Posibilidades del empleo de un analizador de luz solar de bajo coste y registrador de datos en la medida de radiación para agroclimatología

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Resumen
En los períodos tempranos del desarrollo de los cultivos, las condiciones de crecimiento pueden ser críticas para la futura cosecha. Esto es particularmente evidente en cultivos como el maíz. Estas condiciones incluyen no sólo calidad del suelo, humedad del suelo y temperatura, sino calidad y duración de luz solar disponible. Una medida simple del "brillo" no es sin embargo un buen indicador de la verdadera "calidad" de la luz solar disponible. Las investigaciones han mostrado que la presencia o ausencia de longitudes de onda de luz específicas pueden afectar significativamente a la fotosíntesis y por consiguiente, al crecimiento del cultivo. Además, una sobreexposición de los tejidos de la planta a altos niveles de radiación ultravioleta puede resultar dañina. Se sabe que la radiación infrarroja se dispersa a niveles bajos de nubes y niebla y se absorbe significativamente en condiciones moderadas de nubosidad, dando como resultado que al suelo llegan niveles bajos de radiación. La radiación ultravioleta es capaz de penetrar incluso con moderados niveles de nubosidad. La cantidad total de luz solar de calidad recibida por una planta inmadura puede afectar a su posterior cosecha determinando si un cultivo se recolectará peor o su influencia en el uso posterior de fertilizantes. Esta comunicación discute los resultados de un analizador de luz solar autónomo basado en diodos LED y un registrador de datos capaz de distinguir condiciones específicas de luz solar que oscilan desde la luz solar directa, luz a través de niebla, nuboso moderado y luz de luna uniforme. La unidad cuesta menos de 10 euros y puede monitorear más de cuatro meses sin mantenimiento transmitiendo mediante un enlace de radiofrecuencia de 2,4 GHz.
Palabras clave: predicción de cosecha, LED, longitud de onda, fertirrigación.

Possibilities to use a Low Cost Sunlight Analyser and data logger for measuring radiation for agroclimatic purposes

Abstract
In the early stages of crop development, growing conditions can be critical to eventual yield. This is particularly true for crops such as maize. These conditions include not only soil quality, moisture and temperature, but also the quality and duration of available sunlight. A simple measure of ´brightness´ is however not a good indication of the true ´quality´ of the sunlight available. Research has shown that the presence or absence of specific wavelengths of light can significantly affect photosynthesis and hence crop growth. Further, over exposure of plant tissue to high

levels of Ultra Violet radiation can prove damaging. Infra-Red radiation is known to be scattered by weak levels of cloud and haze, and is significantly absorbed by moderate cloud conditions, resulting in lower levels reaching the ground. Ultra Violet radiation is capable of penetrating even moderate levels of cloud. The total amount of quality sunlight received by an immature plant can affect its later yield determining whether a crop is worth harvesting, or influence the later use of fertilizers. This paper discusses results from a low cost, real time, stand-alone LED based Sunlight Analyser and Data Logger capable of distinguishing specific sunlight conditions ranging from direct sun, through light haze, moderate cloud and even moonlight. The unit costs less than 10 Euros and can give in excess of 4 months unattended monitoring transmitting via a 2.4GHz RF link.

Keywords: Yield Prediction, LED, Wavelength, Fertigation.

INTRODUCTION

Unexpected crop failure can have devastating effects on subsistence communities, and have severe financial impact on commercial growers, leading to increased agricultural insurance premiums (Castaneda-Vera, 2015), affecting futures markets (Iizumi et al, 2013), and encouraging over-use of fertilizers, pesticides and irrigation. Many yield prediction algorithms are based on remote sensing NDVI data from satellites (Tewes et al, 2015; Soria-Ruiz et al, 2004), which while useful at estimating biomass and crop health over large areas (Zhang et al., 2015), are subject to noisy data based on climatic conditions (Huang et al, 2013). Growth models are often based on early crop development such as ´R1´ silking in corn (Mourtzinis et al, 2013) or plant height at V6, V10, and V12 (6-, 10-, and 12-leaf) growth stages (Devkota et al., 2015; Yin et al., 2011). Such models incorporate a range of factors including soil types, terrain, climate, farming practices, meteorological data and statistical techniques. However as photosynthesis is critical to plant growth, it is the amount of usable solar radiation that is crucial to healthy crop development and prediction accuracy (Agarwal et al, 2001). The amount of radiation available is usually measured by a wide spectrum pyranometer costing hundreds of Euros.

