An assessment of the temporal sampling frequency of canopy temperature for irrigation scheduling

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Abstract
With advancements in wireless technologies, the use of infra-red canopy temperature sensors for monitoring crop stress and irrigation scheduling has overcome many practical constraints. Real-time collection of data using point-based sensors is dependent upon the efficiency of the communication systems and the capacity of data storage. An informed decision about the required temporal resolution for these sensors will help to avoid the transmission of redundant information and thus reduce energy, processing times and storage requirements.

To determine the optimum sampling frequency for canopy temperature sensors we resampled 1-minute data from field sensors at different time frequencies (5-min, 10-min, 15-min, 20-min, 30-min and 60-min) by either averaging the 1-minute data over the time interval (average data) or by recording the temperature at that time (point data). Stress hours (time above a certain temperature) was then accumulated to assess how the different sampling periods would impact on an irrigation decision.

The inter-quartile-range (IQR) of the standard deviation when temperature was averaged from 5-min to 60-min time frequencies was 0.15 to 0.36 across all sensors. The average data was highly correlated (R 0.98 to 1) with point data. While comparing the daily stress hours at 1-min with different sampling frequencies the differences were statistically significant but practically these differences (< 0.3 hrs per day) were small and were not likely to impact on decision making. This study showed significant opportunity to reduce data transmission requirements in the field but further studies in variable climates can give more insight about the geographic data needs in temporal context.

Keywords
Infra-red, tomatoes, biological thermal optimum, stress hours

Introduction
Infra-red sensors can be used to measure canopy temperature under field conditions for crop water stress monitoring and irrigation scheduling. The direct measurements of canopy temperature have relationship with crop water stress as the water transpired by the plants create a cooling effect. The crop water stress monitoring usually requires continuous measurements of canopy temperature, access to this data in real-time for prompt decision making and data-driven prognosis. The quality of data transmission from sensors installed on agricultural farms is highly variable and depends on the coverage of communication systems, for example, 4G and LoRaWAN networks. Poor network coverage results in gaps in data which can limit the use of data where continuous data streams are required for computations. Identifying the frequency of data required can avoid the transmission of redundant data thus reducing the battery and bandwidth requirements of the communication systems and a benefit to the data storage capacity.

Sensors with on-board processing capacity can sample data at high frequency, perform computations on-board and only transmit the condensed data that is required for the decision making by the end user. This approach will reduce the magnitude of data being transmitted without reducing the sampling interval in data. Reducing the sampling/sensing frequency will further help save energy required for operating the sensor (Bhandari, et al., 2017). Temporal data reduction is cost effective from communication perspective as it involves only computation at a single sensor or recording data less frequently and incurs no communication overhead (Ganesan, et al., 2003). Temporal data reduction is possible by exploiting temporal redundancies, utilising knowledge of data characteristics and use requirements (Ganesan, et al., 2003).

The use of real time irrigation scheduling methods is predominantly limited to subjective judgement. Irrigation decision making in real-time based on canopy temperature by using temperature time threshold i.e. when canopy temperature exceeds a pre-determined certain temperature (biological thermal optimum of the crop) for a certain amount of time (Upchurch, et al., 1996) is a simplified approach that requires canopy temperature as key data input. Although data is usually collected from 1 to 15 minutes interval to compute irrigation decisions, the actual temporal frequency needed for this computation is not established or fully understood. This study aims to determine the minimum temporal resolution required to use canopy temperature for irrigation scheduling based on the temperature time threshold. A close examination of the temporal pattern in data will also help to reveal potential relations with the bio-physical systems and the accuracy of sensors itself.

Methods

The field experiment was conducted by deploying canopy temperature sensors in a processing tomato crop on a corporate farm located in the Central Victoria (35.49S, 143.71E) during the 2019-20 crop season. The crop was grown under sub-surface drip irrigation. Soil type was predominantly Vertosol. Approximately one-month old seedlings were transplanted at different dates. Plant spacing was 36.5 cm and row spacing was 150 cm. Ten point-based infra-red canopy temperature sensors were deployed in pairs as duplicates on different fields with different transplant dates and varieties. The transplant dates were 6 Oct 2019 (Pair-1 and Pair-3), 10 Oct 2019 (Pair-2 and Pair-4) and 28 Oct 2019 for Pair-5. Pair-2, Pair-3 and Pair-4 monitored variety H1175mix; Pair-1 monitored variety H3402mix and Pair-5 monitored a third variety, UG19406. Each sensor pair was about 2 m apart in the same crop row. The four pairs (Pair-1 to Pair-4) were about 0.5 km apart from each other and Pair-5 was about 4 km away from the other pairs. Data was recorded at one-minute frequency for 53 days during the peak growth of the crop (18 Dec 2019 to 8 Feb 8 2020), resulting in 76,320 observations per sensor. The weather data recorded at one-minute intervals was accessed from the nearest Bureau of Meteorological (BOM) station (about 21 km distance from the paddocks). The crop management practices were similar across paddocks according to high-input (water and fertiliser) practices.

