ C$ and accuracy of $\pm 0.5^\circ C$ and a range of temperatures from 0 to $50^\circ C$. These sensors are calibrated against a Landcal P80P blackbody radiation source before deployment. The sensors are set 0.5m above the cotton crop, pointed at a 45° angle at the cotton row, and the actual point measures a $0.2m \times 0.1m$ rectangle of the crop leaf. The sensors transmit TIR measurements every 60 seconds to a field station,
215 which is then averaged over 15 minutes, along with recorded weather information, including air temperature, relative humidity, solar radiation and wind speed. These are downscaled to 60-minute readings to save computational time, without reducing forecasting accuracy as recommended in ([Rogers et al. 2026](#)).

The two datasets, irrigation treatments, rainfall and sowing dates, are described in
220 detail in ([Rogers et al. 2026](#)). The irrigation is furrow and equivalent to $1.36ML/ha$ per irrigation, the number of irrigation and rainfall is described in 3. Here, the available spatial data (such as remote sensing image Figure A.3) is described to focus on spatial modelling.

2.1.1 Shared high-irrigation data

225 Shared high irrigation data were collected from a 64-hectare cotton farm in Carrathool,
New South Wales (NSW) between 15 December 2020 and 05 May 2021. The data
measure the temperature of the cotton canopy across the farm using 16 TIR cam-
eras, referred to as in situ sensors. Carrathool is well-irrigated, does not experience
significant water stress, and is therefore referred to as the high-irrigation dataset. The
230 coordinates of sensors ct_{09} is (145.133,-34.435) and the farm is $800m \times 800m$ (64 ha)
(referenced in Figure A.4). The placement of the sensors is show in Figure 1, showing
a uniform coverage with concentration of sensors towards the centre. Weather data is
recorded from a central weather station.



Fig. 1: The 16 sensors are distributed across 64 hectares ($800m \times 800m$) labelled CT-X YYY, where X ranges from 01 – 16. These are subsequently referred to as ct_X in analyses. The sensors provide full coverage of the farm, with greater concentration towards the centre, where the weather station is located. The sensors designated as DR-X are soil moisture measurement devices and are excluded from the present analysis. The furrow irrigation occurred from the east (right) and travelled across the farm.

2.1.2 High Irrigation Aerial Images

235 The aerial measurements and processing are described in detail in [Deery et al. \(2016\)](#)
and again in [Deery et al. \(2019\)](#). The thermal infrared camera used (FLIRts SC645,
FLIR Systems, Oregon, USA, for which the technical specifications are: $\pm 2^{\circ}\text{C}$ or $\pm 2\%$
of reading; $< 0.05^{\circ}\text{C}$ pixel sensitivity; 640x480 pixels; 0.7 kg without lens; 13.1 mm
lens). This device was set up as a helicopter cargo pod (R44 Helipod II Slim Line
240 Top Loader, Simplex Aerospace, Oregon, USA) attached to a Robinson R44 Raven
helicopter. It was pointed straight down (nadir view), such that the angle of view for
a given image was from vertical up to $15 - 20^{\circ}$ right at the edge. These images were
collected at $\sim 120\text{m}$ at $45 - 65\text{km/h}$.

The TIR images without cloud cover were taken at 11:00 am, 12:30 pm and 2:00 pm
245 on dates 09-02-2021, 25-02-2021, 13-03-2021, & 27-03-2021 for the high irrigation farm
at Carrathool. Images were only collected in the TIR spectrum and require reasonable
canopy coverage to be usable due to soil noise. Each helicopter thermal image has a
resolution of 0.25m. These images (such as Figure [A.3](#)) are not used directly in the
modelling process but are instead utilised to illustrate the model's implementation.

250 2.1.3 Shared low-irrigation data

Shared low-irrigation data were collected from 12 sensors on water-deficient cotton in
Narrabri, NSW, in 2016. The 12 sensors are arranged in three configurations: single-
skip row, alternate-skip row, and solid row, with 4 sensors in each. These sensors are
identified single skip (S1101, S1114, S1121 and S1127), alternate skip (S1102, S1115,
255 S1119 and S1125) and solid row (S1103, S1113, S1120 and S1126), these are referenced

in Figure A.5. The farm is located at the geographic coordinates 149.77°E longitude and 30.32° S latitude. The T_c was recorded from 21 December 2015 to 22 March 2016. The plants in this dataset experienced relatively high water stress as described in Rogers et al. (2026). This dataset is hereafter designated as the low-irrigation dataset.

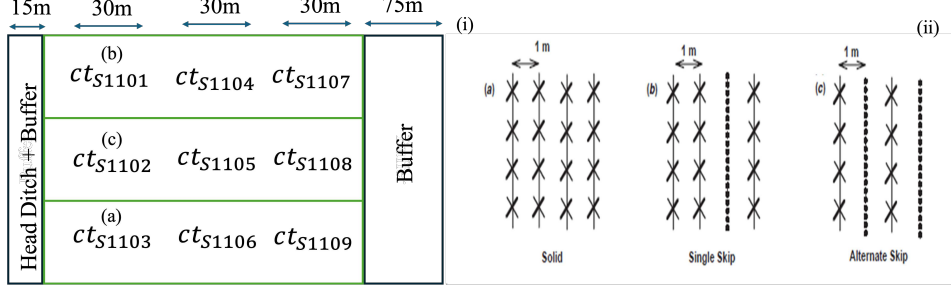


Fig. 2: Low irrigation Narrabri 2016 layout with plot description. Layout (i) shows a 30m plot structure comprising nine plots (numbered 1–9), with one T_c sensor installed in each plot. The corresponding plot numbers identify the sensors, and the row arrangement is consistent across the layout from left to right. Each row is assigned a configuration label: (a) solid, (b) single skip, and (c) alternate skip; these configurations are defined in detail in panel (ii). Within the layout, three distinct 3×3 plot blocks are established one below the other. In the first 3×3 block (as shown), the row configurations are ordered single (b), alternate (c), and solid (a). In the second 3×3 block, the order is solid, single, and alternate, and in the final 3×3 block, the order is alternate, solid, and single. The overall study area encompasses approximately 200 m $\times$ 200 m.

Figure 2 shows a single 3×3 block, the sensors in the 2nd block and labelled starting ct_{S1110} up to ct_{S1119} and then from ct_{S1120} up to ct_{S1129} in the order shown. Each plot shared a buffer, head ditch and irrigation schedule.

Figure 3 highlights the rain and irrigation treatment for the two shared irrigation treatment farms (high and low). This highlights water provided to the crop which justifies the high and low water stress definitions.

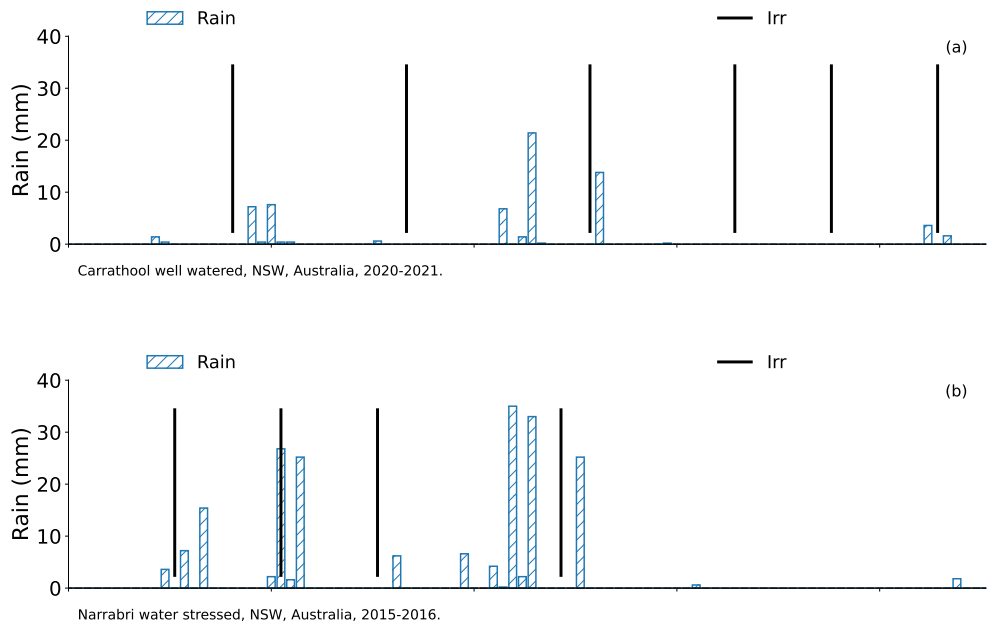


Fig. 3: Rain events are shown by the blue dashed bar according to the amount of rain received up to 40mm. The black bars indicate furrow (surface) irrigation events, which are roughly equivalent to 136mm of rainfall (Smith et al. 2012). The number of furrow irrigations determines the site treatments.

2.2 Practical T_c datasets

Cotton canopy temperature (T_c) is monitored at scale in Australia, with more than 60% of farms currently under observation. Producers who manage multiple fields and/or crops employing diverse irrigation strategies are interested in determining the
270 minimum number of T_c sensors required to achieve accurate and efficient farm-level management.

Over a 1000 in-situ sensors are utilised throughout Australia, by selecting datasets from single growers with at least 7 T_c (at least 4 to validate) sensors within a 15 km spatial cluster, we identify high-density sensor networks suitable for spatial modelling.
275 In total, 22 such locations were identified, comprising between 7 and 37 sensors, for a total of 252 sensors. With 3 examples of such locations shown in Figure 4. These locations encompass a range of crop types, irrigation regimes, and management practices across T_c sensors.

UAV-linear is modelled on these dataset, utilising 3 sensors per site which cover
280 the largest area. By applying UAV-linear to these current production T_c sensors, it is assessed in a practical situation in which it can be readily applied given current sensor coverages (as of 2025) and additional thermal imaging.



Fig. 4: Example of three ‘locations’ which represent practical farms with T_c sensors. The locations have 12, 14, and 18 sensors from left to right, marked by a red arrow. For privacy considerations, the model’s accuracy is not disclosed at the level of individual locations. The T_c sensors cover largely differing conditions and considerable distances (up to $\sim 30km$). The bottom-right value indicates the scale of the farms, covering 5km, 2km, and 5km.