To augment existing crop yield prediction models, it is proposed to provide more detailed information on specific sunlight quality and conditions, making distinction between bright sunlight, light and heavy cloud conditions and even moonlight. This data can specify not only the daily duration of specific conditions, but also ´time of day´ information, particularly important where it is necessary to know if conditions were favourable in the morning (Michael et al, 2008), afternoon or evening. This could replace the pyranometer.

MATERIALS AND METHODS

LEDs are traditionally used for illumination, however when exposed to appropriate radiation, the PN junction generates a reverse current proportional to the brightness level to which the LED is subjected (within limits) [Mimms III, 1992]. These currents are however exceedingly small and the performance of the LED under these conditions is determined by other device characteristics and the methods used to measure them.

Our sensor consisted of three, 5mm, 20-30 degree Beam angle LEDs: firstly a triple die, RGB common cathode LED; secondly a UV LED; and finally a clear lens IR LED. A series of 11, time spaced voltage level readings were taken on each of the 5 LED die channels. Before starting the series on each channel, the analogue input pin was configured as a digital output set to 0 and a dummy ADC reading made to ensure that all of the channel pathway is fully discharged. The first four readings are taken in immediate succession with processor interrupts turned off. These four readings are all taken in less than 0.5ms. Incremental delays of 1ms, and 2ms, are then applied before the 5th and 6th readings respectively. After a further 7ms delay, interrupts are re-enabled and the 7th reading taken. Delays of 20ms, 70ms, 200ms and 700ms, are then applied before the 8th, 9th, 10th and 11th readings respectively. This gives four, linearly time spaced readings followed by seven readings spaced over exponentially increasing exposure times. After all eleven readings are taken, the results are logged and transmitted.

To try to characterize these conditions, metrics were devised relating the 1st (0.1ms exposure time), 4th (0.4ms exposure time), 7th (10ms exposure time) and 11th (1s) readings as a percentage of the maximum ever observed reading for each channel. These are referred to as L1, L4, L7 and L11 respectively. After initial examination of the data, the following were chosen for further analysis: IR L1, IR L11, Red L1, Red L4, Red L11, Green L4, Green L7, Green L11, Blue L4, and UV L7. From these ten reduced metrics, a simple classification ruleset [Holland 86] was derived to determine one of twelve current lighting conditions. These classifications were: Moonless, Moonlight, Light Pollution, Dusk, Dawn, Poor Light, Heavy Cloud, Shade, Light Cloud, Haze, Blue Sky and Direct Sun. As might be expected, the distinctions between Dawn, Dusk, Moonlight and Light Pollution, prove the hardest to define. The classifier output was validated by observation over a 20 hour period, and checked for consistency over all other readings. See table 1.

An Arduino® microcontroller, running at 3.3v and 16MHz, powered by 3*AA alkaline batteries was used. Data was transmitted by a NRF24L01 2.4GHz radio transceiver and logged data onto a WINBOND W25Q32 32Mbit SPI FLASH EPROM. The component cost of the device is under 10 Euros including IP56 housing and batteries.

RESULTS AND DISCUSSION

Photosynthesis is at least a three-step process (Teal, 1990) involving specific wavelengths primarily in the Infra-Red sub-spectrum (Raven et al, 2001). The combined levels of these wavelengths can significantly affect plant growth (Emerson et al, 1943). Further, the daylight conditions also play a crucial part in the development and activities of pollinators and pests (Shepherd et al, 2003) which also have a strong influence on crop yield (Buchmann et al 1996.). A simple, broad spectrum measurement of light intensity does not provide sufficient information to be able to determine specific daylight conditions as different wavelengths of light are affected in different ways by climatic conditions (Wiscombe et al, 1984). Many crops (for example Soya bean, pea, spinach etc.) do not thrive well if over exposed to either intense or prolonged sunlight conditions and UV radiation (Krupa et al, 1989), requiring an ideal balance to provide optimum yield. The growth mechanisms of some plants are known to vary significantly during the daily 24 cycle (Michael et al, 2008), relying on sunlight either in the morning or afternoon.

Figure 1 shows LED readings over a typical sunny day (4th March 2015) with a cloudy afternoon followed by moonlight. The first 20 or so readings (06:35-08:15) show the build-up of Red and IR levels at 1 second exposure time, saturating at about 90% of the maximum ever observed voltages. As the day progresses, the 0.1ms readings for Red and IR can be seen to rise, fluctuating occasionally with the passage of light clouds and haze.

