WATER STRATEGIES

Application of remote sensing in spatial irrigation scheduling

Our Land and Water Science Challenge

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Client	Our Land and Water Science Challenge
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Summary

Findings

While the science of calculating crop coefficients using remote sensing has been around since the 1970's, a robust commercial product is not yet available. This is partly due to the lack of available high resolution satellite imagery.

Over the last two years many more satellites have been launched with the capability to provide high resolution data on a daily time step, however the project still found issues with the quality and frequency of high-resolution satellite data available for the 2020-21 season. This made it difficult to provide accurate irrigation scheduling decisions based purely on satellite imagery for the entirety of the growing season.

However, by interpolating the sparse satellite data, a reasonable model of crop cover was obtained, but such an approach is not commercially viable without being automated and integrated into a software platform. For example, the combination of SWAN Systems water balance model, alongside weekly high-resolution satellite data has the potential to provide farmers and growers more accurate irrigation scheduling information.

One practical output was achieved from the project - a method of calculating crop coefficients for any crop, based on crop growth stages. Water Strategies now uses this calculator to assist irrigation scheduling with two clients.

Next Steps

High resolution (0.8m) satellite data on a daily basis will now be available via Planet for the 2021-22 irrigation season. Using this data, it will be possible to continue refining the crop coefficient calculations. Water Strategies therefore intends to investigate the potential to extend this research project given the improved data availability.

SWAN Systems are currently working on an update to automatically calculate crop coefficients from remote sensing data. This should be available for the 2021/22 irrigation season. Testing this update in New Zealand conditions and further refining the integration of NDVI data would be useful.

Testing the methodology on a wider variety of crops (later spring sown and summer sown crops) would be useful as the value of remote sensing data is greatest for these crops due to them not reaching full canopy cover until later in the season.

The on-going research would also have a focus on calculating crop coefficients from thermal imagery and NDVI. Recent studies have been completed in the United States (through the University of Nebraska Water for Food Institute) and Australia (through the Smarter Irrigation for Profit program), but from our enquiries no research has been undertaken in New Zealand to date.

Problem

Soil water management can make a huge difference to the profitability and sustainability of a farm. Applying the correct amount of water at the right time is one of the most challenging issues facing growers, especially arable growers. Data must be accurate and timely to maximise returns and minimise environmental issues. Irrigation scheduling has typically been limited to one point measurement in a paddock using a soil moisture sensor. There are several issues with this approach, particularly for arable growers who often have multiple crops under one irrigation system. To be useful, a grower would require one soil moisture sensor per paddock, which gets expensive. They also need to be installed correctly and in a representative location and reinstalled every time a new crop is planted.

Water balance models have long been used in agriculture, but they have many practical challenges, including the need to manually input data and adjusting the crop coefficient to reflect the actual evapotranspiration. Historically water balance models have mainly been available as spreadsheets or web based manual data entry platforms which have not been user friendly for growers. Web-based automated water balance models are becoming available but to date there has been no way to automatically calculate crop coefficients throughout the growing season and feed them back into the water balance model.

Finding accurate crop coefficient data that is relevant to New Zealand conditions and the crop varieties grown here is extremely difficult. Remote sensing using satellite data either through NDVI or thermal imagery or a combination of the two has been used to calculate crop coefficients (Neale CMU, et al 2005).

Potential evapotranspiration calculations estimate crop water use assuming the crop canopy is fully covering the ground. Autumn sown crops are generally fully covering the ground by the time irrigation will be needed in spring so it can be safe to simply assume full cover for calculating the water use of these. However, spring and summer sown crops may not be fully covering the ground by the time irrigation is needed and wide row crops may not fully cover the ground at any stage of their growth. For these situations, a representation of crop cover is required for estimating water use. However, a single crop coefficient may not be sufficient to account for the variability within a paddock (Neale CMU, et al, 2005).

Aim

This project aim was to use the SWAN Systems platform, an automated water balance model alongside remote sensing data to calculate the crop coefficients throughout the irrigation season.