Using 1-minute data, the difference between consecutive observations (lag-1 difference) was calculated for both the canopy temperature and air temperature. The one-minute data was averaged at different time frequencies (5-min, 10-min, 15-min, 20-min, 30-min and 60-min) to represent a hypothetical situation in which sensors have on-board capacity to average the recorded data at 1-min frequency at a certain time interval and transmit only the averaged data to central system. Hereafter this averaged data transmitted will be called average data. Data was also resampled to assess the difference with averaging data by simply recording the data at a point in time. In this case, data was sampled at similar time steps in parallel with average data; hereafter this data will be called point data. The average data, for example at 5-min is average of every 5 observations from that step to the following four observations while point data is just that point in time.

The crop stress time was calculated at different time frequencies (1-min, 5-min, 10-min, 15-min, 20-min, 30-min and 60-min) for both average and point data. We used a hypothetical value of 25 ^{o}C (canopy temperature) as biological thermal optimum for tomatoes. These sub-daily values of stress time were accumulated to calculate daily stress hours at different underlying temporal frequencies for average and point data. For accumulation of daily stress time only daytime (7:00 to 20:00 hrs) data of canopy temperature was used.

Results and Discussion

The spread of the canopy temperature was between 16.29^{o}C to 26.35^{o}C (IQR – Inter Quartile Range) with the highest observation at 41.55^{o}C and the lowest at 3.69^{o}C. For the air temperature the IQR was 18 to 29.8^{o}C with the highest at 46.7^{o}C and the lowest at 7.8^{o}C.

The lag-1 difference

The plots of lag difference provide a visual assessment of the change in temperature over 1-minute interval (Fig. 1).

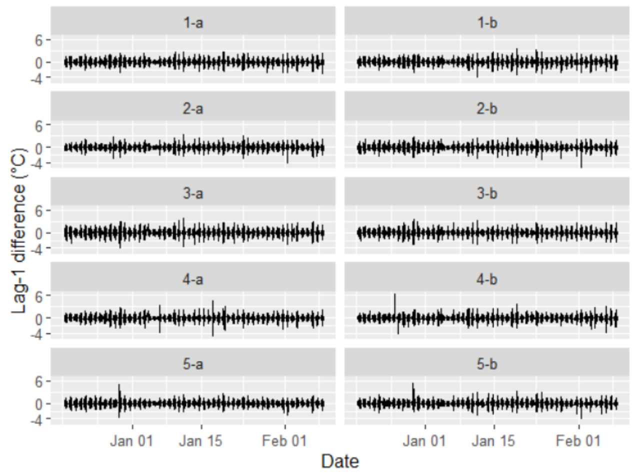

Figure 1. The lag-1 difference during day-time (sunrise to sunset) across different sensors

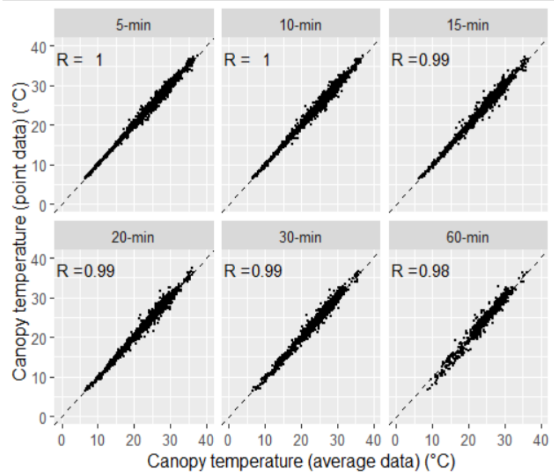

Figure 2. Relationship between day-time average data and point data across different sampling frequencies for sensor 1-b.

The IQR of lag-1 difference of canopy temperature data was ±0.16 with maximum lag-1 difference of 12^{o}C and minimum of -11^{o}C (not shown). There were 5 to 34 observations of consecutive peaks/troughs (increases/decreases) above 1.5^{o}C, and 1 to 4 observations > 3^{o}C across the different sensors. The isolated peaks and troughs > 2^{o}C occurred between 19 and 59 times across sensors and those of >3^{o}C occurred 1 to 6 times. For BOM air temperature data, IQR of lag-1 difference was ±0.1 with maximum lag-1 difference of 2.5^{o}C and minimum of -9.3^{o}C. There were no consecutive peaks/troughs above 1.2^{o}C.

Though the BOM station 21 km from the paddocks, IQR of the fluctuation of temperature over 1 minute were similar. The air temperature continually fluctuates causing consecutive peaks and troughs. The consecutive peaks and troughs of above 1.5^{o}C indicate that fluctuations in canopy temperature are greater than those in air temperature. Air temperature observation in the proximity of canopy temperature sensors may give a better evaluation of the small step fluctuations of canopy temperature, though not measured in this study.

