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Review Article
Remote Sensing Derivation of Land Surface Temperature for Insect Pest Monitoring

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Abstract
Temperature has major influence in insect development and outbreak. At present, the common method of collecting temperature information mainly relies on ground weather stations. However, this method is unfeasible for a large-scale area as weather stations distributions are sparse. This, however, can be compensated by the temperature measured through remote sensing satellites known as Land Surface Temperature (LST). Hence, this paper reviews the advantages and disadvantages of Thermal Infrared (TIR) and Microwave (MW) sensors for the acquisition of LST. This review will focus on the availability, suitability and adaptability of those sensors in providing LST for insect pest monitoring with the comparison being concentrated on their spatial and temporal characteristics, along with their accuracies.

Key words: Land surface temperature, thermal infrared, microwave infrared, pest outbreak monitoring, sensor characteristics

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INTRODUCTION

Pests remain as a constant risk in agricultural production because they can infest crops and cause substantial monetary losses to industry. In Malaysia, major insect pests responsible for damage in oil palms are bagworms, *Metisa plana*, *Pteroma pendula* and *Mahasena corbetti* (*Lepidoptera*: *Psychidae*), nettle caterpillars, *Darna trima* (*Lepidoptera*: *Limacodidae*) and rhinoceros beetle, *Oryctes rhinoceros* (L.) (*Coleoptera*: *Scaeabaeidae*). A severe infestation of bagworms could destroy 33-50% of the yield[1-4], while a high abundance of nettle caterpillars and rhinoceros beetles were shown to significantly reduce yield by about 25-30%[5,6] for over the next two years of infestation. Reports on the economic damage and losses caused by these pests are still limited[5-7]. In the example of bagworms, which is the most economically important insect pest of oil palm[4], it is estimated that 10% of the damages could cause a loss of approximately USD 2,032 ha^{-1}. This would eventually cause a loss of USD 2.62 billion for 2 consecutive years.

With the development of various pest control techniques, such as cultural, mechanical, biological, genetic and chemical control, pesticides became the primary means of solving the problem of having pests in agriculture production. Effective pest management are usually associated with the use of chemical pesticide as important tool to contribute to high farm yield[8]. However, these control methods for pests are not very satisfactory due to local health hazards, pesticides residues to consumers, build-up of resistance of pest and contamination of the environment[9]. It also contributed to the decreasing of natural enemie's population[10]. Simultaneously, precise and efficient pest early warning technology combined with communication technology and cloud computing for agriculture sector is still in the research and development stage. The key to this strategy is to detect pests as early as possible and take scientific prevention immediately. However, the construction of the pest outbreak forecasting system is relatively complex, owing to a large number of site-specific data variables, such as physical landscape, nutrients and organisms[11] and climatic driving variables for instance, the change in solar intensity that could account for the magnitude and distribution pattern of altered mean temperature and precipitation globally.

At present, the method of gathering information regarding diseases and insect pests mainly relies on periodical manual field surveys, sampling and analysis[12,11] as well as meteorological data[13-15]. Unfortunately, the traditional ground-based survey method is inefficient, as well as time and labour intensive, which often requires specialist knowledge in addition to being unfeasible for a large-scale area[16,17,11]. Meteorological data, however, were used to forecast pest outbreaks based on knowledge of the biology and ecology of the pests. For example, a high temperature allows insects pests to breed continuously and develop faster[18], therefore, this knowledge was used in developing a forecasted warning of pest's infestation. In the temperate region, when the overwintering eggs of *Tipula pagana* hatch or their first adults emerge from the overwintering, pupae is basically an emergence warning[19-21]. Moreover, in the tropical region, the insect pest warnings for *Helicoverpa armigera* are usually the first occurrence of a pest attack in the crops or the first invasion of migratory pests from adjoining areas[22-24].

Herbivorous insects are difficult pests to control due to their high fecundity and short lifecycles, in addition to their capability to destroy about 20% of the global crop production each year[25]. Generally, insect abundance and distributions are regulated by several biotic factors, such as natural enemies and beneficial plants and abiotic factors, such as wind, temperature, sunshine, humidity and rainfall[26]. Often, the interactions between these factors in the environment are interrelated. Among the abiotic factors, temperature is the key factor explaining abundance and distributions of insects[27-29]. Previous studies have shown that temperature influences the rate of growth, survival, reproduction, density and dispersal of insects[30-32]. According to Bale *et al*.[33], the effects of temperature are likely to be more significant than any other factors for insect species to establish a viable population.