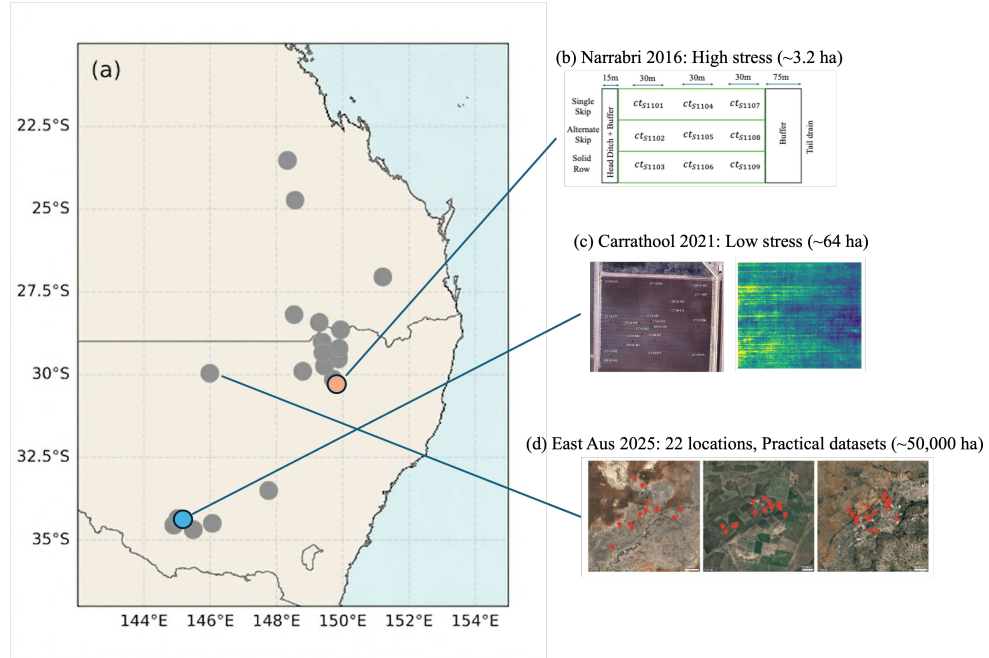


Fig. 5: Summary of datasets used in spatial forecasting. The entire dataset location is shown in (a), the experimental layout for Narrabri high stress dataset (b), NDVI for the variable stress dataset (c), Carrathool map with sensors and TIR image (d) and the 22 locations representing the practical datasets. These 4 datasets, cover 400 in-situ T_c sensors and are explored for spatial forecasting of T_c

2.3 Dataset comparisons

Table 1: Comparison of sensor T_c values within each dataset. The comparison is conducted from 26 January to 23 March for the two single-farm irrigation data sets, and from 01 January to 01 April for the practical datasets. The sensor outputs are compared in a pairwise manner, and the mean value and dispersion (standard deviation) of these comparisons are computed. For the practical datasets, the values are the averaged across the 22 datasets. The first subset $T_c > 28^\circ\text{C}$ represents the T_c above 28°C (for either sensor) while $T_c \leq 28^\circ\text{C}$ is both below. The stress-hours difference is calculated weekly. The final column compared the expected number of irrigations that each sensor would trigger under a weekly 31.5-hour threshold. The practical dataset cannot be compared on irrigation as it includes different crops. Figure A.4 and A.5 show pairwise distributions of the single-farm datasets.

	$T_c \leq 28^\circ\text{C}$ diff ($^\circ\text{C}$)	$T_c > 28^\circ\text{C}$ diff ($^\circ\text{C}$)	SH diff weekly (<i>hrs</i>)	Irrigations
High irr. (16)	0.67 ± 0.56	1.66 ± 1.11	5.43 ± 4.00	5.13 ± 1.83
Low irr. (12)	0.61 ± 0.48	2.25 ± 1.53	6.23 ± 2.56	10.33 ± 1.03
Practical	1.23 ± 0.53	1.95 ± 0.93	11.42 ± 8.41	NA

Table 1 and Figure 5 summarise the dataset properties, characteristics and location. Figure 5 shows the three datasets used along with their locations, size and description/treatment. This shows the datasets have high coverage of Australia’s East coast covering large amount of conditions and as a result are a comprehensive evaluation of the spatial forecasting model.

Table 1 summarises sensor variation using pairwise comparisons of the mean differences and deviations in temperature ($^\circ\text{C}$) and stress-hours (SH) calculated. The largest sensor differences for $T_c > 28^\circ\text{C}$ occur in the low-irrigation dataset, likely driven by the water deficit (Wanjura et al. 2004). The well-irrigated dataset, by contrast, shows relatively low sensor temperature variation for $T_c > 28^\circ\text{C}$. Both datasets nevertheless show considerable weekly stress-hour differences of $> 5\text{hrs}$.

295 The practical dataset shows a higher $T_c < 28^\circ C$ error than the other datasets,
as expected under differing conditions. Additionally, the stress-hour difference and
 $T_c > 28^\circ C$ are similar to those observed in sensors with different irrigation treatments.
These significant but comparable differences indicate that many locations likely have
similar conditions (crops, management, *etc*), while others differ substantially.

300 The daily stress-hour threshold for irrigation is 4.45 *hrs* when extrapolating over
a week, decisions are often made at a 31.5 *hrs* threshold for irrigation (Conaty 2010).
Table 1 shows the average and variance of irrigation decisions determined by sensors
based on this threshold. For the high-stress dataset, this comparison is not sensible as
all sensors are highly stressed, and regardless of sensor placement, irrigation will be
305 recommended most weeks (hence 10 irrigations).

A more realistic comparison is provided by the high-irrigation dataset, where sen-
sors recommend an average of five irrigations, near the lower end of the mean number
applied to cotton grown in Australia (Australian Government 2025b). Showing that,
within a shared-irrigation farm, T_c sensors may differ by approximately two irriga-
310 tion events. This difference is substantial and highlights how the sensor position can
strongly affect not only individual irrigation decisions but also the total number of
irrigations (Conaty 2010). In this setting, spatial forecasting of T_c has the potential
to improve irrigation decisions.

2.4 Spatio-temporal Model

315 As discussed, because we are handling a limited number of in-situ sensors in each
 T_c dataset and because local effects are strong, we do not observe sufficiently strong

spatial autocorrelation (see an example in e.g., Fig A.1) to model T_c using geostatistical or machine-learning (ML) methods. Instead, drawing on accurate T_c time series forecasting models (Rogers et al. 2026; Shao et al. 2019; Anon 2025), a T_c spatial interpolation model (Peters and Evett 2004b), and the relatively stable spatial structure of T_c , we propose UAV-linear for shared irrigation forecasting.

For UAV-linear, the first step is to build a time-series forecast for three in situ sensors using weather data. Although any suitable time-series model could be used, we utilise lightGBM, auto-ARIMA and periodiCTs, because they are high-performing T_c forecasters; moreover, auto-ARIMA and periodiCTs produce smooth forecasts that can integrate well with UAV-linear (Rogers et al. 2026; Ke et al. 2017; Hyndman and Khandakar 2008; Anon 2025; Garza et al. 2022). The forecast for sensor ct_s at hour t of the week is denoted by $\hat{T}_{ct_s}(t)$. Details of the forecasting methods are provided in (Appendix 5.1). The models use either a full weather variable set, consisting of historical air temperature, relative humidity, solar radiation and wind speed, or air temperature alone to forecast. These two covariate sets are compared because they represent low- and high-information weather-forecast scenarios (Rogers et al. 2026).

The second step of UAV-linear is to spatially interpolate the forecast to any location within the management area. To adapt the simulation model of (Peters and Evett 2004b) for time-series forecasting – where pre-dawn T_c is unavailable, and fewer sensors are available to fit the Gaussian model – we design a generalised version of the scaling and Gaussian approach. For a 7-day forecast, this generalisation combines a daily sine wave with a peak at 14:00 and uses the reference difference $T_{ref} - T_{obs}$ as an

adjustment to the curve (Peters and Evett 2004b). The UAV-linear forecast $\hat{T}_{ct_x}(ct_s, t)$
 340 for location (ct_x) at time t , based on reference sensor ct_s , is then defined as follow:

$$\hat{T}_{ct_x}(ct_s, t) = \begin{cases} a_1 \hat{T}_{ct_s}(t) + a_2 [g(t) * (\bar{T}_{ct_x}(t_i) - \bar{T}_{ct_s}(t_i))] + a_3 t_{day} + a_4, & \text{if } 9 \leq t_{hour} \leq 21 \\ \hat{T}_{ct_s}(t), & \text{otherwise.} \end{cases} \quad (1)$$

$$g(t) := \sin \left(2\pi * \frac{t_{hour} - 8}{24} \right) \quad (2)$$

$$t \in (0, 24 * 7), \quad t_{hour} = MOD(t, 24), \quad t_{day} = t // 24 \quad (3)$$

$\bar{T}_{ct_a}(t_i)$, where $a = x$ or s , denotes the mean T_c from 11:00-14:00 for location ct_x .
 The 11:00-14:00 time window is chosen because it provides the most informative air-
 borne measurements (Deery et al. 2019) and captures the daily maximum T_c near
 14:00, which is strongly correlated with water potential and is used to interpolate T_c
 345 curves (DeJonge et al. 2015; Peters and Evett 2004b; Burke et al. 1988). Furthermore,
 averaging three midday values reduces the influence of potential cloud cover (when
 using remote sensing), wind, humidity, and other noise associated with a single time
 point. The 9:00-21:00 limit is adapted from Peters and Evett (2004b), during which
 most water-stress-related differences in T_c occur, that is, daytime differences (Figure
 350 1) (Blum et al. 2013; Chatfield 1975).

In our case, we use weekly in-situ sensor (ct_a) values from 11:00-14:00 to derive $\bar{T}_{ct_a}(t_i)$. These ‘simulated images’ take a temporal slice of (ct_a) continuous measurements to produce UAV-linear forecasts at location a . Using actual sensor values enables continuous-time validation of our spatial forecasts. It avoids potential discrepancies between in situ sensors and airborne TIR (Sobrino et al. 2006). $\bar{T}_{ct_a}(t_i)$ is updated at 7- & 14-day intervals, representing realistic revisit times for UAV or satellite TIR imagery (Stavros et al. 2017; Roy et al. 2014; Sishodia et al. 2020; Allu and Mesapam 2025). The final parameter, t_{day} , represents the number of days since observation of the ‘simulated image’ and is included to capture a possible linear trend over time. The model can forecast any location within the management area when weekly image observations are available, however, to rigorously validate the spatial forecasts, in situ sensors are used.