At about 14:45 the cloud cover starts to increase and the sensor then falls into the shadow of a nearby building. As evening approaches all LED voltages fall and by19:35 even IR11 and R11 readings have reached a minimum. During the night, the LEDs detect light pollution, but for about an hour (00:20-01:25) Moonlight is detected, Through-out daylight hours UV levels rise and fall in a steady curve.

Figure 2 shows both a numerical representation of the classifier output (Moonless = 100, Direct Sun = 133) and the percentage of saturation voltage LED readings for R1 and IR11 for the 32 day period 13th March 2015 through 13th April. This period presented a particularly varied selection of weather conditions including stormy heavy rainfall for several days (March 17th to 20th) followed by several days with heavy night time cloud cover lasting until 27th of March. These conditions improved to give clear night skies allowing detection of the waxing and waning of the full moon on the night of 3rd/4th April.

Figure 3 plots the Minutes of Direct Sun (MDS), Maximum Temperature (MT), Daytime Average Temperature (DAT) & Minutes of Moonlight for the same 32 day period. The waxing and waning of the full moon is clearly seen between the 31st of March and the 6th of April. There is a degree of positive correlation between MDS recorded by the Sunlight Analyser and both MT and DAT, however this is not linear and is presumably dependent on a range of other factors such as night time cloud cover, humidity, wind speed and direction etc. A linear regression analysis of MDS with DAT gives a Correlation Factor of 0.6683, the result being skewed by the 5 high temperature readings above 24ºC which occur during the fine weather recorded between March 27th and 31st. During this time, the minutes of Direct Sun, would probably have been even greater had the sensor not fallen into the shade of a nearby building in the afternoons. If these 5 ´outriders´ have their values artificially capped to 21ºC then the correlation factor increases to 0.7715.

CONCLUSIONS

These results demonstrate that the Sunlight Analyser can measure the relative strengths of several wavelength components of sunlight and classify a wide range of light conditions ranging from Direct Sun, through Hazy Cloud, Poor Light and Moonlight. It identified the full moon where cloud conditions allowed. Whilst it is not possible to correlate the classifications of the Sunlight Analyser with the output of a similar device, it has been demonstrated that the classification output for Direct Sun correlates to the locally recorded average day-time temperature with a correlation factor in excess of 77%.

A larger field trial for the Sunlight Analyser is proposed, comparing results to those from a commercial solar radiometer (Pyranometer). If successful, it is proposed to co-locate units with crops for which true yield information can be made available to verify the usefulness of the device as an aid to Yield Prediction.

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Table 1. Classifier ruleset.

Direct sun/Poor light	Dawn/Dusk ...	Dark	Cloudy
(IR1 > 50) = DIRECT SUN (R4 < 20) = goto dark ... (R1 > IR1 *0.8) AND (R1 > 15) = BLUE SKY (IR1 > R1) AND (R1 > 4) goto cloudy ... (B4 > IR1) AND (B4 > 10) = SHADE POOR LIGHT (IR1 > 50) = DIRECT SUN	(IR11 < 55) AND (IR11 > previous IR11) = DAWN DUSK	(G11 > 30) = goto dawn/dusk ... (R11 > 15) AND (G4 > 0) = LIGHT POL (R11 > 5) AND (R11 * 3 > IR11) = LIGHT POL (IR11 < 12) OR (previous IR11 < 12) = NO MOON MOON	(G4 > 35) = HAZE (G4 > 15) = LIGHT CLOUD HEAVY CLOUD