Ibrahim *et al*.[34] demonstrated that the effects of temperature on the development and survival of bagworm species conformed to the insect's trend to increasing temperatures until the optimum was reached[35,36]. The optimum temperature for the development and survival for *Pteroma pendula* is in the range of 25-30°C whereas for *Metisa plana*, the optimum temperature is slightly higher, which is around 30-35°C. Furthermore, at their respective optimum temperature ranges, both *Pteroma pendula* and *Metisa plana* have a relatively high percentage of eggs to adults. According to Aneni *et al*.[37], a dry season with higher seasonal temperature recorded a greater abundance of leaf miners, such as *Coelaenomenoder aelaeidis* and predatory ants in oil palm plantations. These indicated that the oil palm ecosystem was prone to insect pest attacks as a result of the increasing temperature.

In contrast, some studies show negative correlation between temperature and insect pests' abundance[38-40]. Marchioro and Foerster[41] found that the abundance of diamondback moth, *Plutella xylostella* in Southern Brazil was not influenced by temperature variation and was tolerant to a wide range of temperatures. In response to temperature, the insect pests of mung beans thrips (*Thrips tabaci*) was observed to have a negative and significant correlation ($p<0.05$) with temperature[42-44]. Furthermore, the aphid population dynamics of *Lipaphis erysimi* on Indian mustard and oil seed Brassicas with temperature were found to be negatively correlated. These showed that temperature as the factor influencing insect development and growth may vary due to different insect thermal requirements and development. The understanding of this factor is crucial in order to understand the changes in insect population densities because they do not stay constant for long.

The advancement in geospatial technology, which comprises of remote sensing, Geographic Information System (GIS) and Global Positioning System (GPS) have previously benefited agricultural communities through applications of crop nutrient and pest and disease status monitoring[45-48]. The presence of remote sensing tools offers rapid, harmless and cost-effective means to obtain necessary information on the triggering factor of pest outbreaks, such as temperature, relative humidity and their natural enemies. Early detection via geospatial technology potentially (i) Reduces labour time and cost, (ii) Limits environmental pollution and (iii) Improves precision farming by controlling pests before they spread[49]. Large area crops could be synchronously monitored with the help of remote sensing technology.

Remote sensing provides a possible solution to the traditional methods of intensive sampling and can significantly provide timely and accurate information for pest monitoring[50,51]. Previously conducted researches depicted that the presence of pests, such as aphids, whiteflies, as well as thrips in greenhouses and field crops could be detected using different image processing techniques based on cognitive vision system[52], image and video processing algorithms[53-55], binocular stereo[56], acoustic sensor[57] and back propagation neural network[58]. Furthermore, remote sensing can greatly support the early warning and monitoring of insect pests through the provision of quantitative information on air and land temperature. Several conducted studies[59-64] have demonstrated the benefits remote sensing utilization in terms of satellite derived land surface temperature (LST) in monitoring insect pest over the conventional use of temperature retrieved from ground weather stations such as higher spatial and temporal resolution and reasonable accuracies. Lensky and Dayan[59] highlighted the major advantage of MODIS LST product that was high spatial characteristic of which enabled them to capture spatial variability of temperature within a finer scale in comparison to ground weather stations. T his study aimed that spatial variability of climatic conditions, driven by topography, was responsible for a three weeks delay for *Heliothis* spp., from the pupal stage into the adult stage. The authors concluded that LST played an important role in capturing this variability and hence, helped in increasing the accuracy of insect outbreak prediction. An attempt has been made by Sprintsin *et al.*[60] to develop an early detection mechanism of Mountain Pine Beetle (MPB) *Dendroctonus ponderosae* infestation through combination of LST and shortwave infrared reflectance (SWIR) provided by Landsat ETM+. The principle of the detection was based upon differences in transpiration cooling and canopies temperature, of which these parameters were translated into indices known as Temperature Condition Index (TCI) and Moisture Condition Index (MCI). Through this indices, the authors managed to differentiate the areas that were affected from the unaffected areas in the early attack stage of MPB. However, lack of available cloud free satellite images limited the potential of the indices. Furthermore, Yones *et al.*[61] reported a difference of approximately 59.22 DD when comparing DD calculated from air temperature simulated from the NOAA satellites and air temperature from ground weather stations. This DD value was translated to a reasonable difference of 2.85 forecasting days for the outbreak of cotton leaf worms, *Spodoptera littoralis*. This finding was further supported by Da Silva *et al.*[62] who stated that there was a significant linear relationship between the accumulated DD of South American tomato moth, *Tuta absoluta* (*Lepidoptera*: *Gelechiidae*) calculated using LST obtained from the MSG satellite and accumulated DD computed from the conventional in-situ meteorological temperature data. The authors highlighted the main restriction of LST data that was cloud presence that attributed to underestimated LST values and difficulties to remove partial cloud pixels. However, these limitations were compensated by the availability of LST data that was better than scarcely distributed ground weather stations. Blum *et al.*[63,64] on the other hand used tree canopy temperature provided by the integration of MODIS LST and in-situ data to model the population fluctuation trends of olive flies, *Bactrocera oleae*. Significant, strong correlation coefficients of $r = 0.74$ and $r = 0.82$ has been attained when a comparison was being made between the seasonal population obtained from the model with adult-olive trapping data.