Methodology

Background

The trials were conducted on an organic vegetable farm at Hororata, Canterbury. The farm grows a range of table vegetables for the domestic market as well as seed crops for export. The two crops studied were winter milling wheat and table potatoes. The sites were irrigated using Valley center pivots without VRI irrigation. The soil is predominately a Wakanui_1a.1 with a 0-60cm profile available water of 96 mm (Lilburne LR et al, 2012).

Sensors

An AquaCheck soil moisture sensor was installed that measured soil moisture and soil temperature at 100, 200, 300, 400, 500 and 600 mm depth. A Davis rain gauge was installed outside of the irrigated area on the farm. All sensors were monitored using Halo Systems telemetry. Data was recorded and relayed to the Halo Systems website every 15 minutes.

Two SI-111 Infrared Radiometers were installed in the potato paddock to measure canopy cover. This data was recorded using a Campbell Scientific datalogger.

Satellite data was obtained through SWAN Systems via the Sentinel-2 and Planet satellites and through DataFarming via the Planet satellite. Please note: the Planet data only became available late in the season (from February 2021).

The soil moisture sensor was installed in the winter wheat in September 2020, the rain gauge was also installed at this time. It was removed on 20th January 2021, when the wheat was due to be harvested.

Two infrared radiometers were installed in the table potatoes (Agria variety) in December 2020, when the crop was striking. The soil moisture sensor was installed in February 2021.

The location of the sensors is shown in Figure 1.

Figure 1: Farm map

Water Balance Model

The irrigation scheduling was completed using the SWAN Systems platform for both crops. The weather data was collected from the rain gauge installed on farm and the remainder of the weather data (humidity, solar radiation, air temperature and wind speed) was collected through Dark Sky virtual climate network and NIWA weather stations. SWAN then calculates the reference crop evapotranspiration (ETo) for the paddock. The irrigation data was collected via Valley's AgSense software and imported automatically into SWAN.

Soil details including field capacity, permanent wilting point, irrigation targets, drainage coefficients and working depth are entered into SWAN.

Crop parameters including the planting data, growth stages and crop coefficient and duration for each stage are recorded.

The SWAN Systems model then takes all the above parameters and calculates the required irrigation application for each irrigation management unit for the next seven days. Preferences can be set for priority and minimum and maximum irrigation applications.

Crop Coefficients

The development of the canopy of crops follows a predictable pattern, increasing as a sigmoidal function of thermal time until the canopy is closed and then showing a linear decrease as the crop matures.

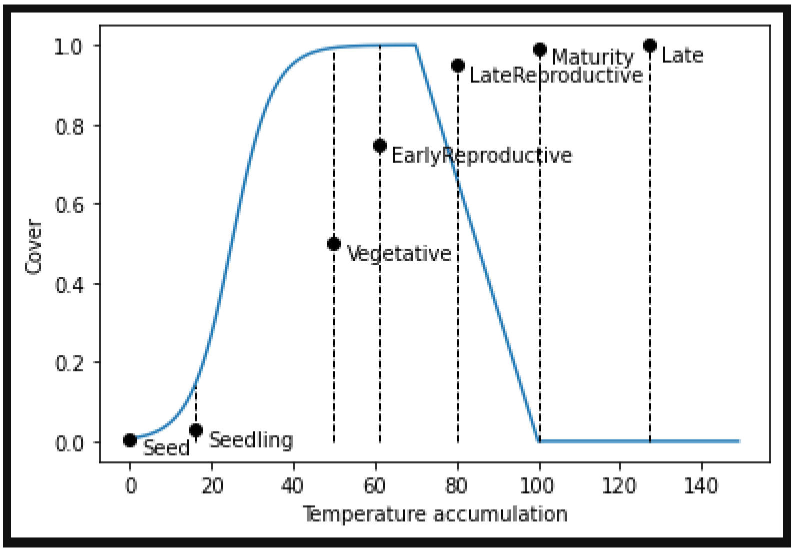

Figure 2: Crop coefficient curve

The parameters for the curve above can be derived for any crop (provided relevant temperature data is available) from sowing date, harvest date and the stage at which the crop is established (seed or seedling) and harvested (Vegetative, Early Reproductive, Late Reproductive, Maturity or Late).

