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Retrieval of Canopy component temperatures through Bayesian inversion of directional thermal measurements

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Abstract

In remote sensing evapotranspiration is estimated using a single surface temperature. This surface temperature is an aggregate over multiple canopy components. The temperature of the individual components can differ significantly, introducing errors in the evapotranspiration estimations. The temperature aggregate has a high level of directionality. An inversion method is presented in this paper to retrieve four canopy component temperatures from directional brightness temperatures. The Bayesian method uses both a priori information and sensor characteristics to solve the ill-posed inversion problem. The method is tested using two case studies: 1) a sensitivity analysis, using a large forward simulated dataset, and 2) in a reality study, using two datasets of two field campaigns. The results of the sensitivity analysis show that the Bayesian approach is able to retrieve the four component temperatures from directional brightness temperatures with good success rates using multi-directional sensors ($\mathcal{R}_{\text{spectra}} \approx 0.3$, $\mathcal{R}_{\text{gonio}} \approx 0.3$, and $\mathcal{R}_{\text{AATSR}} \approx 0.5$), and no improvement using mono-angular sensors ($\mathcal{R} \approx 1$). The results of the experimental study show that the approach gives good results for high LAI values ($\text{RMSE}_{\text{grass}} = 0.50$ K, $\text{RMSE}_{\text{wheat}} = 0.29$ K, $\text{RMSE}_{\text{sugar beet}} = 0.75$ K, $\text{RMSE}_{\text{barley}} = 0.67$ K), but for low LAI values the measurement setup provides extra disturbances in the directional brightness temperatures, $\text{RMSE}_{\text{young maize}} = 2.85$ K, $\text{RMSE}_{\text{mature maize}} = 2.85$ K. As these disturbances, were only present for two crops and can be eliminated using masked thermal images the method is considered successful.

1 Introduction

The retrieval of canopy component temperatures is of great importance for the calculation of evapotranspiration by remote sensing. Evapotranspiration in remote sensing is usually calculated by applying energy balance models like SEBAL (Bastiaanssen et al., 1998), and SEBS (Su, 2002). Such algorithms are highly sensitive to errors in the retrieved kinematic temperatures and emissivities.

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In most remote sensing energy balance studies only a single surface temperature is used (Su, 2002; Jia et al., 2003a). This surface temperature is calculated from the emitted radiances using Planck's radiance function, with emissivities estimated a priori or calculated using techniques like temperature emissivity separation (Payan and Royer, 2004 and Gillespie et al., 1998). This method is widely used and produces good results. It can however only retrieve a single surface temperature.

For heterogeneous canopies, the assumption of a single surface temperature is not correct. Timmermans et al. (2008) showed that in this case the temperatures of the individual canopy components will differ significantly. Thermal remote sensing sensors, like ASTER usually have a spatial resolution of more than 60 m (Yamaguchi et al., 1998). The measured radiation by these sensors will be an aggregation of radiation emitted by the different canopy components. This aggregation generates a high level of directionality. For example, as the optical path through the canopy is large for more oblique viewing angles, the thermal brightness temperature will depend more on vegetation than on soil for these angles (Verhoef et al., 2007a). The level of directionality further depends on several parameters like the temperature of the individual canopy component and LAI.

Directional remote sensing is therefore the best tool for the retrieval of canopy component temperatures. Jia et al. (2003b) showed that the retrieval of multiple independent temperatures requires multiple observations to avoid an indeterminate system.

Most of the parameter retrieval studies deal with the optical part of the spectrum, illustrated by D'Urso et al. (2004) and Knyazikhin et al. (1998). Only a few studies have investigated the retrieval of kinematic component temperatures (Kustas and Norman, 2000; Yan et al., 2001; Jia et al., 2003b). These studies limit the number of retrieved canopy component temperatures to two, namely those of soil and canopy.

The objective of this research was to create an inversion scheme to retrieve four component temperatures. This inversion scheme was tested on the forward simulated brightness temperatures. A sensitivity analysis was performed with various satellite configurations, from single view and single band to multiple view and multiple bands.

Finally a case study was performed using data from two field campaigns: EAGLE 2006 and AGRISAR 2006. The directional brightness temperatures that are used were measured using various instruments attached to a goniometer.

2 Methodology

5 Biophysical parameters can be retrieved with high accuracy using radiative transfer models (Gastellu-Etchegorry et al., 2003). The success rate and number of parameters that can be retrieved depends on 1) the inversion method, 2) the number of independent observables and 3) the sensitivity of the modelled remotely sensed data to surface properties.

10 The inversion algorithm has been implemented into a Matlab program. This program has been run on a multi-processor system. The data flow of this program is shown in Fig. 1. The different aspects of the inversion, like the algorithm and the radiative transfer model are, discussed in the following paragraphs.

2.1 Traditional retrieval algorithms

15 According to Kimes et al. (2000) retrieval algorithms can be divided into three major classes: neural network, look-up tables and optimization schemes. The accuracy of neural networks and look-up tables depends on the number of pre-computed “training” values and on the interpolation between these “trained” values (Picton, 2000). This interpolation can not be performed over singularities like the hot spot, despite recent advances have been made for look-up table methods by Gastellu-Etchegorry et al. (2003). Optimization methods do not have this limitation, because of the radiative transfer model that is used. Optimization methods are inherently suitable to handle arbitrary viewing and observing angles. Therefore the optimization method is still the most used inversion technique in directional remote sensing.

25 A simple optimization update is based on the Gauss-Newton method (Tarantola,

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2005), see Eq. (1).

$$\Delta p = (\mathbf{J}^T \mathbf{J})^{-1} \mathbf{J}^T \Delta r \quad (1)$$

Here Δp denotes the changes in the parameters for retrieving the correct parameter set, Δr denotes the difference between the observed variables and simulated variables, and \mathbf{J} denotes the local sensitivity of the model.