Hence, the purpose of this review, is to discuss and compare the usage and application of remote sensing satellite for temperature, specifically Thermal Infrared (TIR) and Microwave (MW) sensors in monitoring insect pest population abundance in agriculture.

REMOTE SENSING APPROACH

Monitoring and predicting insect development and outbreak using a fixed date calendar can be difficult as developmental thresholds for insects are different from one species to another. Hence, insects monitoring and prediction should be based on a temperature-based principle[62], of which the most common method utilized is the Degree Days (DD)[65-71,62]. Apart from DD, there are other several methods that have been used to describe the effect of temperature on insects development, for example, temperature-dependent phenology model[72], regression model[73,74], analysis of covariance (ANCOVA)[75] and Seasonal Autoregressive Integrated Moving Average (SARIMA)[76].

Degree day is a thermal unit that is used to indicate the amount of accumulated heat needed for insects to undergo their developmental stages prior to time[77,62]. The calculation involves two different thresholds as shown in Eq. 1, (i) minimum developmental threshold or baseline temperature of which no development will occur at temperatures below this threshold, or alternatively stated as the minimum temperature required for insects to start to develop and (ii) maximum developmental threshold or cut-off temperature of which no development will occur at temperatures above this threshold or the maximum temperature of which insects stop to be developed[77].

$$DD = \frac{(Tmin+Tmax)}{2} - \text{Baseline temperature} \qquad (1)$$

Where, Tmin stands for minimum temperature of the day and stands for maximum temperature of the day.

Different types of temperature data are able to be used in DD calculations depending on the habitat of the pests, commonly: air temperature, land surface temperature (LST) and soil temperature. Air temperature and LST are different from one another in terms of the magnitude they cover and the technique used to measure them. Air temperature is measured 1.5-2 m above ground, which is sparse over a large geographical area (>10 km) and due to this, it is not able to capture topographic and other geographic effects that might have affected the ecology of the pests. However, LST is associated with a relatively high spatial heterogeneity because a distance of several metres could stimulate the temperature changes by several degrees due to the influence of emissivity and other thermal properties of different surfaces and materials[78]. Land surface temperature is derived from satellite with a TIR or a MW sensor at a finer scale, which has the ability to capture the geographic and topographic elements over an area.

The TIR on board of satellites observe the thermal infrared radiation emitted by earth surface at the range of a wavelength from 3.0-14.0 µm through 2 thermal windows that usually operate in the range of 3.0-5.0 µm as well as 8.0-14.0 µm. The main principle that allows this operation is the fact that all objects that have a temperature above absolute zero 0°K or -273.16°C or a -459.69°F possess kinetic heat, which is the energy of particles in random motion. When these particles collide with each other, electromagnetic radiation will exit from the object and this radiation is called radiant flux. Radiant flux is measured in watt unit and this flux concentration is referred as radiant temperature and there is usually a highly positive correlation between radiant flux and the true kinetic energy of an object.