The equation 3 defines a residual harmonic equation based on the residual between a reference sensor (ct_s) and other sensors (ct_x), together with a harmonic g function with 24 hours and a maximum at $t_{hour} = 14$ —the definition of g matches the observed smoothness and daily periodicity of T_c . The contribution of g is illustrated in Figure 6 (e), which compares the reference curve (orange), the prediction without the harmonic adjustment (blue), and the prediction with the $a_2 * g$ adjustment (green). For $T_c > 28^\circ C$, the time-series forecast MAE using only the reference is $1.30^\circ C$, and is reduced to $0.48^\circ C$ after applying the $a_2 * g$ adjustment. Across 100 UAV-linear fits, the harmonic parameter a_2 was found to be highly significant ($p < 10^{-10}$).

2.5 Spatio-temporal model training and comparison

To estimate the regression parameters (a_i) in Eq. (1), multiple sensor forecasts from known historical data are required, one of which serves as the reference forecast. UAV-linear forecast accuracy depends on the number of known sensors, increasing rapidly from two to three known sensors and plateauing after four (see Figures A.6 and A.7). Accordingly, a_i are estimated by linear regression using three known sensor forecasts. For the two shared-irrigation datasets, the final three known sensors are chosen to perform similarly to the median performance of 100 randomly sampled three-sensor combinations (see Figures A.6 and A.7). For the complex spatial datasets, 10 groups of three to four sensors that provide the greatest spatial coverage are selected for forecasting, reflecting how sensors might be placed in practice.

UAV-linear is compared with two baselines: a forecast for the target location using all historical T_c data, representing an ‘ideal’ spatial T_c forecast, and a forecast from the reference sensor, representing a ‘no-transfer’ forecast. Given the problem’s specificity and the lack of observed spatial autocorrelation, no other suitable ST models are available for comparison. All forecast comparisons are evaluated using three metrics, MAE for T_c , MAE for $T_c > 28^\circ C$ and daily stress-hours MAE. These metrics, together with the forecasting methods, are described in Appendix 5.1.

Given that a forecast from a known sensor using periodiCT is currently used for irrigation management on more than 60% of Australian cotton farms, demonstrating equivalent accuracy for spatial forecasts supports their practical applicability.

Figure 6 illustrate how UAV-linear is utilised to produce a spatial forecast. Figure 6 (e) compares the UAV-linear T_c forecast (dotted green), the unknown sensor to be

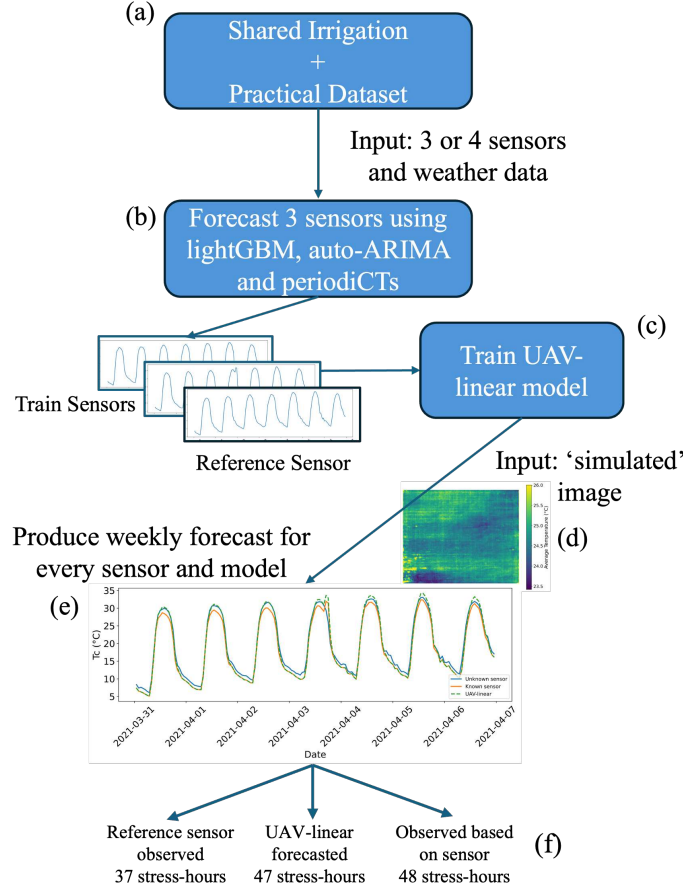


Fig. 6: Schematic of forecasting for shared and practical irrigation datasets. The shared and practical datasets in (a) use UAV-linear. Three (or four) sensors are selected and forecast using the three time-series models shown in (b). These three forecasts, together with the selected reference sensor, are then used to train the UAV-linear model in (c) (Section 2.4). Because the trained UAV-linear model can produce a forecast from a midday T_c reading, inputting a simulated image in (d) yields a forecast at every point, shown in (e). The forecast stress-hour shows the difference for each prediction, with the reference differing over 10 hours from UAV-linear and it differing from the true curve by 1 hour (f).

395 predicted (solid blue), and known reference sensor (solid orange), to show how UAV-linear adjusts the reference forecast. UAV-linear captures the actual curve accurately and is much closer in stress-hour prediction and able to make accurate irrigation

decisions. UAV-linear aims to use minimal weekly T_c image information to derive forecasts at each unknown sensor.

3 Results

This section illustrates the advantages achieved by the UAV-linear approach.

3.1 Captures the ST structure of T_c

UAV-linear is compared to independent models with access to historical values, a no-transfer model which uses the reference sensor forecast, *i.e.*, $\hat{T}_{ct_x}(ct_s, t) = \hat{T}_{ct_s}(t)$ and an ML model using location coordinates as input. The UAV-linear model forecasts are produced using accurate T_c forecasting models, lightGBM, auto-ARIMA and periodiCTs (Ke et al. 2017; Shao et al. 2019; Anon 2025; Hyndman and Khandakar 2008).

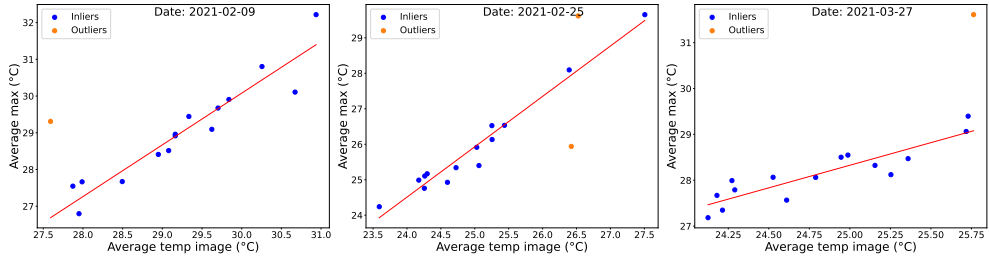


Fig. 7: Correlation between the mean start of week temperature and the average weekly maximum for the high irrigation dataset. The start-of-week temperature is the mean of the hourly sensor T_c from 11:00-14:00 at the start of the week, and the average maximum is the mean T_c of the next 7 daily maximums. Linear regression on these values (excluding outliers $\pm 2\sigma$ in yellow) predicted the average maximum across a week. These three regressions show a R^2 of 0.90, 0.96 and 0.80. The remaining forecasting dates are shown in Figure A.8 for the high-irrigation dataset and in Figure A.9 for the low-irrigation dataset.

UAV-linear assumes the spatial variation in T_c is relatively stable over a weekly
 410 interval, and as a result (Peters and Evett 2004b), diurnal interpolation can be extrapolated over a week. This assumption is supported by Figures 7, A.8, A.9, which indicate that the maximum T_c is correlated to the mean midday T_c at the start of the week. These high correlations occur for most dates before mid-March. Accordingly, T_c sensors with higher temperatures at the start of the week will, on average, maintain
 415 higher temperatures throughout the week. This serves as the basis for UAV-linear to interpolate forecast T_c curves spatially over a week.

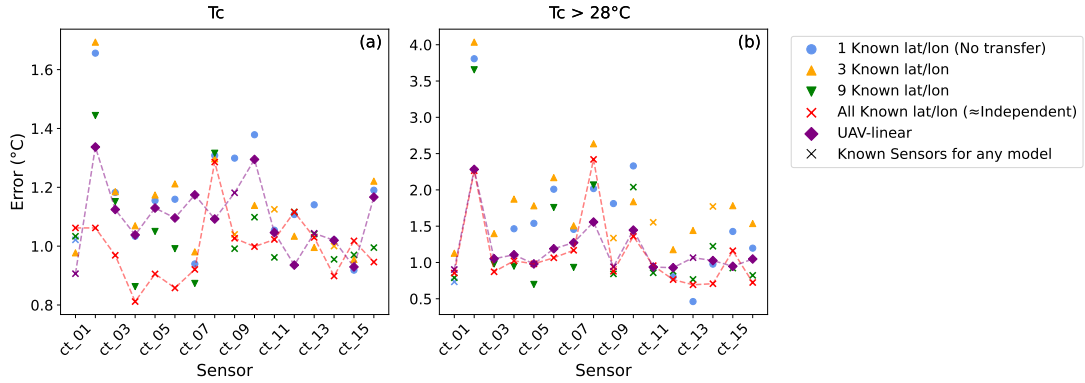


Fig. 8: UAV-linear using lightGBM for forecasting compared to a trivial spatial lightGBM model. The two spatial methods are compared for weekly forecasts from 1-26 to 3-09 with MAE on T_c for (a) and $T_c > 28^\circ C$ for (b). The trivial spatial lightGBM model is trained with longitude and latitude covariates on 1, 3, 9 and 16 (all) sensors using latitude and longitude covariates as shown for a blue circle, yellow triangle (up), green triangle (down) and red $\times$ respectively, while UAV-linear is a purple diamond. A $\times$ marker indicates the sensors known by each model, while unknown sensors are marked by their respective symbols. While not the same model, all known perform with very similar accuracy to the independent model as expected.