The high consecutive peaks/troughs can be either a sensor error, crop anomaly (biological change) or due to ambient atmospheric conditions. By comparing these with other nearby sensors we can determine the likely causal factor behind these peaks/troughs. When these peaks/troughs appear across nearby sensors these changes are likely related to ambient atmospheric conditions. Whereas peaks/troughs only present in a single sensor can be an indication of malfunctioning of the sensor. For example, the spike of 6.34^{o}C sensor 4-b on Dec 25, within a minute, is clearly a sensor error. The time of occurrence and whether these are sustained, or just one-off errors of these anomalies will be harder to detect in data sampled less frequently.

Average and point canopy temperature data

The IQR of the standard deviation when temperature was averaged from 5-min to 60-min time frequencies was 0.15 to 0.36 across all sensors. For data within this IQR, there was consistently lower standard deviation at 5-min that increased gradually as the time interval increased. The increase was only 0.04 to 0.06 standard deviation with a maximum difference at 30 min but the increase in standard deviation from 5-min to 60-min was 0.33. This increase was due to the diurnal pattern of the temperature change over time. The standard deviation outside the bounds of IQR was 1.93 to 6.19 across all sensors, irrespective of averaging frequency. The average data was highly correlated with point data, especially the lower temperature range which had a very narrow spread at 5-min to 15-min (Fig. 2).

Time Temperature Threshold of average and point data
The maximum daily difference of stress hours i.e., the difference between maximum stress hours and minimum stress hours on a single day across different time frequencies was 2.8 hrs (IQR: 0.3 to 1) for average data and 2.7 hrs (IQR: 0.3 to 0.8) for point data. The stress hours were highly correlated between average and point data with correlation coefficient of 0.97 at 60-min and 0.99 at all other frequencies. The relationship between daily stress hours at 1-min with average data at different frequencies for a single sensor is shown in Fig. 3a. The relationship was strong from 5-min to 15-min, it then decreased slightly with an R^2 of 0.98 at 60-min. The results were similar with point data except that at 60-min the R^2 was 0.97. The daily stress hours at 1-min were compared across all time frequencies using paired t-test for both average and point data. The differences were statistically significant but practically these differences on daily basis are small and are not likely to impact on decision making (Fig. 3b).

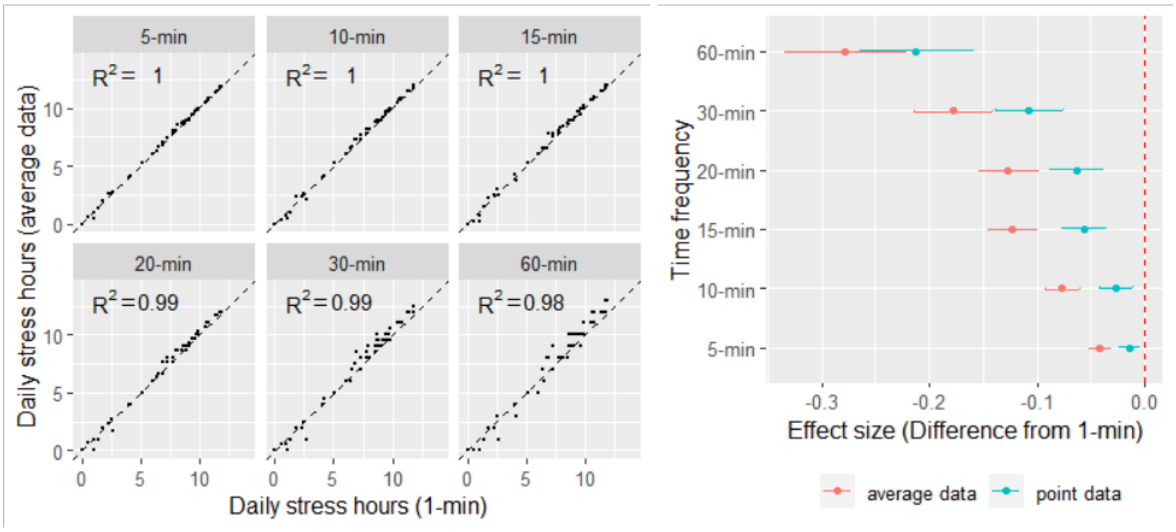

Figure 3. Relationship between daily stress hours at 1-min with average data (a) and effect size of difference between 1-min with different time frequencies for both point and average data (b)

A lag of up to 60 minutes in an irrigation call may not be a significant delay where irrigation is not frequent. But in the irrigation systems with more frequent irrigation will benefit more from reasonably high frequency observations.

Conclusion

Stress hour accumulation requires continuous observations but is a time weighted index and is less likely to be affected by changing the sampling frequency to up to 30 minutes between readings. Beyond this the diurnal patten of increasing temperature during the day and decreasing during night can create a bias in canopy temperature aggregation between average and point data. This can affect the irrigation decision making depending upon the crop and the irrigation system. While the current irrigation scheduling practice is predominantly based on the subjective judgement, digital approaches can facilitate irrigation decision making. Further studies in variable climates can give more insight about the geographic data needs in temporal context. The locations with more frequent turbulent events need further evaluation.

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