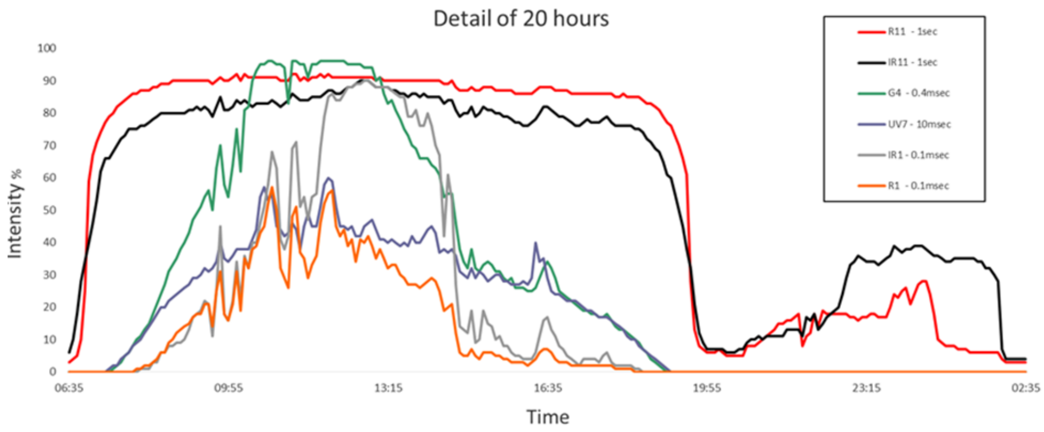

Fig. 1. LED readings over a typical sunny day with cloudy afternoon and moonlight.

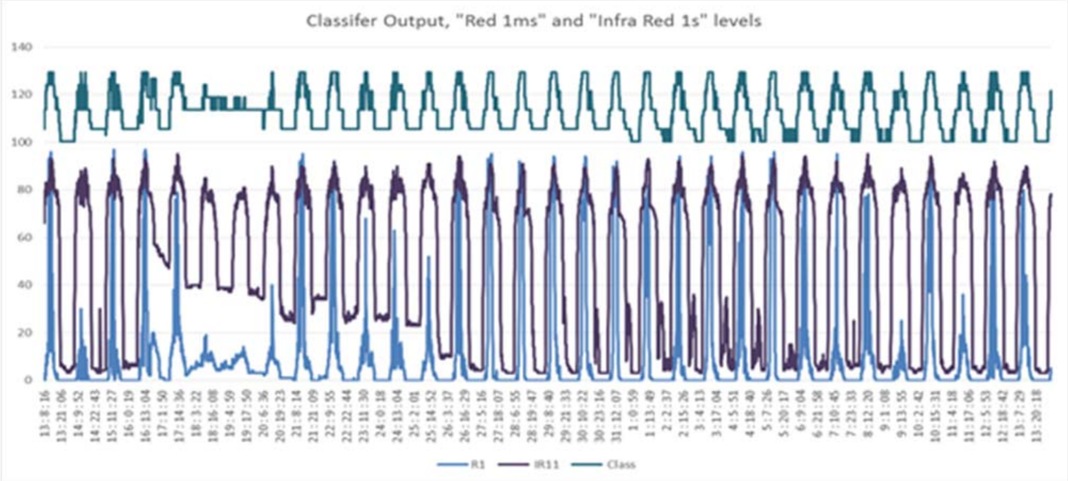

Fig. 2. Analysis of sunlight conditions for 32 days, 13th Mar 15 – 13th Apr 15.

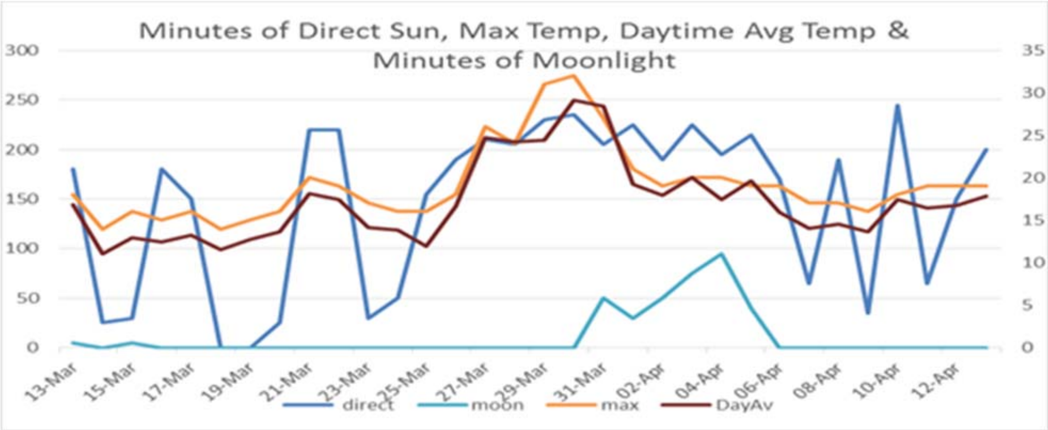

Fig. 3. Minutes of Direct Sun, Max Temp, Daytime Avg Temp & Minutes of Moonlight.