Results

Satellite NDVI Data

The reflectance of field surfaces correlates with the size of the canopy cover and many satellites are equipped with instruments to measure reflectance. It is possible to purchase time coarse normalised difference vegetation index (NDVI) data for each field on a farm. The potential difficulty with this data is good measurements are only possible when a satellite is passing during daylight in cloud free conditions.

To determine how this data might be used we have graphed NDVI information from wheat and potato crops below. For each graph, the blue points show NDVI data that were recorded when cloud cover was less that the threshold specified (10, 20 or 30%). Where a threshold of 10% is used the valid data sit at the envelope of all data recorded and could be reasonably interpolated to represent the crops canopy pattern. However, as the threshold is increased several errant points are classed as valid and the interpolation between these points does not give a good representation of crop the crops actual cover. The interpolated patterns of NDVI can then be used to calculate crop cover with the following equation which assumes cover is linearly related to NDVI between a minimum ($NDVI_{min} \approx 0.18$) and maximum ($NDVI_{max} \approx 0.8$):

$$Cover = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}$$

Patterns of cover estimated from interpolated NDVI data are shown by the solid green lines in Figure 3. This provides a sensible pattern of cover when applied retrospectively. However, for real time irrigation scheduling we will need to extrapolate from the last valid measurement to the current date and this would need to be done by assuming the NDVI is represented by the most recent valid measurement until a new valid measurement is collected. The cover pattern calculated from data extrapolated in this way is shown by the dashed line in Figure 3. There was up to 6 weeks between valid measurements and the estimated cover can lag well behind the actual cover when using this method.