Figure 8 shows the spatial forecasting of UAV-linear compared to the trivial lightGBM method of including latitude and longitude covariates to capture the spatial

variation of T_c sensors. The trivial lightGBM forecast using three sensors is signif-
420 icantly worse than the UAV-linear forecast (which also uses 3 sensors) across all
unknown locations. It only becomes comparable to UAV-linear when 9 out of 16
sensors are known. A UAV-linear model with only 3 known sensors can produce
 $T_c > 28^\circ C$ forecasts with accuracy equivalent to that of a lightGBM model using all
sensor history. Importantly, UAV-linear captures the outliers ct_{02} and ct_{08} , which the
425 longitude-latitude model does not capture, and for ct_{08} , which is poorly forecast by
the independent ‘all known’ model.

3.2 Optimal ST forecasting of T_c

The latter analyses focus on capturing $T_c > 28^\circ C$ and stress-hours as the UAV-linear
model focuses on these quantities and only interpolates during the day.

Table 2: The performance of UAV-linear against the independent models and no-transfer models for all datasets and forecasting models. The MAE values of $T_c > 28^\circ C$ and daily stress-hour error are presented for models ordered UAV-linear|independent|no-transfer models, where the base forecasting models are lightGBM, auto-ARIMA and periodiCTs, respectively.

	LightGBM	Auto-ARIMA	PeriodiCTs
High irrigation $T_c > 28^\circ C$	1.70 1.47 2.30	1.22 1.23 1.78	1.95 1.88 2.34
Low Irrigation $T_c > 28^\circ C(^{\circ}C)$	1.41 1.43 2.23	1.57 1.53 2.23	1.58 1.48 2.34
High irrigation $SH(hrs/day)$	1.04 0.93 1.29	0.53 0.62 0.67	1.17 1.12 1.19
Low Irrigation $SH(hrs/day)$	0.84 0.82 1.20	0.70 0.87 1.52	0.98 0.96 1.12

430 Table 2 lists the forecast errors of UAV-linear with all base models for the low and high
irrigation datasets. UAV-linear, using time-series models, improves over the no-transfer
approach and excels on the low-irrigation dataset, which exhibits significant sensor-
to-sensor variation. For this dataset, the performance of UAV-linear is within $0.05^\circ C$

of the independent model and improves in forecasting stress-hours. Furthermore, it
 435 greatly improves over the no-transfer approach on average by $0.75^{\circ}C$ and 0.5 stress-
 hours per day for lightGBM and auto-ARIMA base forecasters (or around 35 – 40%).

Table A.1 further summarises the UAV-linear model across the two datasets, show-
 ing that UAV-linear performs nearly as well as the independent models, which had
 access to historical data from all sensors. Additionally, UAV-linear largely improves
 440 over the no-transfer models for $T_c > 28^{\circ}C$ (28.7%) and stress-hours (23.0%) across all
 three models. The large difference highlights the significant spatial difference between
 sensors. These results indicate that UAV-linear can effectively capture spatial varia-
 tion for crucial temperature-threshold conditions, provided there is data from 3 in-situ
 sensors and a weekly repeat of the T_c ‘image’.

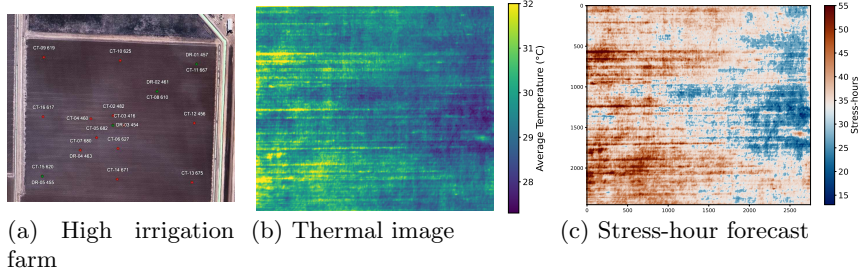


Fig. 9: Observed, average thermal and stress-hour 7-day forecast images for the 09 February 2021 for the high irrigation dataset. The image (a) is from Google Earth with sensor locations shown, (b) is the average temperature of three calibrated thermal images from 09 February 2021 at 11:00, 12:30, 14:00 and (c) is the 7-day forecast stress-hour image from UAV-linear. Image (c) is set to colour segments red, which are expected to exceed the $31.5hr$ weekly stress limit, which causes a call to irrigation (Conaty et al. 2012). The images (b,c) are rotated and set within the farm boundary seen in (a), with the soil showing on the left of the farm cropped to remove noise.

Figure 9 shows that UAV-linear can utilise aerial images and forecasts from ct_{01} , ct_{09} and ct_{13} to produce an ST forecast. Converting these ST forecasts to the accumulation of stress-hours shows the areas of the farm that may need more attention or treatment. This allows monitoring water stress at every location on the farm and spatial irrigation management using the stress-hour approach.

3.3 Accurate stress-hour forecasts for practical spatial data

Table 3: Comparison of UAV-linear model with independent models, no-transfer models for 22 practical spatial datasets and 252 sensors. UAV-linear with base model lightGBM was used for forecasting 22 spatial T_c datasets, and the average and standard deviation of $T_c > 28^\circ C$ (T_{c28}) MAE and stress-hour error over the datasets are shown. UAV-linear model is compared to the lightGBM independent and baseline (no-transfer) model - models and metrics defined in Section 2.4. The model runs 10 combination of 3 random sensors for datasets with ≤ 10 sensors (9 datasets) and 4 otherwise (13 datasets). The spatial distribution of error is shown in Figure A.10.

	UAV-Linear MAE for $T_{c28}(^\circ C)$	UAV-Linear stress-hour err. (<i>hrs/day</i>).
UAV-linear	1.91 ± 0.31	1.33 ± 0.19
Independent	1.66 ± 0.23	1.14 ± 0.16
No-transfer	2.17 ± 0.63	1.71 ± 0.54

Table 3 shows UAV-linear ability to interpolate for a large number of practical spatial datasets. The model performance for $T_c > 28^\circ C$ is poorer than for single farm irrigation datasets and is $0.25^\circ C$ less accurate than the independent model and only $0.26^\circ C$ more accurate than the ‘no-transfer’ model. However, the improvement in stress-hours of 0.38 hrs/day over ‘no-transfer’ is greater, whereas in the independent model it remains at 0.17 hrs/day . The UAV-linear model also shows a similar deviation to the independent model and a much lower deviation than the ‘no-transfer’ approach, indicating consistent accuracy across locations (see Figure A.10).

4 Discussion

460 Presented is a spatio-temporal T_c forecasting method for spatial precision irrigation on shared irrigation farms. Building on the best T_c forecasting methods, UAV-linear is a novel residual harmonic method which combines T_c spatial and forecasting models to produce accurate forecasts for two locations with shared irrigation farms and reasonably accurate and consistent forecasting for a large range of practical spatial T_c 465 datasets with differing management (Rogers et al. 2026; Peters and Evett 2004b).

4.1 Spatial forecasting of T_c with UAV-linear

For ST forecasting, our proposed UAV-linear model builds upon the best T_c 7-day covariate-driven time-series methods (lightGBM, auto-ARIMA and periodiCTs) (Ke et al. 2017; Hyndman and Khandakar 2008; Anon 2025; Peters and Evett 2004b; 470 Rogers et al. 2026) and (Peters and Evett 2004b,a) diurnal interpolation model. UAV-linear ability to accurately spatio-temporal forecast shows that extending the diurnal interpolation is robust over a weekly horizon and for applying to forecast T_c curves. Achieving accurate spatio-temporal forecasts utilising three T_c in-situ sensors and weekly images, which are fairly low-cost and practical requirements. The T_c spatial 475 forecast for stress-hour management will allow effective determination of dynamic irrigation maps and whole-farm considerations across cotton farms (see Figure 9).

UAV-linear achieves similar accuracy to the independent models (with known history) for shared irrigation farms, for both $T_c > 28^\circ C$ and stress-hours (Table 2 and A.1). This result means UAV-linear achieves accuracy equivalent to the time-series

480 forecast at the location, against a forecast of which all history is known. In most practical scenarios with limited spatial data, where complex T_c mechanisms cannot be captured, a spatial forecast as accurate as one that uses all historical T_c data is ideal. As a result, UAV-linear is as accurate as or more accurate than the independent periodiCT model, which is currently used for planning T_c -driven irrigation, with direct
485 practical implications (Petrusa et al. 2021).

UAV-linear is focused on forecasting daytime and particularly hotter conditions where T_c variation, water-stress and stress-hours occur. For the low-irrigation dataset, an ST forecast is particularly important due to the high spatial variation of $T_c > 28^\circ C$ conditions (Table 1), which lead to variation in stress-hours, heat-stress, water-
490 stress and likely yield. For the high-stressed, low irrigation dataset, UAV-linear using lightGBM and auto-ARIMA improves over the ‘no transfer’ approach by 35% – 40% in all metrics (Table 2).

Spatial forecasting in low-stress conditions is also crucial. In low stress situations, T_c is often close to the irrigation threshold for stress-hours, and even a small spatial
495 variation in T_c in space can cause different irrigation suggestions (Conaty 2010) (Table 1). This variation is observed even for the low-stress farm, where the number of irrigation calls can differ substantially between sensors (2 between sensors, Table 1), with an average difference of 40% (Conaty 2010). For these conditions, UAV-linear improves over the ‘no-transfer’ approach by around 30% for lightGBM and auto-ARIMA (Table
500 2).

This significant difference in $T_c > 28^\circ C$ between stressed crops and stress-hours (irrigation calls) for well-watered crops highlights the issue with assuming uniform

irrigation based on a single T_c sensor in all situations. It shows the importance of a spatial forecast under both well- and poorly-watered conditions, highlighting the benefit of the spatial forecaster UAV-linear for T_c management.

Even with sufficient accuracy, UAV-linear requires weekly images, which is costly and often the bottleneck for applying these methods. A reduction in image frequency can help make UAV-linear more feasible (Ben-Gal et al. 2025). For the high irrigation dataset, Figure A.11 shows that fortnightly ‘images’ only increased prediction error by $0.13^\circ C$. While Figure A.12 shows that UAV-linear forecasting from a fortnightly ‘image’ for the low irrigation dataset increased error by $0.3^\circ C$, and was particularly inaccurate for sensors that are outliers of the weekly maximum correlations in Figure A.9. The difference in error changes is likely due to the low-irrigation treatment and higher water stress, which cause a more dynamic spatial structure in T_c (González-Dugo et al. 2006; Evans et al. 2000). Given the importance of capturing spatial variation of T_c under high-stress conditions, a TIR image repetition interval of one week is ideal. However, if economic constraints prevent this imaging frequency, a 2-week imaging interval may provide reasonable accuracy for spatial decisions under standard conditions (Ben-Gal et al. 2025).