Newton methods are relatively easy to implement and converge fast (quadratically). To improve upon this convergence the Newton method was modified independently by Levenberg and Marquardt (Fox, 1997). The Levenberg-Marquardt (LM) algorithm is a trust-region modification of the Gauss-Newton algorithm (Moré and Wright, 2003).

$$\Delta p = (\mathbf{J}^T \mathbf{J} + \mu \mathbf{I})^{-1} \mathbf{J}^T \Delta r \quad (2)$$

here μ is a scalar that controls the numerical stability of the algorithm, see Verhoef (2000). This (non-negative) scalar is updated per iteration. When μ is small the LM method approaches the quadratic Newton convergence; when μ is large the LM method approaches the steepest descent method. This LM method is still used in current researches (North, 2002). Both methods however still lead to instability as can be shown using singular value decomposition.

If the input parameters of the model are linearly dependent on each other, the input-output relationship will be non-unique. This results in an ill-posed inversion scheme, making it impossible to retrieve unique sets of parameters. Single Value Decomposition (SVD) will not only diagnose this problem but will give you a useful numerical answer (Press et al., 2007). The SVD method states that a Jacobian matrix \mathbf{J} can be decomposed as

$$\mathbf{J} = \mathbf{U} \mathbf{S} \mathbf{V}^T \quad (3)$$

with \mathbf{U} column-orthogonal ($\mathbf{U}^T \mathbf{U} = \mathbf{I}$), \mathbf{S} diagonal and \mathbf{V} orthogonal ($\mathbf{V}^T \mathbf{V} = \mathbf{V} \mathbf{V}^T = \mathbf{I}$). This results in the relation $(\mathbf{J}^T \mathbf{J}^{-1}) \mathbf{J}^T = \mathbf{V} \mathbf{S}^{-1} \mathbf{U}^T$, which illustrates why the Gauss-Newton method may be suffering from difficulties, since the matrix of singular values \mathbf{S} may

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contain zeros. This happens when there is linear dependence, and in that case the matrix inversion is impossible. For small singular values the corresponding change of model input parameters becomes very large, which leads to numerical instability.

2.2 Bayesian optimization algorithm

5 Kimes (2000) and Verhoef (2007b) showed that the ill-posed problem of model inversion can be reduced if a priori data is used. The addition of a priori information transforms the original Newtonian update rule, Eq. (1), into Eq. (4).

$$\Delta p = \mathbf{V} (\mathbf{S}^2 + \mathbf{I})^{-1} [\mathbf{S}\mathbf{U}^T \Delta r + \mathbf{V}^T \Delta p_a] \quad (4)$$

10 Here Δp_a denotes the difference between the current parameter set, p_m , and the a priori values, p_a , and Δr denotes the difference between the measurements, r , and modelled observations, r_m . The variables are normalized by the respective standard deviations of the parameters, assuming a Gaussian distribution. The variable Δr is normalized using the sensor accuracy.

15 The final solution of the inversion is then given by Eq. (5). It can be seen that when the sensitivity of the model is high the model solution will dominate the solution and when it is low, the a priori solution will.

$$p_s = \mathbf{V} (\mathbf{S}^2 + \mathbf{I})^{-1} [\mathbf{S}^2 \mathbf{V}^T p_m + \mathbf{V}^T p_a] \quad (5)$$

20 A priori information on the temperature is extracted from the shape of the directional thermal brightness temperature. The path length through the canopy depends on the viewing angle; for oblique viewing angles θ_o , the optical path length will be large and the measured brightness temperature will depend mainly on the vegetation itself. $T_v = T_b(\theta_o = \max(\theta_o))$, and for nadir looking angles, the optical path length is at a minimum and the measured brightness temperature will depend more on the soil. $T_v = T_b(\min(\theta_o))$.

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The standard deviation used to normalize this a priori information is calculated using the upper and lower limit for the vegetation and soil, assuming a Gaussian distribution. The upper and lower limits for soil are set to -5°C and 100°C , and for vegetation 0°C and 42°C .

5 2.3 Sensitivity and uncertainty

This Bayesian update rule not only solves the ill-posedness of the inversion problem, but also takes into account the sensitivity of the model and uncertainties in input/output parameters. The sensitivity of the radiative transfer model to the input parameters is captured by the diagonal matrix \mathbf{S} . The uncertainty of the model and measurements is captured by the normalization of Δr and Δp_a . For example, if the sensitivity is low, the values in \mathbf{S} will become nearly singular. In that case the update rule will be largely dependent on the a priori values.

2.4 Radiative transfer models

The radiative part of the Soil Canopy Observation, Photochemistry and Energy fluxes (SCOPE) model was used in the inversion. SCOPE is a soil-vegetation-atmosphere transfer model. It calculates the biophysical and spectral fluxes for individual leaves. It scales these fluxes up to canopy level. SCOPE uses existing models of radiative transfer, micrometeorology and plant physiology. It uses a numerical version of the 4SAIL model.

The original SAIL model (Verhoef, 1984) is a one-dimensional directional radiative transfer model. SAIL has been used in many studies. It also has been validated several times by studies like the RAMI comparison (Pinty et al., 2000, 2004; Widlowski et al., 2007). Recently, Verhoef et al. (2007a) have expanded the earlier versions of the model in order to simulate also thermal radiative transfer inside a canopy, see Eq. (6). As the optical part of the spectrum can be solved analytically, this part of the model is very efficient both in computer resources as in physical representation. The calculation of

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the directional thermal brightness temperature increases computation time only slightly. This makes the SAIL model ideal for inversion of thermal brightness temperatures.

$$E_o = r_{so}^* E_s + r_{do}^* E^- + \varepsilon_v^* H_c + \varepsilon_s^* H_d + \varepsilon_v^{**} (H_h - H_c) + \varepsilon_s^{**} (H_s - H_d) \quad (6)$$

Here, E_o is the directional radiation, E_s the downwelling solar radiation, E^- the downwelling diffuse radiation, H_h and H_c are the hemispherical thermal radiation fluxes for sunlit (hot) and shaded (cold) leaves, H_s and H_d are the hemispherical thermal radiation fluxes for sunlit and shaded soil. The parameter r_{so}^* is the total reflectance for direct radiation, r_{do}^* is the total reflectance for diffuse radiation, ε_v^* and ε_s^* are the effective emissivities for sunlit and shaded vegetation, and ε_v^{**} and ε_s^{**} are the effective emissivities for sunlit and shaded soil. These parameters are calculated by SAIL using single leaf thermal emissions and single leaf reflectance/transmittance spectra (Table 1).