However, it is worth noticing that objects of a same kinetic energy level do not necessarily possess a same radiance temperature depending on the object emissivity. The emissivity of an object can be influenced by several factors, the first being colour: Darker colour objects are usually better absorbers and hence, have a higher emissivity compared to lighter coloured objects. Second is surface roughness: The greater the surface roughness in relation to incidence wavelength, the greater the surface area for energy emission and absorption. Third factor is moisture content: Objects with higher moisture content have a greater ability to absorb energy and hence, higher emission. This is followed by compaction: degree of soil compaction has the ability to affect emissivity. Next is field of view: Resolution will affect the emissivity of object viewed. Followed by wavelength: Emissivity is wavelength dependent and lastly, viewing angle: Emissivity of an object can vary with the sensing viewing angle.

Apart from emitting infrared radiation, earth surface also emits MW radiation. This radiation can be measured as brightness temperature by passive MW sensors. MW radiation is emitted at a relatively lower energy level when compared to infrared radiation and thus, the radiation must be collected over a larger region in order to collect sufficient energy and consequently, this low energy level characteristic contributes to a lower spatial resolution of MW sensors. This radiation is also able to penetrate haze, light rain, smoke and snow, which is the opposite of the TIR. The retrieval of LST from MW sensors are based on the Planck blackbody radiation principle and Rayleigh-Jeans approximation ,which stated that microwave radiance of the ordinary surface features are linear to the real temperature[79].

A huge number of different multiband TIR sensors on-board a variety of satellites are able to provide LST, namely Thermal Infrared Sensor (TIRS) on-board Landsat

8 (10.60-11.19 µm and 11.5-12.51 µm), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) on-board TERRA (8.125-8.475, 8.475-8.825, 8.925-9.275, 10.25-10.95 and 10.95-11.65 µm), Moderate Resolution Imaging Spectroradiometer (MODIS) on-board TERRA/AQUA (10.780-11.280 and 11.770-12.270 µm), Advanced Very High Resolution Radiometer (AVHRR) on-board National Oceanic and Atmospheric Administration (NOAA) (10.3-11.3 and 11.5-12.5 µm) and Spinning Enhanced Visible and Infrared Imager (SEVIRI) on-board Meteosat Second Generation (MSG) (9.80-11.80 and 11.0-13.0 µm). The most common algorithm used to retrieve LST from TIR sensors is Split Window Algorithm (SWA), which was developed by incorporating three major LST influencing elements: (i) Water vapour content, (ii) Surface emissivity and (iii) Sensor viewing angle. Overtime, SWA was continuously developed and modified to fit the LST retrieval process by different TIR sensors[80-91].

The use of TIRS based LST were reported to achieve reasonable accuracies in comparison with ground temperature data, as reported by Parinussa *et al.*[92,93] (MODIS, Standard Error (SE) = 2.17-6.5 K, R^2 = 0.80-0.97), Zhong *et al.*[94], (MODIS, Percentage Error (PE) = 0.3-18.4%, AVHRR, PE = 4.1-22.4%), Hachem *et al.*[95] (MODIS, Mean Difference (MD) = 1.8 K, R = 0.97), Yu *et al.*[96] (MODIS, Mean Absolute Error (MAE) = 2-3K), Jiang *et al.*[97] (MODIS, Root Mean Square Error (RMSE) = 4.53°C) and Atitar *et al.*[98] (MSG, RMSE = 1.9K). The most commonly used TIR sensors to measure LST are TERRA/AQUA MODIS[76,99,100] and NOAA AVHRR[101] owing to the frequent revisiting time of two images per day. Nonetheless, between these two sensors, MODIS was found to result in better accuracies of LST derivation in comparison with in situ data, as reported by Hachem *et al.*[95], where the former depicted an average PE of 8.3% whereas the error of the latter was 10.5%. The mean of the differences between the LST products acquired from these sensors were 2-5 K as reported by Batra *et al.*[102].