In addition to reducing image size, applying spatially precise irrigation to furrow-irrigated farms may be more cost-effective. Cost-effectiveness comes from ‘imaging’ costs shared across a larger farm size. This benefit may be diminished as furrow irrigation farms have less capability of spatially varying irrigation (Ben-Gal et al. 2025). Furrow irrigation can alter flow rate, direction, and amount, which can lead to variable irrigation, however, it offers less control than pivot systems (Silburn et al.

2013; Smith et al. 2009, 2012). The potential higher cost-benefit of applying UAV-linear and spatial irrigation to furrow-irrigated farms should be assessed to determine whether it can improve crop outcomes for growers.

4.2 Improving spatial forecasting for practical farms

530 For limited data and shared irrigation farms, a simple ST model is practical to use with UAV-linear. The shared irrigation datasets exhibit spatial variation in T_c only with distance, high-stress variation, and furrow irrigation, when in reality, many other spatial effects may be present. Currently, most farms have a single T_c sensor and having several sensors may not be economically viable. Applying this method to the
535 current sensor application would require using sensors across different farms. The sensors across different farms experience heterogeneous effects from soil, management, crop type, *etc.*, which will likely complicate the spatial variation of T_c . To assess a more realistic scenario, 22 practical spatial datasets from the 2024-2025 cotton season with single-sensor coverage are evaluated.

540 Table 3 shows that for this practical dataset, the UAV-linear $T_c > 28^\circ C$ error is ($0.24^\circ C$) worse than the independent forecast. UAV-linear assumes the temporal behaviour is shared across locations, which, for these locations, is often not the case, leading to decreased forecast accuracy. Importantly, for UAV-linear, the stress-hour forecast accuracy, which determines the irrigation decision, is reasonably accurate
545 ($+0.17hrs/day$) despite being less accurate than the independent model. However, compared to the single sensor forecast, UAV-linear is $0.38 hrs/day$ more accurate and 3-fold less uncertain. The improved consistency is significant, as one standard deviation

amounts to an increase in error of 7 hours per week for the ‘no-transfer’ model and only 1 hour per week for the UAV-linear model compared to the independent model. Given that a decision is based on a 31.5 *hr* threshold, an extra 7-hour error can significantly affect the irrigation decision. Finally, combining the improved forecast method from [Rogers et al. \(2026\)](#) and UAV-linear achieves higher stress-hour accuracy than the current method periodiCT with all historical information. As a result, even across different farms, this model achieves sufficient accuracy for effective practical application.

While UAV-linear could reduce the number of sensors required in densely packed across-farm situations (1 sensor per farm) compared to shared irrigation (3 sensors per farm), it has clear limitations. To improve UAV-linear performance across these situations, several avenues exist. The current results make minimal effort to select the most informative sensors, instead by considering the placement of the three sensors the forecast can be improved. The placement should consider previous seasons, soil properties variability, elevation and crops to maximise spatial variance of T_c and water stress ([Paterson et al. 2018](#); [Liu et al. 2020](#); [Ben-Gal et al. 2025](#)). Furthermore, using additional spatial covariates, such as remote sensing (CWSI, evapotranspiration), irrigation, soil, and management information, can capture spatial dependencies in T_c to improve the model. Utilising additional spatial information to inform sensor placement and improve modelling can enable spatially managed irrigation under widely varying conditions, reducing the need for T_c sensors ([Ben-Gal et al. 2025](#); [Chandel et al. 2025](#)).

To integrate this additional information, a more complex model can be developed. Spatial information, combined with a larger number of in situ T_c sensors, can be

used to develop a more general forecasting model. This general forecasting model can learn more complex spatial variation in T_c and create accurate, high-resolution spatio-temporal T_c forecasts. Currently, T_c sensors are used to monitor on 60% of Australian cotton farms, however, they are largely unstudied, representing a significant amount of underutilised T_c data. Incorporating a large number of sensors, along with detailed spatial information, can enable modelling of more complex effects and interactions, such as the T_c interaction with soil properties, environment, and rain (Webber et al. 2018). A large-scale data-driven deep learning approach was combined to capture these complex effects, producing a powerful spatial forecasting model for T_c (Wikle and Zammit-Mangion 2023). This model may consider adapting the success of the simpler UAV-linear model to this general framework to provide accurate T_c -domain-driven spatio-temporal forecasting (Wikle and Zammit-Mangion 2023).

5 Conclusions

For shared irrigation and practical T_c monitoring on cotton farms, UAV-linear is introduced to overcome the deficiencies of single-sensor T_c management and enable dynamic, whole-farm-scale decision-making for Australian furrow-irrigated farms. UAV-linear relies on the consistent spatial pattern of elevated T_c and shared temporal behaviour (Figure 7, A.8, A.9) to forecast T_c . UAV-linear has reasonable data requirements for relatively low-cost implementation, combining simulated weekly TIR images and 3-4 in-situ sensors. UAV-linear accurately spatially forecasts crop T_c under shared irrigation treatments for three different time-series forecasting models and both low and high irrigation datasets. The method achieves an ST forecast as effective as a

known-history forecast, which is currently used for effective irrigation practices. This method is a novel approach to combining ‘thermal images’ (simulated), in-situ T_c sensor and future weather conditions to produce a forward-looking spatial irrigation decision (McCarthy et al. 2010; E. J. Sadler et al. 2002; Ben-Gal et al. 2025; Peters and Evett 2008). UAV-linear is additionally able to provide consistent and reasonable stress-hour predictions and irrigation decisions for practical spatial locations that do not share management (Table 3).

In all scenarios, UAV-linear shows a large improvement in stress-hour forecast accuracy over a single-sensor forecast. These results highlight a limitation of the current practice, as the placement of the single sensor can significantly affect the T_c management outcome in both high- and low-stress locations (Table 1). The simplicity of UAV-linear comes at a cost, as it can not capture complex spatial variation in T_c . By combining UAV-linear with a more global, data-driven model (a large number of T_c) and more spatial information, more sophisticated spatio-temporal T_c models can be developed (Wikle and Zammit-Mangion 2023). Overall, this study develops and evaluates low-cost, accurate spatial forecasting methods, enabling more T_c -driven, precise irrigation of Australian cotton farms, potentially saving water, preventing quality and yield losses, and providing significant economic benefits.

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Appendix

5.1 Time-series forecasting methodology

5.1.1 Cross-validation forecasting design

For known irrigation datasets (non-practical), forecasting model training begins on the 1st of January and evaluation on the 26th of January, both to ensure reasonable

canopy coverage and consistency across datasets. The practical dataset from 2024-2025 used a newer sensor capable of removing soil noise internally, so training started on the 22nd of December and forecasting on the 1st of January. All datasets are forecast with 7-day horizons, with the previous horizon provided to the model for retraining before forecasting the next horizon. To forecast from the in-situ sensors, historic weather covariates are used. For the known irrigation, the weather set uses observed hourly air temperature, relative humidity, solar radiation, and wind speed from a central weather station to generate the forecast for each dataset. For the newer dataset, a 1-day weather forecast from the Bureau of Meteorology (BOM) is used, and solar radiation is not provided ([Australian Government 2025a](#)).

5.1.2 Models and hyperparameter selection

LightGBM uses hyperparameter tuning via the optuna package ([Akiba et al. 2019](#)), enabling efficient hyperparameter search. Specifically for lightGBM, hyperparameter tuning is done via cross-validation (CV) over the training set, varying the horizon length. The model is trained on half of the training set, then iterated over increasing horizon lengths until the end of the training set. MAE is calculated for each iteration and averaged to give a CV score ([In and Jung 2022](#)). ARIMA parameters are estimated by optimising the model’s AIC ([Hyndman and Khandakar 2008](#)). PeriodiCT has a parameter that defines the periodic kernel, which is set to 4 hours, as recommended by [Shao et al. \(2019, 2025\)](#). The model LightGBM is from the scikit package ([Pedregosa et al. 2012](#)), periodiCT models are provided by [Shao et al. \(2019, 2025\)](#), and the auto-ARIMA model is from the NIXTLA forecasting package ([Garza et al. 2022](#)).

5.1.3 Validation metrics

Our chosen residual validation is mean average error (MAE). Given true T_c (y),
 855 forecasted T_c ($\hat{y}$) and the length of forecast n the metric is defined.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y - \hat{y}|$$

MAE is assessed on T_c , $T_c < 28^\circ C$ or $T_c > 28^\circ C$ for both the low and high
 irrigation datasets. Additionally, the daily stress-hour ($SH(h_j)$) error is calculated
 860 for each sensor (T_{c_i}) and accumulated over the horizon (h). Noting that in practice,
 stress-hour estimates are provided for every horizon to consider irrigation, meaning the
 average error for prediction on each horizon is important (as opposed to the estimate
 over a season).

Stress-hours are defined with a T_c and solar radiation (SD) lower limit and a relative
 865 humidity (RH) upper limit known as lower relative humidity (LRH), approximated
 using air temperature (A) (Upchurch et al. 1996; Wanjura and Upchurch 1997). The
 starting date of the i th horizon is represented by h_i and $T_{j+h_i} > 28^\circ C$, I_{j+h_i} are the
 canopy temperature threshold and BIOTIC RH/SD threshold indicators, respectively,
 for each time period j after h_i .

$$\text{Daily Stress Hour Diff.} = \sum_{h_i}^H \frac{|SH(h_i) - \widehat{SH}(h_i)|}{h}, \quad SH(h_i) = \sum_{j=1}^h (I_{j+h_i} * [T_{j+h_i} > 28^\circ C])$$

(4)

$$I_l = [SD_l > 0.54 \text{ kW/m}^2] * [RH_l < LRH_l] \quad (5)$$

$$LRH_l = 408.8 - (16.57 * A_l) + 0.17983 * A_l^2 \quad (6)$$

$$H = \{s, s + h, \dots, s + mh\}, \quad s = \text{First forecasting date} \quad (7)$$

870 The use of stress-hours along with MAE on T_c , $T_c < 28^\circ C$ or $T_c > 28^\circ C$ to ensure the models are assessed on both the accuracy and bias of their forecast, their performance during standard and hot conditions and use in irrigation management through stress-hours.