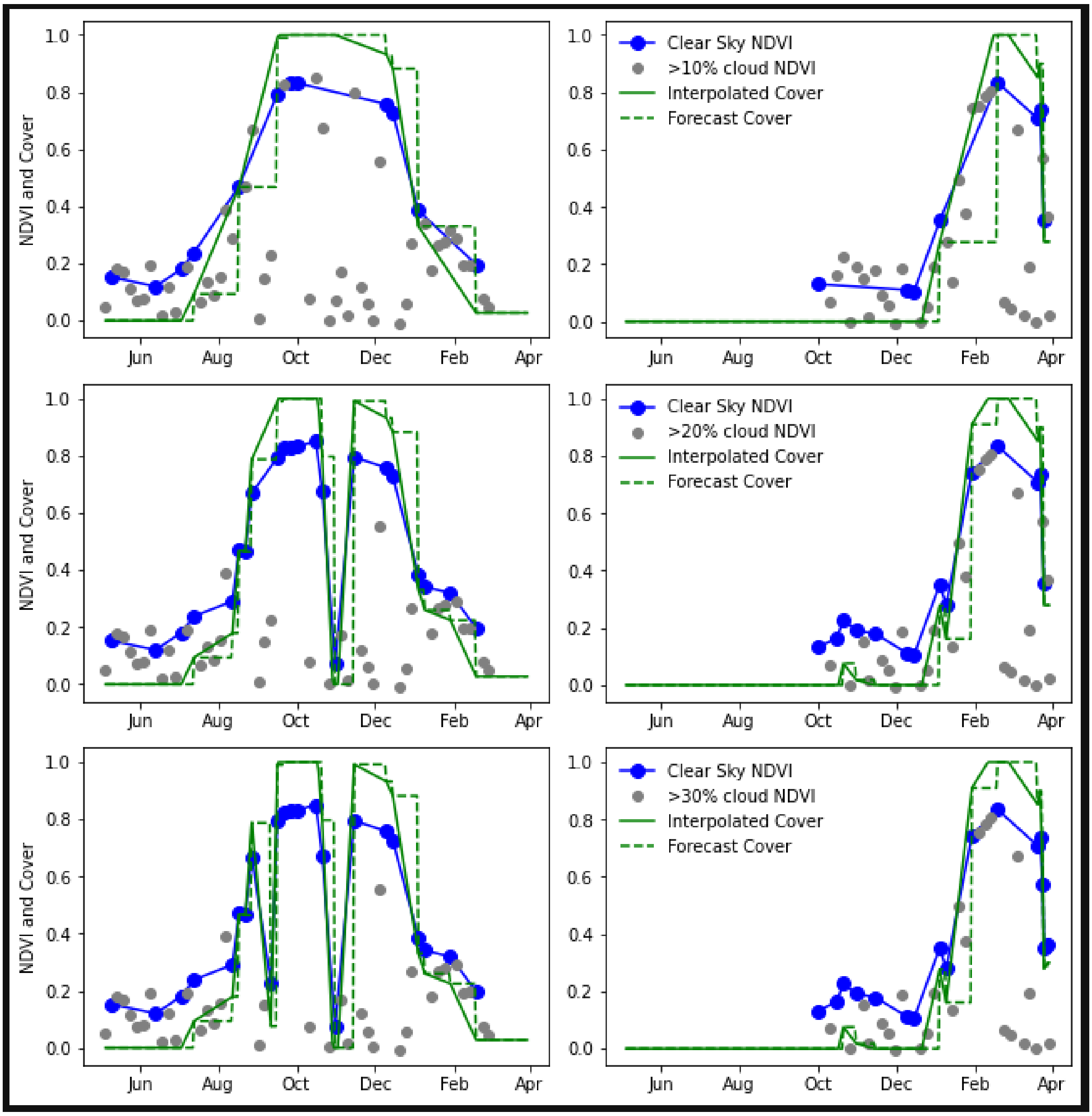

Figure 3: NDVI and crop cover

Figure 4 shows the cover patterns estimated by the sigmoidal model and the extrapolated NDVI data compared to the values interpolated from the NDVI data. The interpolated values give the most realistic representation of the cover pattern for the wheat crop, and this is well approximated by the sigmoidal model.

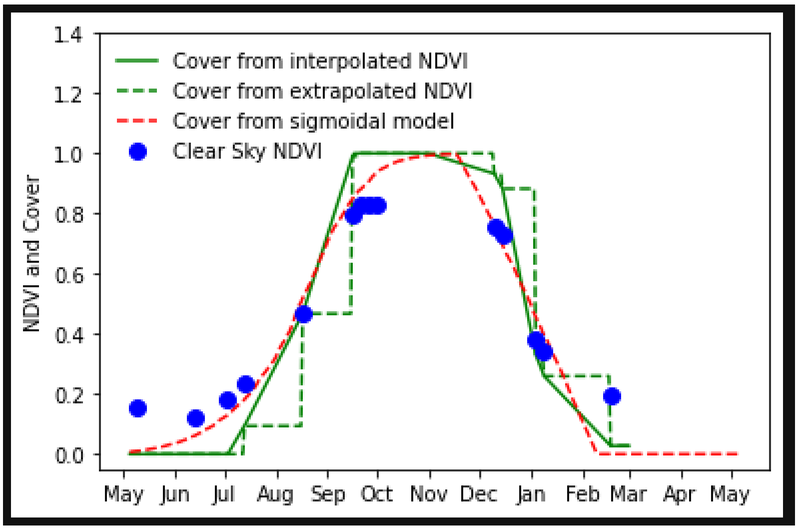

Figure 4: Crop cover patterns

Water Balance Model Results

A simple water balance model (Figure 5) was run with local weather data and different representations of crop cover used to estimate soil water content. This was compared with soil water content measured in the field with a single sensor. Unfortunately, weather data was only available from October until mid-January, so we were not able to test when the canopy was expanding or the very end of the crop. There are also several limitations in the observed data as it is only a single point measurement, and the shallowest sensor (10cm) did not capture most of the irrigation and small rainfall events because they did not soak down to that depth. However, comparing the soil water content from 5 – 65 cm with the water profile measured by the water sensors gave a useable test of the different approaches. There was very little difference between the three approaches from November to mid-December as the crop was at full cover and all three approaches gave numbers that were also close to full cover. However, as the crop matured, and green cover declined the constant full cover approach gave substantial deviations from the measured soil water content. The sigmoidal model and the extrapolated NDVI data gave similar results although during this period and had closer agreement with the observed soil water than the constant cover.