Differences in the accuracy level of space derived LST measurements were mainly influenced by several factors, such as maintenance programs by data service providers, derivation of water vapour within the TIR algorithm used, different passing times, different measurement angles and different spatial resolutions. Generally, MODIS LST product out performs the AVHRR LST primarily due to ongoing improvements, maintenance and up-to-date algorithms[103]. This is further supported by the development of the versioning system that resulted from the effort of constant reviews of MODIS LST product[104], apart from the accuracy of MODIS LST product, which is less than 1 K[105]. In contrast to the well-maintained MODIS LST product, AVHRR LST product is slightly of lower quality, owing to the lack of metadata layers in the AVHRR product, specifically data describing the time of acquisition, satellite zenith and azimuth angle, which results in data usage and interpretation difficulties. Additionally, AVHRR LST also underwent insufficient cloud masking, which reduced the LST by several degrees[78], contributing to the accuracy gap.

Different ways of deriving water vapour content were found to affect the ability of SWA algorithm to retrieve accurate LST. Similar SWA can be utilised to retrieve LST for MODIS and AVHRR. The water content term for AVHRR is estimated by using the Split Window Covariance Variance Ratio (SWCVR) using brightness temperature and satellite observation angle. Water vapour content for MODIS, on the other hand, is derived directly from the transmittance of MODIS thermal bands (band 31 and 32) because these two terms were found to statistically satisfy a linear relationship[91].

Furthermore, the differences between overpass times among sensors have affected the accuracy of LST, due to the fact that LST is highly dependent of atmospheric conditions, especially the presence of clouds. If AVHRR and MODIS are taken as an example, these sensors have a different overpass time with MODIS usually crossing at midday whereas AVHRR is making the same pass one or two hours later. This has caused images acquired from AVHRR to be contaminated by clouds more than that of MODIS and thus, lowers the accuracy[94].

Varying accuracies of LST products also have resulted from different sensors, chiefly due to different viewing angles leading to differences in surface sensed by sensors[106,78]. This matter was given attention in the development of SWA for LST retrieval by MSG2 SEVIRI by taking its angular dependency into consideration. Variations in the viewing angle (0-60°) found to increase the standard deviation of LST measured by as much as 54%. In the application of SEVIRI, measurements made at nadir from the combination of thermal band of (8.7, 13.4, 10.8 and 12.0 µm) showed the lowest standard deviation in the estimated LST. When the viewing angle was increased to 50°, the standard deviation consequently increased to almost one[98].

Another essential characteristic to evaluate for space derived LST is spatial resolution among sensors. Spatial resolution directly manifests spatial heterogeneity, which refers to pixel values that reflect the mixture of different type of land covers, such as bare soil, vegetation and water bodies. For instance, while ASTER and MODIS sensors are on-board of the same satellite, TERRA, implying that the observations were made from the same height and coincident nadirs, nevertheless, they have different spatial resolutions, which is 1km for MODIS and 90 m for ASTER. The differences of ASTER and MODIS LST were approximately 3 K over a semi-arid area and this disparity was related to the differences in spatial resolution apart from the different retrieval algorithms used[107,108].

The utilisation of LST derived from TIRS sensors are subject to a few vital considerations, such as the retrieval of LST from TIR sensors would only be applicable under cloud-free conditions. This is due to the ability of clouds to jeopardise the data retrieved from satellites by preventing the sensor to capture the radiance emitted from the earth surface, leading to a mixture of earth surface and cloud emission and consequently, an underestimation of LST values. While this situation can somehow be fixed by the application of atmospheric correction techniques to eliminate pixels with cloud cover, this is not the best solution because the elimination of pixels can lead to data loss and thus, lower the accuracy of LST retrieved[109]. Nevertheless, MODIS offers a solution to this problem by providing a freely available 8 days average clear-sky product, which is MOD11A2.