5.2 Autocorrelation in high irrigation data in-situ sensors

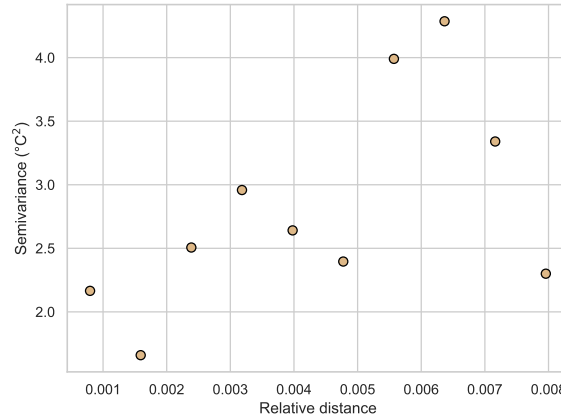


Fig. A.1: Mean semivariogram of T_c for the high irrigation dataset at 14:00. The mean semivariogram is produced by taking the semivariogram values for every day at 14:00 at every sensor location and averaging them. The 14:00 time point corresponds to the typical daily maximum in T_c , at which spatial variability is also maximised, thereby providing the strongest signal for characterising spatial dependence.

Visual inspection of the semivariogram in Figure A.1 indicates a relatively large nugget effect (approximately $1.5\text{--}2.0^{\circ}\text{C}$), implying that a substantial fraction of the total variance is attributable to sub-sensor-scale variability, short-range canopy heterogeneity, or measurement error. Semivariance increases only weakly with distance and approaches values suggesting limited spatial structure. Decreases in semivariance are observed for close-relative distances of 0.003-0.005 and 0.006-0.008. This behaviour is inconsistent with a stationary, monotonic spatial process. It likely reflects sampling limitations, averaging across days, or edge effects at large lags rather than meaningful long-range spatial correlation. The dominance of the nugget component and the absence of a stable sill at longer distances indicate that midday canopy temperature exhibits only weak spatial correlation under high irrigation. Thus, spatial-variance-based methods are unlikely to outperform UAV-linear, even with sufficient spatial data.

5.3 Remote sensing TIR image comparison to in-situ T_c sensor

Figure A.2 shows that the standardised error is similar to or higher than the deviation between TIR image points at the sensor's location. Given that the difference between in-situ sensors and UAV TIR image readings exceeds the variation between locations for the UAV readings, it becomes difficult to validate or combine thermal measurements from these data sources. Given the already low error of $0.6\text{--}0.75^{\circ}\text{C}$ compared to reported accuracies of around $1\text{--}1.5^{\circ}\text{C}$ (Gadhwal et al. 2023; Sobrino et al. 2006), to achieve higher agreement likely requires an increase in the spatial variation being modelled (*e.g.* more coarse resolution, different site/crop). However, this may come

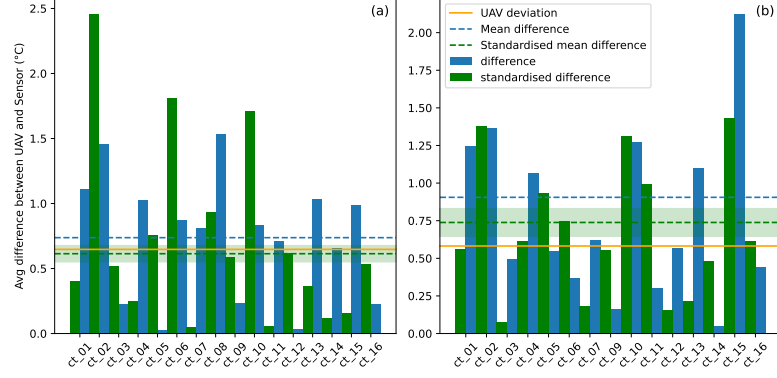


Fig. A.2: Difference (MAE) between thermal image sensor and in-situ sensors relative to variation of aerial TIR image. The error between sensor and image values is the difference between the start of week averages for (a) 02-09-2021 and (b) 02-25-2021, averaged for images at 11:00, 12:30 and 14:00. The average of these differences is shown by the blue horizontal line, with the green standardised difference line 1-standard deviation in the highlighted area. The average difference is between 0.75°C and 0.9°C , and, standardised, it is between 0.6°C and 0.75°C . Calibration of the image is performed using linear regression of 4 in situ sensor values, the image acquisition time, and the T_c value. The orange ‘UAV deviation’ line represents the deviance between image values across all sensor locations. Sensor differences 2σ out were removed (ct_{08} on right).

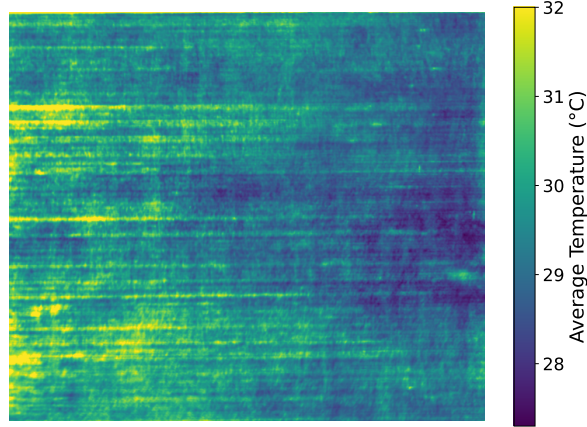


Fig. A.3: Thermal infrared (TIR) image from aerial flight on the 9th of February 2021 over Carrathool. The image is restricted to below 32°C to limit soil noise. The description of the image is in Methods 2.1.2.

at the cost of higher errors. In this case, a focus on larger and more varied datasets may enable data fusion. However, given the medium-sized 64-hectare, high-irrigation field, these results call into question whether data fusion of in situ sensor data and remote-sensing thermal imagery is feasible for farm-scale spatial analysis of cotton.

5.4 Data Comparison for shared irrigation dataset

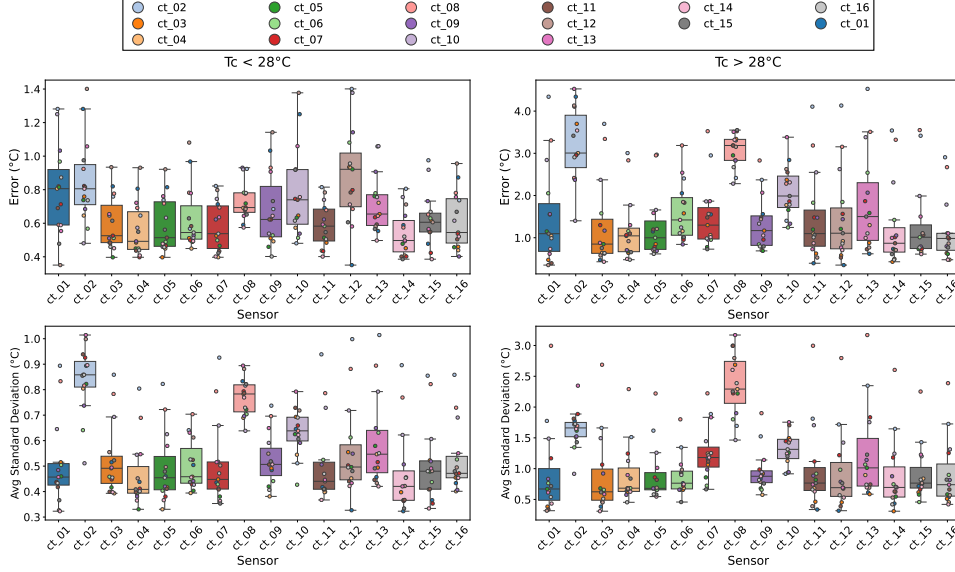


Fig. A.4: Shows the pairwise comparison of both mean difference (top row) and deviation (bottom row) of all sensors for the high-irrigation dataset. The boxplots represent pairwise comparisons of a sensor (labelled on the x-axis) with all other sensors, where the points are coloured according to the sensor being compared. The left column plots are for $T_c < 28^\circ\text{C}$ and the right column for $T_c > 28^\circ\text{C}$

Figure A.4 shows ct_{02} and ct_{08} as clear outliers in T_c behaviour especially for $T_c > 28^\circ\text{C}$. Figure A.5 shows large difference for $T_c > 28^\circ\text{C}$, 3-fold larger than $T_c < 28^\circ\text{C}$. Two outlying sensors ct_{S1103} , ct_{S1126} are present, matching those with poor UAV-linear accuracy in Figure A.12.

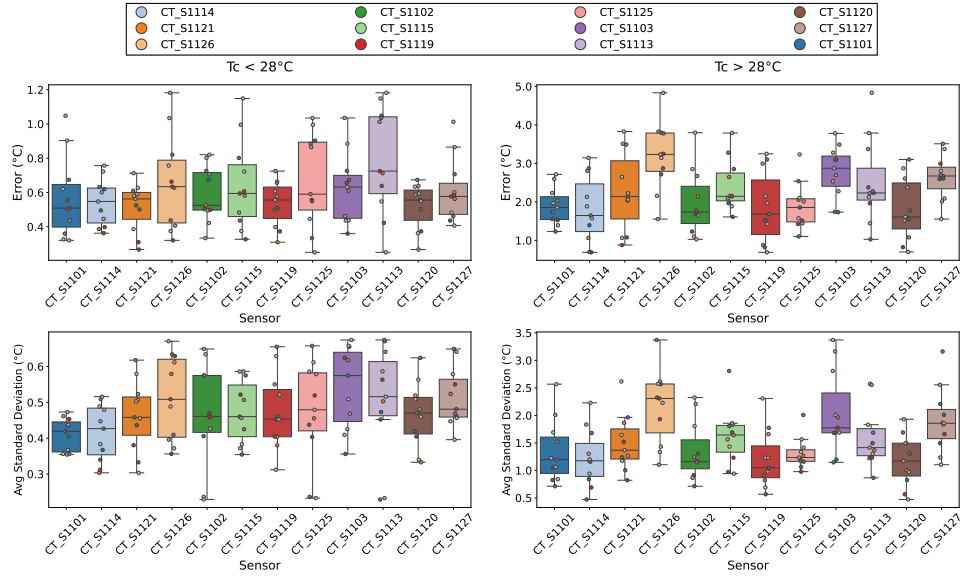


Fig. A.5: Shows the pairwise comparison of both mean difference (top row) and deviation (bottom row) of all sensors for the low-irrigation dataset. The boxplots represent a sensor (labelled on the x-axis) pairwise comparison with all other sensors, where the points are coloured according to the sensor that it is being compared to. The left column plots are for $T_c < 28^\circ C$ and the right column for $T_c > 28^\circ C$

Figures A.4, A.5 show each dataset has differing sensor T_c and $T_c > 28^\circ C$ variation. The high-irrigation dataset shows limited variation, except for 3 outlying sensors, whereas the low-irrigation dataset shows high variation across all sensors. As a result, utilising any single sensor to determine irrigation may largely disagree with the majority of other sensors and may not be representative of farm needs.