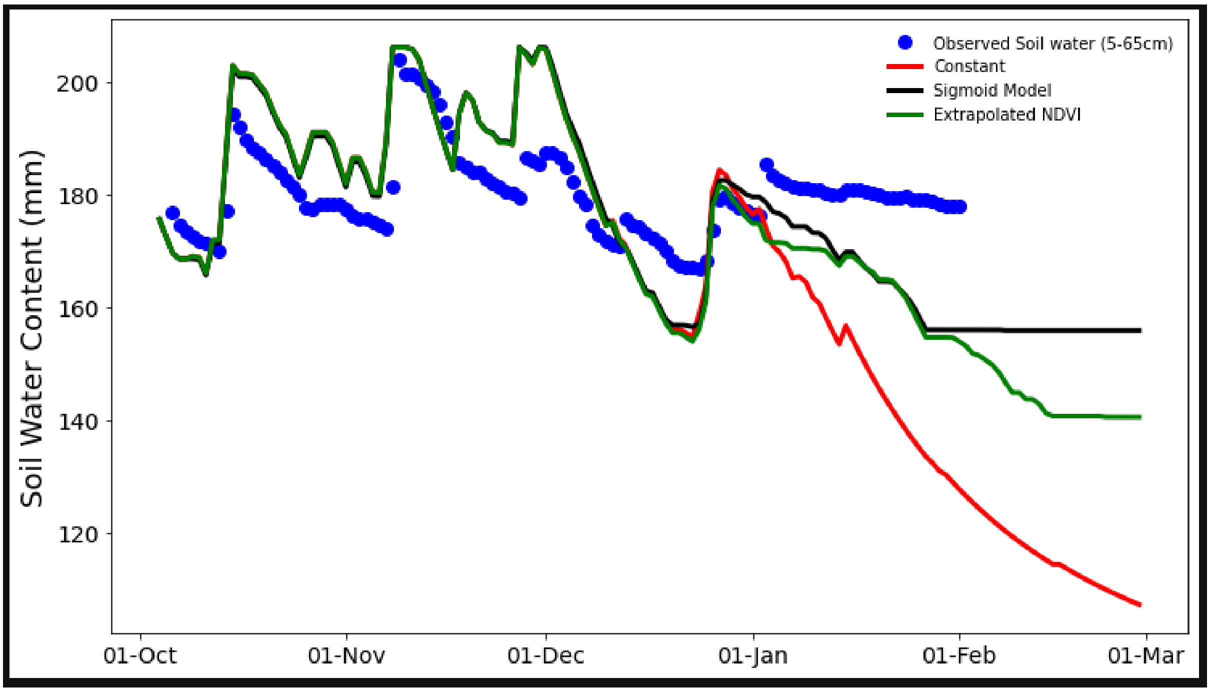

Figure 5: Water balance model

These results infer using an approach that gives a realistic representation of canopy cover to estimate water use will enable more accurate irrigation scheduling.

Integrating canopy cover measurements with water scheduling models

The water balance used in the previous section contained the full Penman-Monteith formulation of potential evapotranspiration (Allen et al 2006):

$$PET = \frac{\Delta(R_n - G) + \rho_a C_p (e_s - e_a)/r_a}{\left(\Delta + \gamma\left(1 + \frac{r_s}{r_a}\right)\right)\rho_w \lambda}$$

Parameters were calculated from local meteorological data in the usual way.

R_n is net radiation calculated using global radiation measured on site following (Allen et al 2006).

r_s was assumed constant at 70 which is a suitable value for a well-watered wheat crop.

r_a was calculated from wind data and crop height assuming height increased with accumulated temperature from zero a sowing to a maximum value of 1m when the crop had completed heading.

Estimates of transpiration were taken as:

Transpiration = min(PET × Cover, Potential extraction)

Where potential extraction was calculated as a function of the available water content in the soil.

Estimates of evaporation were taken as:

Evaporation = min(PET × (1-Cover)), Potential diffusion)

Where potential diffusion was calculated as a function of the water content in the top 5 cm of soil.