However, microwave sensors have an advantage over TIR sensors, in which their measurements are not easily hindered by clouds and rain, due to the ability possessed by the sensors to observe microwave emissions that are capable to penetrate clouds. Among MW sensors that are LST providers include: Advanced Microwave Scanning Radiometer (AMSR-E) on-board AQUA, Advanced Microwave Scanning Radiometer 2 (AMSR-2) on-board Global Change Observation Mission (GCOM-W1), Thermal Microwave Imager (TMI), on-board Tropical Rainfall Measuring Mission (TRMM), Special Sensor Microwave Radiometer (SSM/I) and Special Sensor Microwave Imager/Sounder (SSMIS) on-board Defence Meteorological Satellite Program (DMSP). Microwave sensors commonly use Ku band (18 GHz) and Ka band (37 GHz) with a preference leaning towards the usage of Ka band because it is able to balance the reduced sensitivity to soil surface characteristics with a relatively high atmospheric transmissivity. Apart from that, vertical polarisation is preferable over horizontal polarisation in order to retrieve LST because it is less susceptible to the changes in soil moisture at an incidence angle of 50-55°.

The usage of MW sensors to provide LST estimation has showed reasonable accuracies as compared to ground data. Some of the accuracies are reported in Parinussa *et al.*[92] (AMSR-E, Standard Error of Estimate (SEE) = 1.5K-4.5K), Parinussa *et al.*[93] (AMSR-E, SSM/I, TMI, SE = 2.1K-4.9K, R^2 = 0.74-0.97) and Gao *et al.*[110] (AMSR-E, r = 0.7) and Zhang *et al.*[111] (AMSR-E, R^2 = up to 0.86). Furthermore, LST product from MW were frequently compared to LST product from TIR sensors, especially the established MODIS. The performance of this TIR sensor was widely compared with AMSR-E because both of the sensors were on-board the same platform. Reports detailing the comparison accuracies can be found in Parinussa *et al.*[92] (SE = 4K, R^2 = 0.93-0.97) and Chen *et al.*[112] (average error = 2-3°C). Additionally, a comparison between the AMSR-E successor, AMSR-2 and MODIS demonstrated R^2 = 0.5 for the anomalies and R^2 = 0.8-1.0 for raw time series[93].

The ability of MW sensors to retrieve LST under cloudy and rainy conditions has given them the potential to provide alternative means to reduce the temporal gap of LST obtained from TIR sensors. Under wet conditions, AMSR-E had the ability to provide 4 times more frequent data compared to MODIS and advantageously, the former depicted a higher correlation to ground data (r = 0.7) as compared to the latter (r = 0.42)[110]. While the tested area was over humid tropical forest, the availability of TIR LST data was reduced by as much as 80% due to crop transpiration and thus, the MW based sensor served as a better alternative.

Despite being able to perform under wet conditions, the performance of MW sensors can still be compromised by rain bearing clouds or active precipitation with droplets to the size of wavelength (8 mm or 37 GHz), primarily due to the ability to scatter the MW emission. Additionally, the use of MW sensors to retrieve LST are hampered by the presence of snow, frost and frozen soil surfaces, which are attributable to the inability of MW sensors to discriminate the emissivity sensed over these surfaces[111].

Another demerit of MW sensors is its use over mixtures of bare soil and dense canopy areas. Within the AMSR-2 field of view, the cooling effect from the canopy transpiration during the day can mislead the soil temperature to be higher. This effect is worsened by the relatively low spatial resolutions of MW sensors in which the heterogeneity of the earth surface may not be captured in a single pixel[111,93]. In contrast, TIR sensors have relatively higher spatial resolutions and thus, they are able to represent soil and canopy temperature separately. Among TIR sensors that are able to provide LST data, Landsat TIRS and TERRA ASTER are considered to be high spatial resolution sensors, which are 100 and 90 m, respectively. Other satellites with medium spatial resolution sensors are TERRA/AQUA MODIS and NOAA AVHRR of 1 and 1.1 km and low spatial resolution, MSG SEVIRI with 4.8 km. However, MW sensors, offer LST with a relatively lower spatial resolution as compared to TIR sensors starting with GCOM-W1 AMSR2, which offers LST at 10 km spatial resolution. This is followed by several other MW sensors on-board satellites that provide LST at 25 km spatial resolutions, which are: TRMM TMI, AQUA AMSR-E and DMSP SSMIS. DMSP SSM/I sensor offers LST at a wider expanse of 28-37 and 43-69 km.