5.5 Sensitivity of analyses to number of sensors

Figures A.6, A.7 explore the accuracy of the UAV-linear model with a changing number of known sensors. Figures A.6, A.7 show that the optimal number of sensors to fit UAV-linear is around 3-4 T_c sensors. While three T_c sensors show reasonable accuracy, the fourth sensor reduces variation by limiting the effect of the outlying sensor. Given that one of the known sensors is also the relative sensor acting as an intercept for T_{ct_s} (Eq 1), with 3 sensors, only 2 sensors fit the harmonic a_2 parameter, which explains the higher error and variance. However, given the aim of a low-cost method, three T_c sensors are recommended for this methodology.

For each dataset, sensors were chosen to represent the median performance of the three sensor subsets. In reality, the sensors can be placed to capture the greatest extent of spatial variation, potentially improving model performance beyond the median. The reference sensors that cause high error generally correspond to the sensors that do not fit the curves shown in Figure 7. For example, reference sensors of outliers ct_{16} , ct_{02} show poor performance as reference sensors. It should also be noted in Figure A.6, A.7 that the magnitude of error largely differs over fortnights, with most between $0 - 2^\circ C$ MAE for three sensors, but two periods (before April) between $0 - 4^\circ C$ MAE. These differences highlight one issue with the UAV-linear method, where seasonal performance may be highly variable.

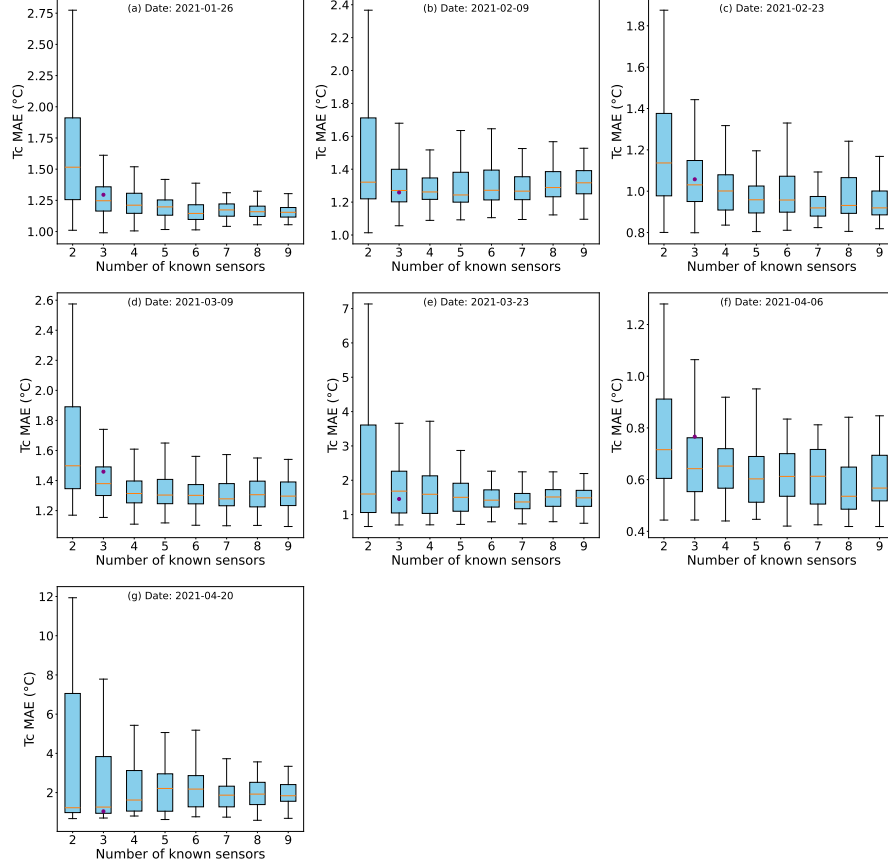


Fig. A.6: UAV-linear model performance by number of input known T_c sensors for all dates for the high-irrigation dataset. The distribution is calculated by sampling the MAE for $T_c > 28$ for 100 randomly chosen unique known sensor combinations of the corresponding size. A purple dot is plotted to show the error of the subset of sensors (ct_{01} , ct_{13} , ct_{09} where ct_{01} is the reference) used in all other analyses.

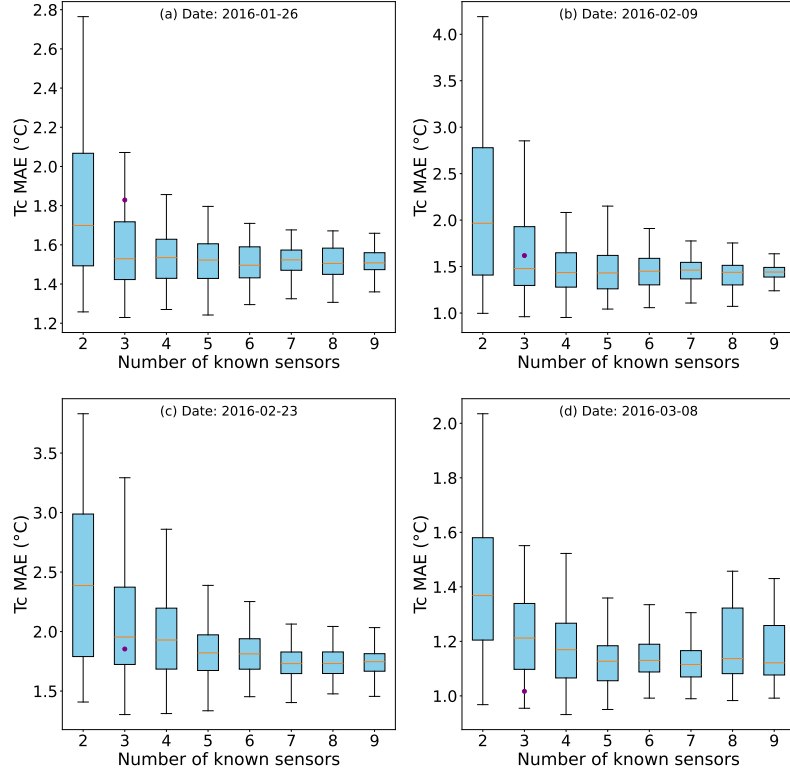


Fig. A.7: UAV-linear model performance by number of input sensors fit for all dates for the low-irrigation dataset. The distribution is calculated by sampling the MAE for $T_c > 28$ for 100 unique known sensor combinations of the corresponding size. A purple dot is plotted to show the error of the subset of sensors $((ct_{S1101}, ct_{S1126}, ct_{S1125})$ where ct_{S1101} is the reference) used in all other analyses.

5.6 Weekly maximum correlations

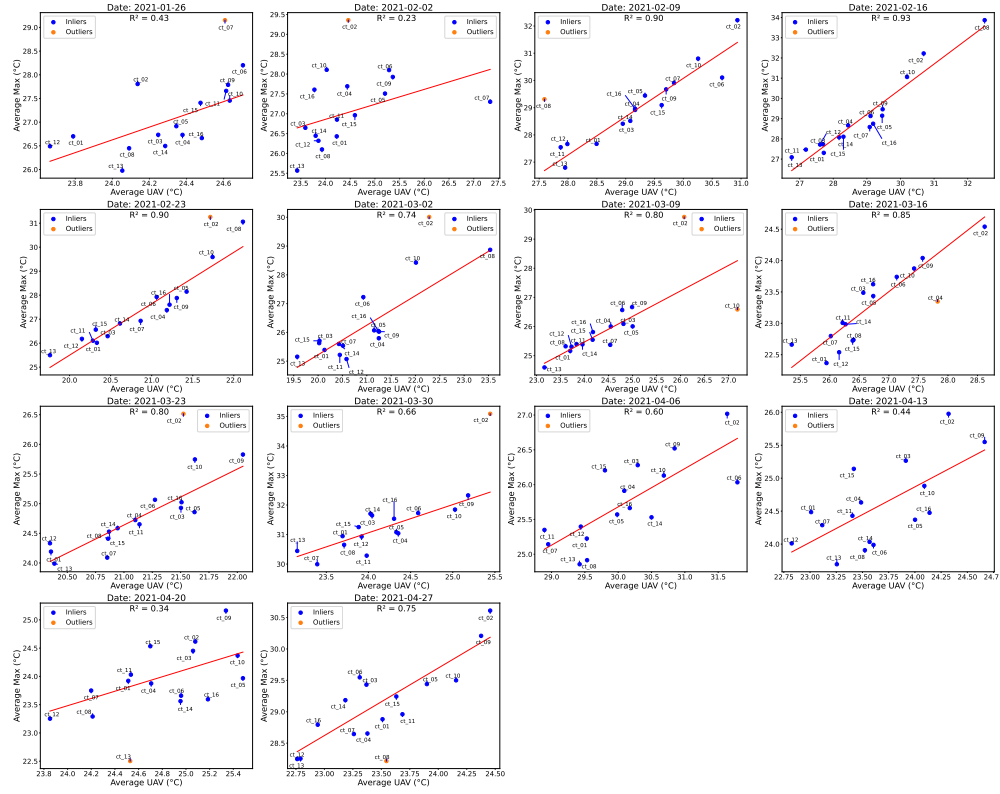


Fig. A.8: Correlation between average start of week T_c and average weekly maximum for the high irrigation dataset. The start of week T_c is the average of the hourly sensor T_c from 11:00-14:00 (inclusive) at the start of the week, and the average maximum is the average T_c of the next 7 daily maximums. Linear regression on these values, excluding outliers $\pm 2\sigma$ away in yellow, predicted the average maximum across a week from the start of the week T_c . Included are weekly forecasting dates from the start until the end of the dataset, where each point label corresponds to an in-situ sensor as labelled in Figure 9 (a).