Using the full Penman Monteith equation in this way allowed for explicit integration of the effects of changes in crop height and crop cover. An alternative approach is to use the same formulation of PET to calculate potential water use with r_a as a constant and then apply a crop coefficient (k_c) multiplier that accounts for changes in crop height and cover (Allen and Pereira 2009). Some scheduling systems take this approach as it allows for the user to vary k_c relative to their specific crops as the crops develop. However, this leaves the challenge of how the user should set k_s.

In this project we developed a spreadsheet that takes estimated values of crop height and cover to estimate values of k_c based on the approach outlined by Allen and Pereira (2009).

$$k_c = k_e + k_{cmax} \times k_d$$

Where k_e is the coefficient for evaporation and k_{cmax} is the maximum crop coefficient for the crop and k_d is a canopy density coefficient.

$$k_e = (1\text{-Cover}) \times k_{emax} \times 1/I_{freq}$$

Where k_{emax} represents the evaporation (relative to potential) that would occur when the soil is fully wet and I_{freq} is the approximate frequency of irrigation. $1/I_{freq}$ will decrease as wetting becomes less frequent which captures the effect of increasingly drier soil surface having a lower evaporation.

$$k_d = \min\left(1, 1.5, Cover^{\frac{1}{1+height}}\right)$$

The formulation for estimating k_{cmax} given by Allen and Pereira (2009) is for calculation daily using inputs of crop height, wind speed and relative humidity. As the intent of the spread sheet was to provide undated estimates of k_c less frequently and alternative calculation was derived using an empirical function:

$$k_{cmax} = k_{cmax0.1} + \frac{(k_{cmax2.5} - k_{cmax0.1}) \times height}{h_{hf} + height}$$

Where $k_{cmax0.1}$ and $k_{cmax2.5}$ were k_{cmax} values derived for canopy heights of 0.1 and 2.5m, respectively, and h_{hf} is a shape parameter. Values of 0.9, 1.45 and 2.0 were derived for $k_{cmax0.1}$, $k_{cmax2.5}$ and h_{hf}, respectively, by calculating the ratio of PET with different canopy heights (using the full PET approach outlined above) relative to PET with a standard height of 0.3 m. These values were then plotted against height and the above function fitted as shown in Figure 6. It must be noted that the parameters derived using the above approach depend on the radiation, temperature and wind values used in calculating PET so values that were typical for the location were used.

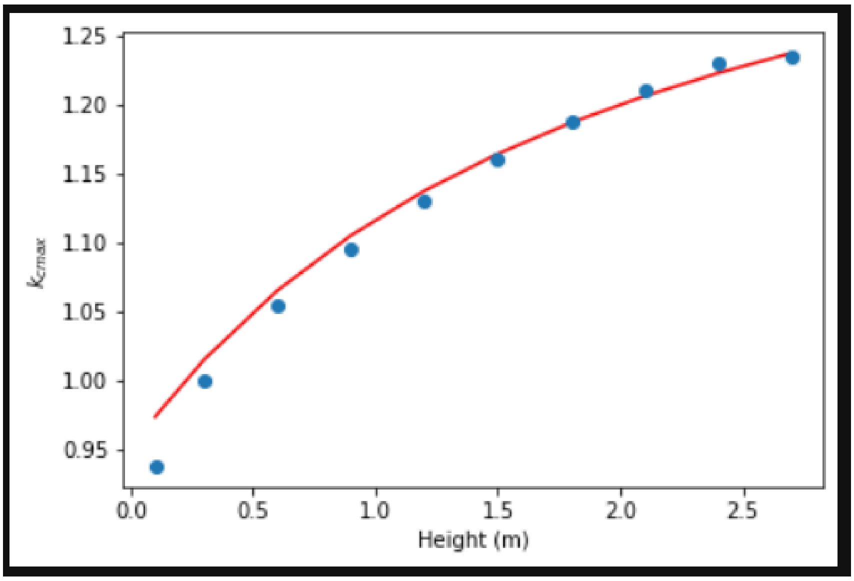

Figure 6: k_{cmax} values

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