Single leaf reflectance is calculated by the PROSPECT model (Jacquemoud et al., 1990). This model is able to parameterize the leaf reflectance using 5 parameters. These parameters are listed in Table 2.

Emitted single leaf thermal radiation is calculated using Planck's radiance function on basis of the component temperatures (Table 2). Planck's equation, Eq. (7), calculates the emitted flux per wavelength and bandwidth (Quattrochi and Luvall, 2004):

$$H(\lambda) = \pi I(\lambda) = 2\pi \int_{\lambda_1}^{\lambda_2} \frac{hc^2}{\lambda^5 \exp[(hc/\lambda kT) - 1]} d\lambda \quad (7)$$

here λ is the wavelength (m) in, h denotes the Planck constant (Js), c the speed of light, k Boltzmann's constant (JK^{-1}) and T the temperature of the component (K). The integration is performed over bandwidth $\lambda_2 - \lambda_1$.

The soil reflectance is not modelled but a standard spectrum, gravelly soil, is taken from the DART spectral database (Gastellu-Etchegorry et al., 2004) and Lambertian reflectance is assumed. The soil thermal emission are calculated using the Eq. (2), but with the sunlit and shaded contact temperatures, T_h and T_d .

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3 Case study

The algorithm is test using both simulated and measured data of directional brightness temperatures. Concurrently to the acquisition of the directional brightness temperature in the field, measurements on vegetation structure and emissivity were performed.

5 In time-limited field campaigns the chance of encountering all these scenarios needed for a thorough sensitivity analysis is very small. In order to explore the performance of the algorithm in different conditions, forward simulated brightness temperatures are used. The advantage of forward simulations is that one can also simulate future satellites like SPECTRA (Sobrino and Jiménez-Munõz, 2005; Verhoef, 2007a).

10 3.1 Sensitivity analysis

The forward simulations were performed for different sensors and for different scenarios. The total number of simulations was 3840 scenarios (consisting of 8 sensors, 8 component temperature profiles, 10 solar Zenith angles and 6 noise profiles.

15 The retrieval algorithm was executed over each of these scenarios three times. The number of parameters to be retrieved was varied during these retrievals, to investigate how close the inversion was to becoming ill-posed.

3.1.1 Sensors

20 In order to investigate the potential of multidirectional remote sensing several sensors have been simulated, see Table 4. These instruments range from broadband ground instrument, like the Irisys 1011 Thermal Camera (Sobrino et al., 2005) to multispectral solo-directional satellite sensors, like ASTER (Yamaguchi et al., 1998) and multispectral multidirectional satellite sensors, like AATSR (Prata et al., 1990).

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3.1.2 Temperature profiles

The number parameters that can be retrieved depend mainly on the number of independent angular measurements. The level of directionality depends mainly on the differences in temperatures of the individual components. The lower the difference in component temperatures, the lower the level of directionality in the brightness temperatures is. This limits the number of independent angular measurements (Li et al., 2003).

Therefore different component temperature profiles were used to investigate the limitations of the retrieval algorithm. In total 8 profiles were simulated, representing summer, winter and autumn/spring profiles and 1 homogeneous profile (Fig. 2).

3.1.3 Solar angles

The shape of the directional brightness temperature depends greatly on the solar angle. The solar angle controls the sunlit fraction of soil and vegetation. Differences in irradiance cause heterogeneity in temperatures through energy balance. A thermal hot spot may be observed when sunlit soil is warmer than shaded soil.

3.1.4 Noise

The directional behaviour of the brightness temperatures can be lost if the noise in the measurement is too high. Different levels of sensor noise were added to the directional brightness temperatures in order to investigate the success of retrieval algorithm, hence:

$$T_{bm}(i_{\text{band}}, i_{\text{obs}}) = T_{bt}(i_{\text{band}}, i_{\text{obs}}) + dT_{bn}(i_{\text{band}}, i_{\text{obs}}) \quad (8)$$

with

$$dT_{bn}(i_{\text{band}}, i_{\text{obs}}) = N_I A_s(i_{\text{band}}) \mathfrak{R}(i_{\text{band}}, i_{\text{obs}}) \quad (9)$$

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The measured brightness temperature, T_{bm} at band i_{band} and observation angle i_{obs} , is calculated as the sum of the “true” brightness temperature, T_{bt} and the noise dT_{bn} . The noise is calculated as the product of a noise level N_j , the sensor accuracy A_s and random value, \mathcal{R} . The random values are generated with a normal distribution ($\text{std}(\mathcal{R})=1$ and mean ($\mathcal{R})=0$).

Note that most researches simulate sensor noise by using the specified noise equivalent temperature difference (NEdT) that is given in the sensor documentations. This study aims to investigate the success rate of the algorithm for other than sensor noise as well. For this reason, the NEdT approach is considered too limited for this study.