Figures A.8 and A.9 show strong correlations from early February to mid-late March for both datasets, which are crucial T_c monitoring periods. Outside these dates, correlations remain moderate but less strong. UAV-linear utilises these high correlations for accurate spatial forecasting.

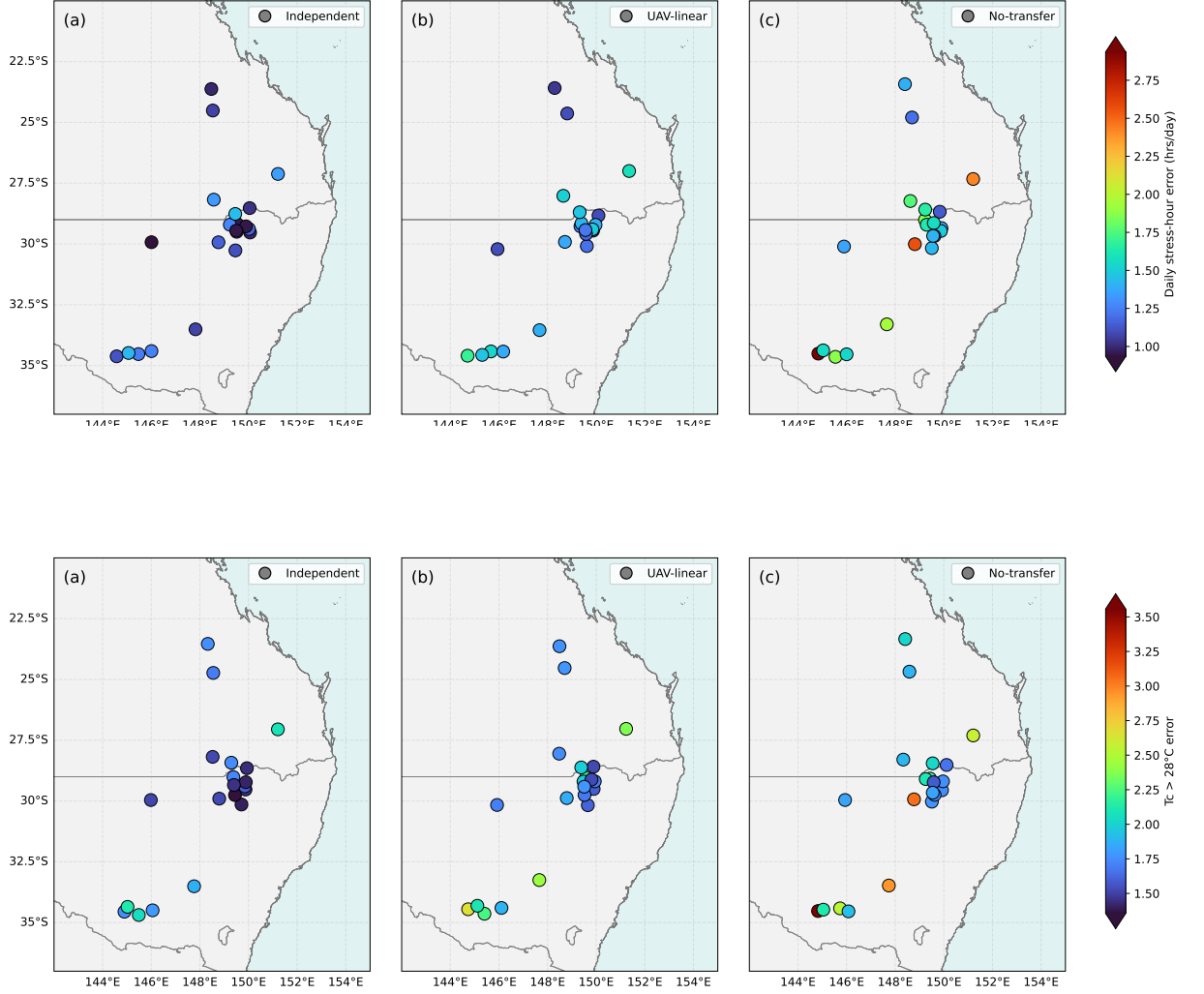


Fig. A.10: UAV linear performance for the 22 practical spatial datasets mapped across Australia. UAV-linear (b) is compared to the independent (a) and no-transfer (c) models. The top row shows the daily stress-hour error, while the bottom row shows the error for $T_c > 28^\circ\text{C}$. Locations are jittered for anonymity.

5.8 UAV linear with 2-week repeat

Comparison of UAV linear for both datasets at weekly and fortnightly simulated

‘image’ frequencies to determine the image frequency requirement.

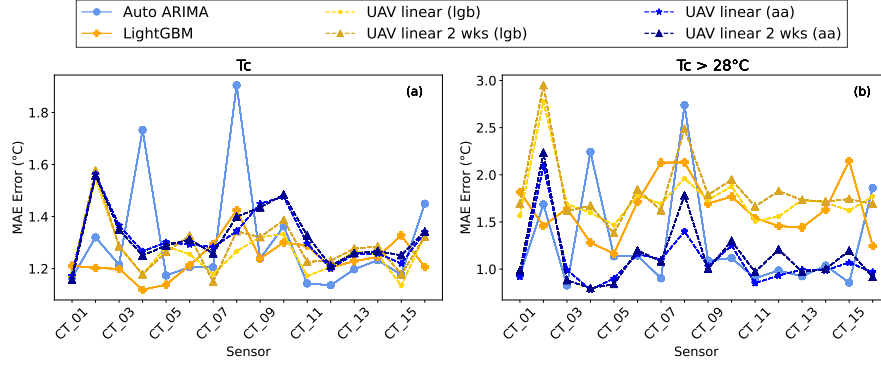


Fig. A.11: Comparison of UAV-linear models for 1 and 2 week ‘image’ repeats and known sensor models for the high irrigation dataset. UAV-linear is modelled using both auto-ARIMA and lightGBM as a base forecaster, with known sensor models shown for reference. The ‘UAV-linear 2 wks’ only has access to spatial data every 2 weeks (See Eq. 1). MAE is compared for all temperatures T_c and $T_c > 28^\circ C$.

Figures A.11, A.12 compare UAV-linear performance for the spatial data ‘image’ provided every 1 or 2 weeks. For the high-irrigation dataset, there is little difference in utilising the ‘image’ every week or every 2 weeks for forecasting ($0.065^\circ C$), implying that the spatial structure of $T_c > 28^\circ C$ remains relatively stable over time. However, for the low-irrigation dataset, dropping to two-week intervals increases error by $\sim 0.15^\circ C$. The first-week forecast remains the same, with the same error; therefore, the increase in error is due solely to differences in the second week. As it is averaged, this amounts to $0.13^\circ C$ in the well-irrigated dataset and a $0.30^\circ C$ increase in the low-irrigation dataset for the second week. These results show that under stressed

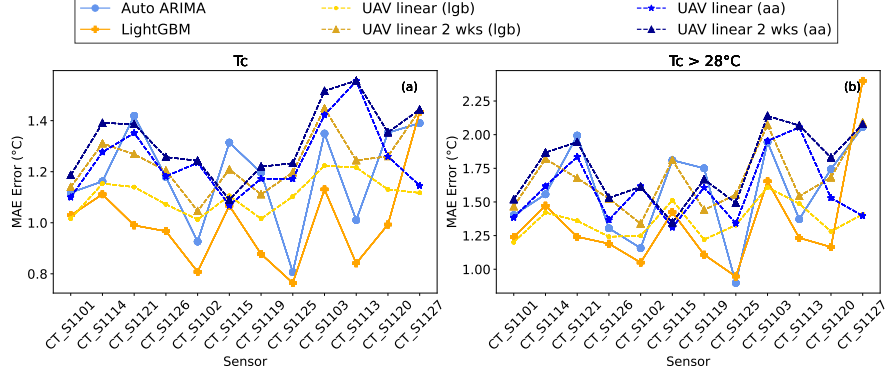


Fig. A.12: Comparison of UAV-linear models for differing image repeats and known sensor models for the low irrigation dataset. UAV-linear is modelled using both auto-ARIMA and lightGBM as a base forecaster, with known sensor models shown for reference. The ‘UAV-linear 2 wks’ only has access to thermal imagery for 2 weeks (See Eq. 1). MAE is compared for all temperatures T_c and $T_c > 28^\circ C$.

conditions, spatial variation is less stable, and in this case, a weekly repeat of the image would be ideal.

5.9 UAV-linear relative performance and by model for known irrigation

UAV-linear is designed as a residual model for any time-series model T_c forecast; however, the performance likely depends on the properties and accuracy of the underlying forecaster. By evaluating a high-performing time-series machine learning model (lightGBM), a statistical/ML model (auto-ARIMA), and the T_c forecaster periodiCT, we assess UAV-linear model-dependent performance on the two shared irrigation datasets.

Table A.1 shows that all models retain a relatively small difference ($< 8\%$) between independent and UAV-linear forecasting, while being significantly better than the ‘no-transfer’ approach. While Table A.2 shows that a lower independent model accuracy

Table A.1: Relative comparison of UAV-linear models with independent models (known sensor) and no-transfer models. The average MAE and stress-hour error improvement from the UAV-linear models compared to the corresponding independent, baseline (no transfer) (*i.e.* UAV-linear lightGBM to ‘lightGBM no transfer’ - models defined in Section 2.4) and averaged over both datasets.

	UAV-Linear MAE for $T_c > 28^\circ C$	UAV-Linear stress-hour err (<i>hrs/day</i>).
Independent	-0.07 (-4.6%)	+0.01 (+2.30%)
No-transfer	+0.63 (+28.7%)	+0.29 (+23.0%)

	MAE for T_{c28} ($^\circ C$)		Stress-hours error (<i>hrs/day</i>)	
	UAV-Linear	Independent	UAV-linear	Independent
LightGBM	1.56	1.45	0.94	0.88
Auto-ARIMA	1.40	1.38	0.62	0.75
PeriodiCTs	1.77	1.68	1.07	1.04

Table A.2: The performance of UAV-linear against the independent model relative to each model. The MAE for $T_c > 28^\circ C$ and daily stress-hour error are shown for UAV-linear and the corresponding independent model for each base method, lightGBM, auto-ARIMA and periodiCTs. The error is calculated as the mean across both datasets.

generally corresponds to a proportionally lower UAV-linear accuracy. As a result, the accuracy of the underlying forecasting model is important for achieving the best results with UAV-linear.