In relation to pest monitoring, LST data derived from high spatial resolution sensors is commonly associated with low temporal resolution, thus making them less preferable. Temporal resolution signifies the importance of investigating the effect of temperature on insect pest's development and outbreak. Hence, frequent data availability is essential in studying insect pests since their life cycles are relatively short, for example, *Plutela xylostela* has an average life cycle of 10.5 days[113], *Metisa plana* has 80-113 days[114] and *Oryctes rhinoceros* has 4-9 months[115] to complete their life cycle, respectively. While many sensors with high temporal resolution have the capability to capture the variations and fluctuations of temperature overtime, currently, the highest temporal resolution is 15 min or 96 times revisiting capability per day, which are being offered by a constellation of geostationary weather satellites, which are MSG SEVIRI. With the availability of four satellites orbiting the earth simultaneously looking over North and South Africa, Europe and South America, they increase the chances of capturing cloud-free imageries. Nevertheless, their coverage for the Asian region is unquestionably occasional, plus the LST are obtainable at a relatively low spatial resolution as mentioned earlier. It is worth noting that despite high temporal resolution justifying the selection of satellite derived LST for examining the effect of temperature on pests, such high temporal resolution is superfluous because changes in insects' development do not occur in such a time period as that of the MSG temporal resolution. While it is important to consider insect lifecycles in weighing the most appropriate temporal resolution for pest monitoring, another important factor that must be taken into account is insect's development rate. Take *Metisa plana* for example, it requires 8.4 days to develop its eggs into first larval insta, another 8.5 days into second larval insta and 12.4 days for its male pupa to develop into a male adult. Following this essential statement, daily or weekly LST data should be able to characterise temperature summation for insect development and lifecycle. Hence, several alternatives can be found on the shelf, with the sensors that are capable of revisiting in 12 h, such as AVHRR NOAA, MODIS TERAA/AQUA, AMSR-E AQUA, AMSR-2 GCOM-W1, TMI TRMM and SSM/I and SSMIS of DMSP. Furthermore, Landsat TIRS and TERRA ASTER can only provide LST variations in every 16 days, considering that their scenes are free from cloud contamination and in reality, the timeframe between usable images could be extended. Consequently, if the *Metisa plana* is being used as an example, important development of such insects would be sorely missed.

Different strengths and limitations possessed by TIR and MW sensors can be put into a good use because they are able to complement each other. The assimilation of both of these sensors would be able to increase the availability of LST data and hence, efforts had been put into assimilating LST obtained from these sensors, for example, LST products retrieved from MODIS on-board TERRA/AQUA and AMSR-2 on-board of GCOM-W1. The merged product had higher revisiting times, but at the expense of declined LST performance compared to the individual products. The performance drop was most likely contributed by the uncertainties in the MW products due to the rain-bearing clouds and active precipitations over the study site.

CONCLUSION AND FUTURE RECOMMENDATION

The LST is known to be one of the main key parameters in the monitoring and management of insect pest outbreaks because insect life cycles are highly temperature-dependent. Ground temperature is measured through point measurements that contribute to high spatial variability because the locations of ground data stations are widely sparse over a region. Contradictory to this, the usage of satellite remote sensing to retrieve LST are able to compensate spatial resolution of LST measurements derived through ground observations with less man-power, shorter time and lower cost. Assimilation of TIR and MW sensors could be the best alternative in retrieving LST products with high temporal and spatial resolutions. However, as mentioned above, the product of the assimilated sensors has not yet achieved the performance of the individual products. Hence, further studies are needed to improve the assimilated products to ensure that products of high spatial, temporal, as well as accuracy could be produced.

SIGNIFICANCE STATEMENTS

This review discovers the ability and potential of remote sensing technology as a platform in providing land surface temperature (LST) data for insect pests monitoring application. This review compares remote sensing derived LST with temperature data obtained from in-situ weather stations and between thermal infrared and microwave sensors in terms of their quality, availability and adaptability for providing LST. The comparisons are focused on their spatial and temporal characteristics, along with their accuracies. As such, this review will be able to assist researchers to evaluate the potential of remote sensing derived LST for applications of pest management such as understanding of insect pest landscape ecology and prediction of their outbreak.

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