3.1.5 Success rate

The success of the retrieval is evaluated using the ratio of RMSE and RMSE_i, see Eq. (10).

$$\mathbf{S} = \frac{\text{RMSE}_m}{\text{RMSE}_j} \quad (10)$$

With

$$\text{RMSE}_m = \sqrt{\frac{1}{N} \sum_i^N (p_m(i) - p_t(i))^2} \quad (11)$$

$$\text{RMSE}_j = \sqrt{\frac{1}{N} \sum_i^N (p_a(i) - p_t(i))^2} \quad (12)$$

Here, \mathbf{S} is the success rate, RMSE_m is the root mean square error between the retrieved parameters and true parameters and RMSE_j is the root mean square error between the retrieved parameters and true parameters. Values for \mathbf{S} lower than 1

denote that the inversion has improved compared to the a priori estimates of the parameters; values for **S** higher than 1 denote that the inversion has deteriorated the a priori estimates.

3.2 Field measurements

5 The field measurements were acquired with an Irisys 1010 thermal radiometer (Sobrinho et al., 2005) that was attached to a goniometer (Timmermans et al., 2009; Li et al 2004). A goniometer is a device enabling complete hemispherical measurements. The total number of angular positions per run was 9. After each run a complimentary run was performed at 45 degrees offset in the azimuthal direction. In the post processing the run resembling cross- and along solar plane closets were selected.

10 The datasets that are used were acquired in two field campaigns. The first dataset contains the field measurements of the EAGLE 2006 field campaign (Su et al., 2007, 2009). This field campaign was organized by the ITC in collaboration with the ESA in the EAGLE framework. The measurements were performed over young maize (LAI=0.2) and tall grass (LAI=2.5). The sites are part of the KNMI measurement facility situated near the Cabauw meteorological tower (Van Ulden and Wieringa, 1996), in the central part of the Netherlands. The second dataset was acquired during the AGRISAR 2006 field campaign. The measurements were performed over mature maize (LAI=1.5), wheat (LAI=4.0), sugar beet (LAI=2.0) and barley (LAI=3.5).

4 Results

4.1 Sensitivity study

Figure 3 shows the success rate **S** of retrieving component temperatures, for the sensors, temperature profiles and noise levels. The values of the component temperatures in most scenarios are not improved using the retrieval algorithm with monodirectional sensors and even deteriorate with increasing noise level:

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1. The improvement of the retrieval depends on the number of unique measurements. The measurements per band are highly correlated (see Planck's function). Therefore no improvement is observed.

2. The retrieval algorithm only improves on the a priori information for temperature profile 1, but the directional brightness temperature of T -profile 1 is does not exhibit directional behaviour. This directional brightness temperature is used as a priori information. As a priori temperature is based on brightness temperature, the retrieval algorithm improves upon first estimation this using the emissivities.

The values of the component temperatures in most scenarios are improved using retrieval algorithm with the multidirectional sensors. Although the success rate reduces with increasing noise levels, only for certain scenarios the success rate becomes unacceptable:

1. The improvement of the retrieval ($S < 1.0$) is apparent for all T -profiles with $N_I < 1.0$. Even for very high noise levels $N_I = 0.8$ the values of the success rate are below 1.0.

2. The success rate for (T -profile=1 @ $N_I > 1.0$) is not acceptable. The retrieval of the component temperatures is actually worse than for monodirectional sensors. For T -profile 1 the directional brightness temperature is uniform over the viewing angles (Fig. 2). The shape of the added noise, controlled by \mathcal{R} , will then dominate the shape of the directional brightness temperature. The retrieval algorithm tries to fit this shape, and therefore consequently will not find the correct canopy component temperatures. In reality the component temperatures will never have a complete homogeneous temperature.

3. For the scenario ($N_I = 1.0$) the success rate predominantly depends on the shape of the random values, \mathcal{R} , which is unacceptable. Note that the added noise in this scenario is of the same order as the sensor sensitivity. This is an order of magnitude higher than usual sensor noise.

The best average success rate for T -profiles 2–7 is achieved by multi-directional sensors: the SPECTRA sensor (0.3), than by the Goniometric setup (0.3) and the AATSR (0.5).

In addition to the retrieval of four parameters, two other inversions were performed to retrieve five and six parameters. The extra parameters to be retrieved were sky temperature and leaf area index (LAI). The overall success rate of these runs is shown in Fig. 4.

1. The success rate for the component temperature remains acceptable, with only a slight reduction when retrieving six parameters.
2. The overall success rates for the retrieval of sky temperature are unacceptable ($S > 1.0$) for AATSR and MODIS. As the success rate of the component temperature is unaffected.
3. The overall success rates for the retrieval of LAI are promising ($S \leq 1.0$). As LAI is usually retrieved using optical measurements this algorithm can be used to enhance this value with the extra information of thermal measurements.

4.2 Field measurements retrieval

Three time series were made with the goniometer during the EAGLE 2006 fieldcampaign. Of the three time series two were made over the tall grass and one time series was made over the maize (Fig. 5–6). The lines represent the mean measured brightness temperature. The error bars denote the RMSE between the measured and the retrieved directional brightness temperature. The RMSE for grass is about 0.5 K and for maize 2.5 K. The difference between the measured and modelled will be explained in detail in the following section (discussion).

The measured brightness temperatures over the grass were performed during two days, 12 and 14 June 2006. The brightness temperatures were higher on the first day than on the second day: on the first day the measurements were performed in the

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afternoon with clear skies, while on the second day the measurements were performed early in the morning with overcast conditions.

The grass temperatures at 15:30 and 15:52 on first day are lower than the soil temperatures. The soil temperature decreases during the day, where the vegetation temperature remains relatively constant. This is caused by the direct illumination sun on the different components. As the sun reaches lower angles, the soil is shaded by the canopy, whereas the leaves high in the canopy still receive sunlight.

The maize temperatures are always lower than the temperatures of soil. Both sunlit maize and soil display the same temporal behaviour as the directional brightness temperature. However shaded maize and soil do not display the same temporal behaviour. This is caused by the structural parameters of the maize. As the maize was very young the vegetation height was about 10 cm and the LAI about 0.2. For high sun angles the thermal image was dominated by the sunlit soil, as the amount of shaded soil is very small due to the height of the canopy. For very low sun angles the thermal image is dominated by sunlit vegetation. The sensitivity of the shaded components is therefore very low for sparse low canopies.

During the AGRISAR campaign the emphasis of the measurements was on the effect of structural differences between crops on the directional brightness temperatures. Therefore the measurements were performed over more vegetation types, but with less temporal resolution (Fig. 7). The lines represent the mean measured brightness temperature. The error bars denote the RMSE between the measured and the retrieved directional brightness temperature. The RMSE for maize, wheat, sugar beet and barley is respectively 2.85 K, 0.29 K, 0.75 K and 0.67 K. The measurements of the maize are left out of for further investigation because of the high RMSE for maize, and the absence of more (temporal) measurements.

The variance in the observed component temperature differs between the crops. The largest variance between the component temperatures is found for sugar beet. Wheat and barley display similar behaviour. Both wheat and barley are considered very homogeneous as they were fully developed, have a large LAI, with similar leaves in terms

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of leaf angles scattering and absorption. This high level of homogeneity causes the relatively small variations in the vegetation temperatures. As the measurements were performed during midday the soil temperature are higher than the shaded vegetation temperatures.

5 4.3 Discussion

The potential of multidirectional imagery has been demonstrated. The retrieval of component temperatures by forward simulated thermal (directional) brightness temperatures is successful for all the directional sensors.

10 Of all possible view angles, the along-track configuration proves the highest potential. The SPECTRA and goniometric configuration have the same success rate. The additional cross solar plane angles therefore do not contribute a lot. Also in space cross solar planes viewing angles are impossible to retrieve. In the field a goniometric setup is preferred. With a SPECTRA configuration the setup should be changed every acquisition due the changing solar azimuth angles.

15 The retrieval of parameters other than the component temperatures by forward simulated thermal (directional) brightness temperatures is not successful for sky temperature and moderately successful for LAI. The sensitivity of directional radiation for sky temperature is very low. As a result the algorithm fails to retrieve this parameter. The sensitivity of directional radiation is very high for LAI, as is also proven in the AGRISAR field measurements. As LAI is usually retrieved using optical measurements the need for retrieval of this parameter through thermal measurements is low. However in the absence of optical measurements, for example in night time, this procedure could be used.

25 The retrieval of component temperatures by measured thermal directional brightness temperatures is successful for all crops except mature maize. The retrieval resulted in a large RMSE between the retrieved and measured directional brightness temperature.

The values of the RMSE between retrieved and directional brightness temperature is influenced by the goniometric setup. In some of the thermal images the aluminum

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tracks of the goniometer are visible, and contaminate the measurement. These tracks have a significant lower brightness temperature than the vegetation or soil. The amount of track visible is much higher for low LAI with low vegetation height than for high LAI with high vegetation height. In the case of the mature maize (AGRISAR) even though the canopy had a high LAI and vegetation height, a gap in the canopy caused the visibility of the tracks. As these tracks usually have a significant temperature than the soil or canopy, the images can be filtered. As this is beyond the scope of this paper has not been considered.

5 Conclusions

A method is presented to retrieve up to four canopy component temperatures from directional measurements. The method inverts the radiative transfer model 4SAIL to retrieve the four component temperatures (sunlit/shaded vegetation/soil). The inversion is based on a modified Gauss-Newton optimization scheme. The modification incorporated the use of a priori knowledge to ensure closure of the inversion problem. Further measures, to ensure closure, were the introduction of singular value decomposition on the Jacobian sensitivity matrix.

The method was tested over a large dataset of forward-simulated data, as a sensitivity analysis. The forward simulations were performed for 8 satellite sensors, 10 solar zenith angles 8 sensors and 6 noise levels. The solar zenith angles varied between 0 and 60 degrees. The temperature profiles were representative of component temperatures in the summer, winter, and autumn. One additional scenario (with homogeneous temperatures) was used, in order to test the system. The sensors that were simulated consisted of ground sensors, existing satellite sensors and future satellite sensors. The sensor characteristics like accuracy were used to normalize the parameters in the inversion scheme. The noise added to the forward simulations is also based on these sensor characteristics. Instead of the NEdT, the noise added to the (directional) brightness temperatures were a percentage of the sensor accuracy. Three retrieval

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runs were performed with four, five and six number of parameters to be retrieved, (four canopy components, sky temperature, and leaf area index).

The results of these sensitivity analyses prove that the algorithm is capable of using the extra information in the directional brightness temperature to retrieve the four component temperatures, and to lesser extent leaf area index. The retrieval of sky temperature fails with this method. Only an improvement on the a priori information was observed when using multidirectional imagery. The success rate of the inversion is good for all solar zenith angles, most temperature profiles and all but the highest noise levels. The success rate for the homogeneous temperature profiles was unsatisfactory. For homogeneous temperature profiles the added noise introduces a shape in the “homogeneous” brightness temperature. The retrieval algorithm will then try to model this shape resulting in a worse estimation of the component temperatures. Fortunately this scenario is rarely observed, as sunlit components will almost always have a higher temperature than shaded components. In the case of cloudy days this scenario may occur, however the satellite will not be able to observe it.

The method was finally run over the datasets from two field campaigns. These datasets included a temporal datasets over grass and maize, and a multi-crop dataset over maize, wheat, sugar beet and barley. The method produced good results for the component temperature. However the RMSE between the measured and retrieved directional brightness temperature exceeded sensor accuracy levels for certain scenarios. This is caused by the aluminum track of goniometric setup that has a different temperature than the four canopy components. As these temperatures are not filtered out of the thermal images, they produce an RMSE of between 0.5 K and 2.5 K, depending on the LAI. We are confident that filtering the images for these tracks will increase the efficiency of the inversion method.

Acknowledgements. This research was performed under the framework of “Modeling radiation, heat and mass (water vapor and carbon) exchanges at the land-atmosphere interface using multi-angular optical and thermal measurements”, project number EO-071. This project was funded by the Netherlands Institute for Space Research (SRON). The EAGLE and AGRISAR

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campaigns were carried out in the framework of the Earth Observation Envelope Program of the ESA, and were partly financed by the EU 6FP Project, SRON EO-071, and the ITC International Institute for Geo-Information Science and Earth Observation. The authors thank, Z. Vekerdy, K. Weligepolage, W. Timmermans and R. Dost for fieldwork and data processing and coordination during the EAGLE and AGRISAR campaigns.

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Table 1. SAIL required Input Parameters. The LAI value given is only used in the sensitivity analysis, as LAI was measured during the field campaigns.

LAI	Leaf Area Index	1.50
H	Hotspot parameter	0.05
LIDF _{<i>a</i>}	Leaf Inclination density function parameter <i>a</i>	−0.35
LIDF _{<i>b</i>}	Leaf Inclination density function parameter <i>b</i>	−0.15
ρ_l	Single leaf reflectance	PROSPECT
ε_v^*	Single leaf emissivity (sunlit)	0.99
ε_v^{**}	Single leaf emissivity (shaded)	0.99
θ_s	Sun zenith angle	[0–60] °
θ_s	Observer zenith angle	sensor dependant °
ψ	Relative sun-object azimuth angle	sensor dependant °

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Table 2. Input parameters for single leaf reflectance and emission.

N	Mesophyll structure parameter	1400	
C_{ab}	Chlorophyll- <i>a</i> and <i>b</i> content	60 000	$\mu\text{g}/\text{cm}^2$
C_w	Water Content	0.009	cm
C_m	Dry matter	0.012	g/cm^2
C_s	Senescent material	0.000	
T_c	Sunlit Leaf Temperature	See Fig. 2	(4°C)
T_c	Shaded Leaf Temperature	See Fig. 2	($^\circ\text{C}$)

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Table 3. Input parameters for soil reflectance and emission.

ρ_s	DART spectral database ()	Gravelly Soil
ϵ_s^*	Soil emissivity (sunlit)	0.95
ϵ_s^{**}	Soil emissivity (shaded)	0.95
T_h	Sunlit Soil Temperature (°C) (hot)	See Fig. 2. (°C)
T_c	Shaded Soil Temperature (°C) (cold)	See Fig. 2. (°C)

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Table 4. Sensor characteristics. ¹ The number of thermal bands shown here is the amount of bands with wavelength $>8 \mu\text{m}$. ² The Irisys 1011 is attached to a goniometric system, enabling complete hemispherical coverage; the number of observations angles is divided over 1 nadir, 4 across-solar-plane 4 across-solar-plane.

Sensor	Nr. Thermal Bands ¹	Thermal Bands Spectrum ¹	Thermal Spectral Resolution	Absolute Thermal Accuracy	Nr. Observation Angles
		(μm)	(μm)	(K)	
Irisys 1011	1	08.00–14.00	6.00	0.5	1 (nadir)
Landsat 7	1	10.40–12.50	2.10	0.6	1 (nadir)
AATSR	2	10.40–12.50	0.90–1.00	0.1	1 (nadir)
ASTER	5	08.12–11.65	0.35–0.70	1.0	1 (nadir)
MODIS	5	08.40–14.39	0.50	0.5	1 (nadir)
AATSR	2	10.40–12.50	0.90–1.00	0.1	2
SPECTRA	2	10.30–12.80	0.50	1.0	7
Irisys 1011 (Goniometer)	8	08.00–14.00	6.00	0.5	9 ²

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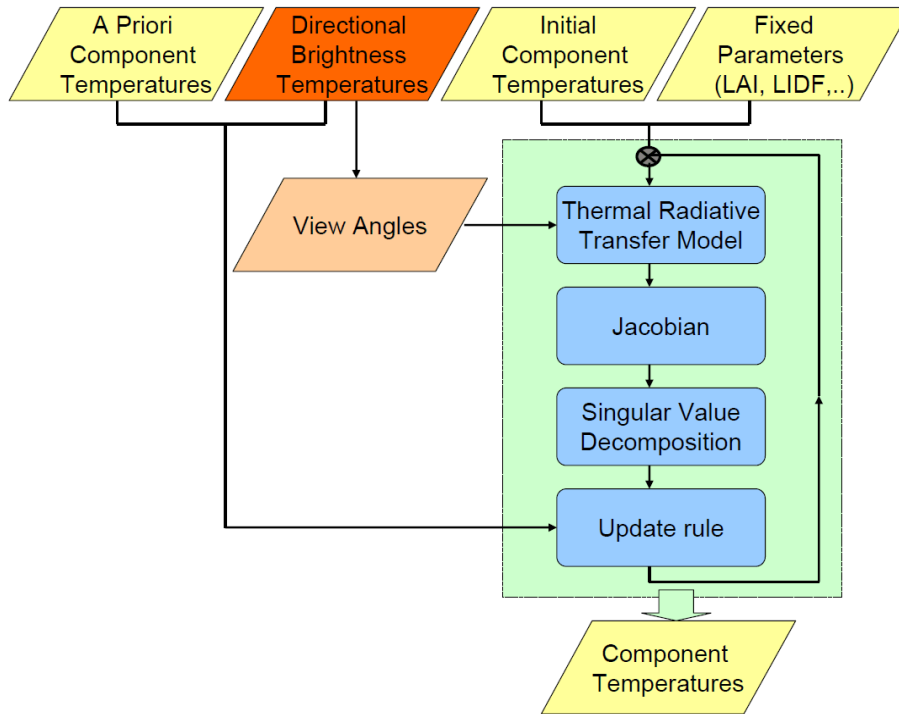


Fig. 1. Bayesian Inversion Scheme.

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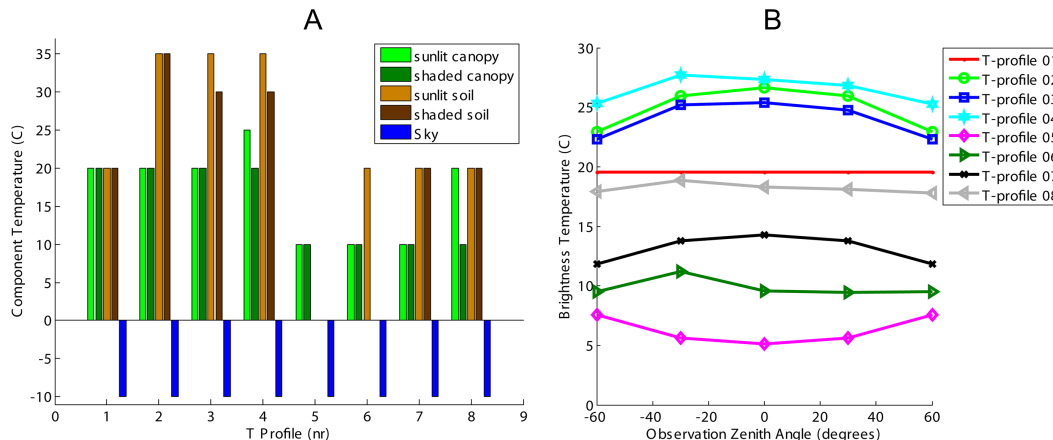


Fig. 2. Temperature profiles. In (A) the temperature profiles are shown. Profile 1 shows the base profile, profile 2–4 represent summer scenarios, profile 5–6 represent winter scenarios, and 7–8 represent spring-autumns scenarios. In (B) the corresponding Directional Brightness temperature for a broadband thermal radiometer is shown. The a-symmetry in the directional brightness temperature is caused by the difference in observed sunlit/shaded vegetation/soil.

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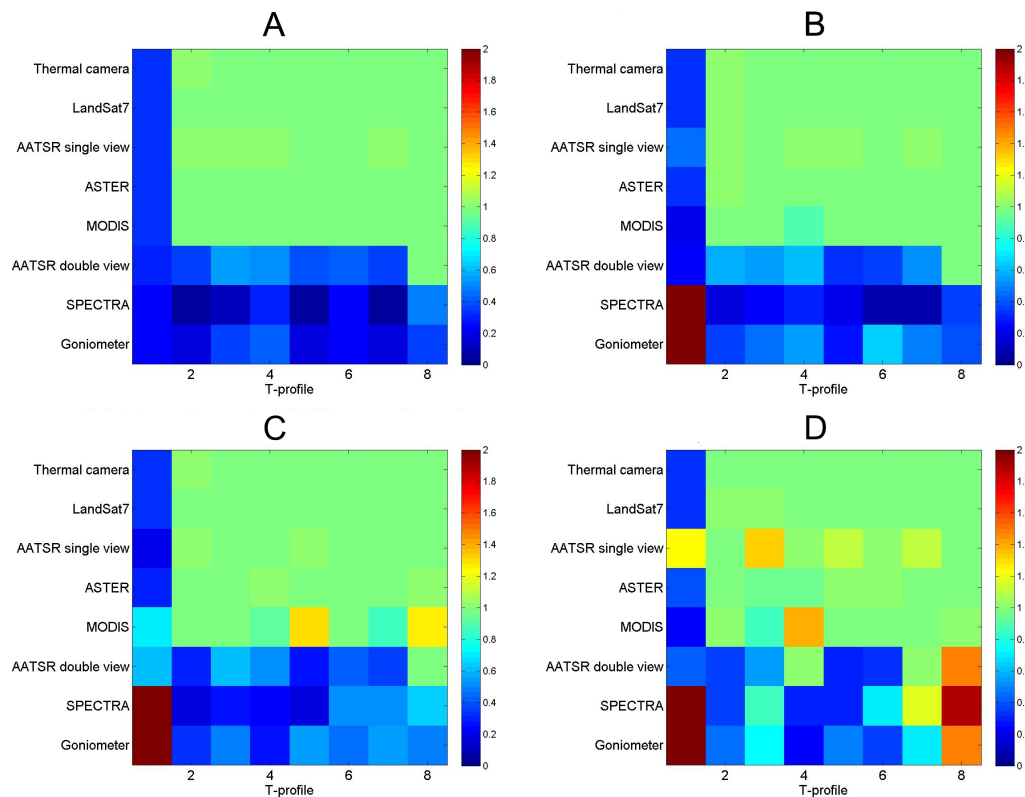


Fig. 3. Success rate of different satellites for different temperatures and noise levels. The solar zenith angle for these simulations was 46.7 degrees. **(A–D)** show the respectively $N_f=[0.0, 0.4, 0.8, 1.0]$.

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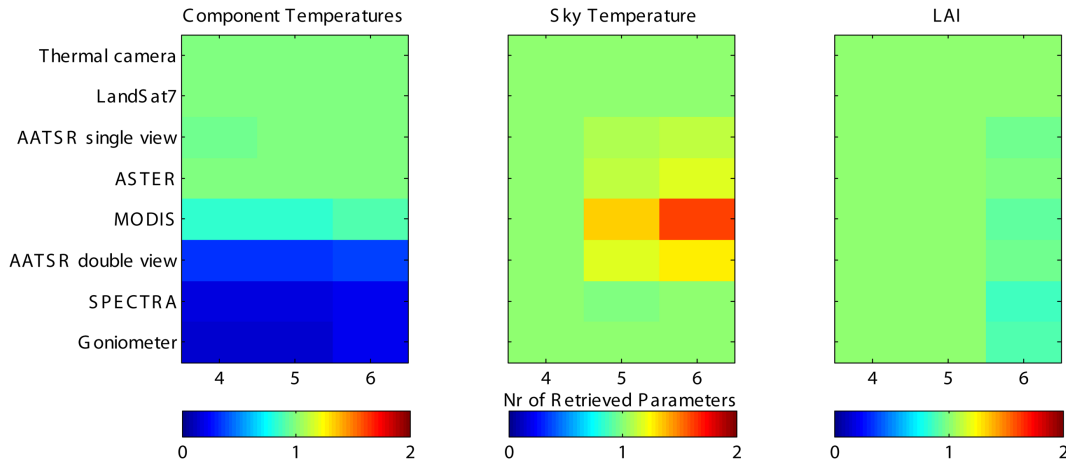


Fig. 4. Success rates on the retrieval of 4, 5 and 6 parameters. In left plot, the success rates of the component temperatures are shown. In center plot, the success rates of sky temperatures are shown. In right plot, the success rates of LAI are shown. The success rate for Sky temperature for 4 parameters is 1.0, as the retrieval of Sky temperature was only performed when inverting 5 parameters. The same applies for the success rates for LAI for inversion of 4 and 5 parameters.

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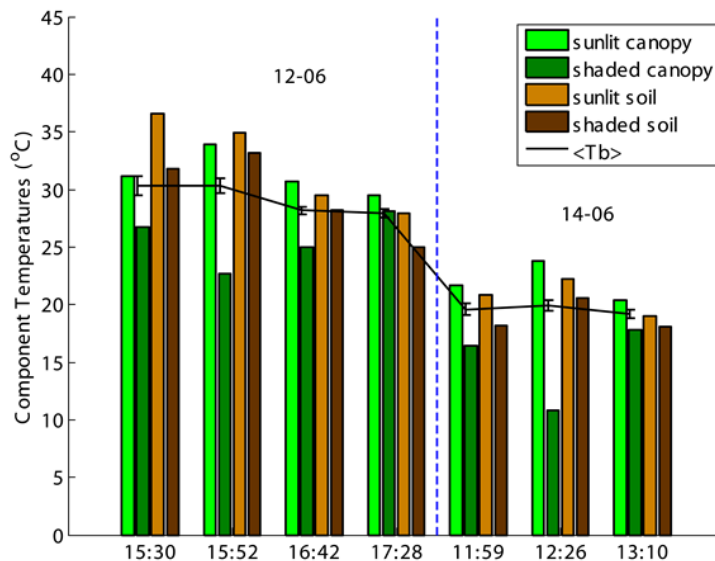


Fig. 5. Retrieved canopy component temperatures of grass on 12 and 14 June 2006. The dots represent the mean directional brightness temperature; the error bars represent the RMSE between the measured and modelled brightness temperatures. The green bars represent the vegetation temperature; the brown bars represent the soil temperature. Light colours represent sunlit components and dark colours represent shaded components. The blue broken line denotes the separation of the measurement days.

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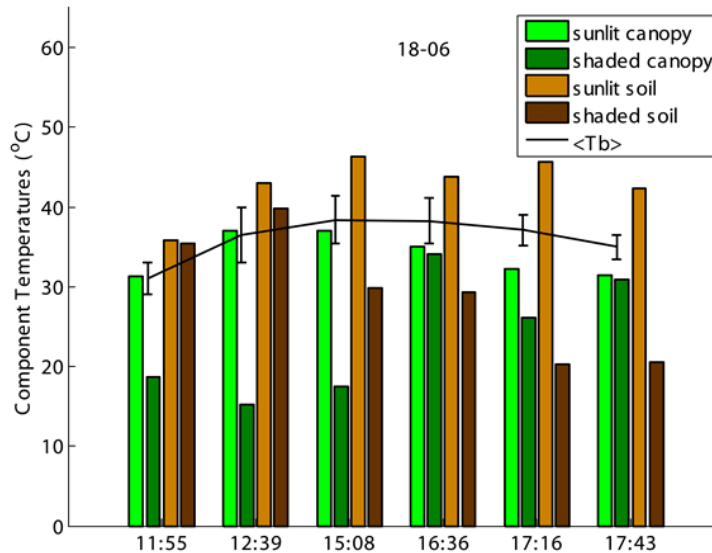


Fig. 6. Retrieved canopy component temperatures of young maize on 18 June 2006. The dots represent the mean directional brightness temperature; the error bars represent the RMSE between the measured and modelled brightness temperatures. The green bars represent the vegetation temperature; the brown bars represent the soil temperature. Light colours represent sunlit components and dark colours represent shaded components.

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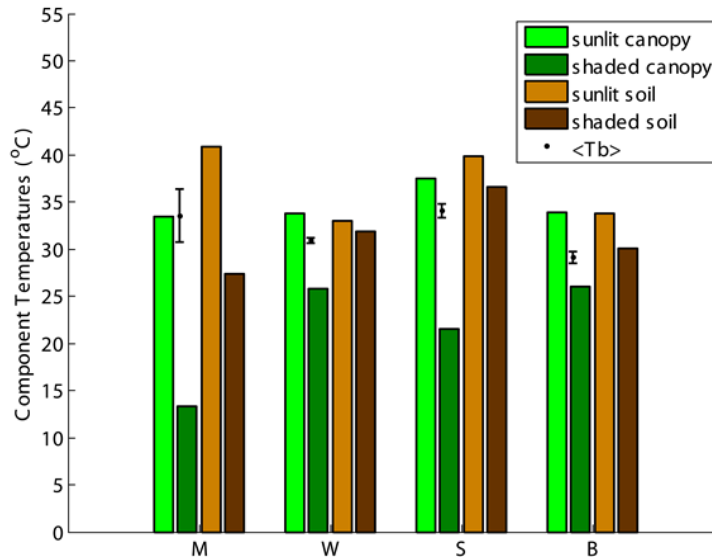


Fig. 7. The retrieved canopy component temperatures of various crops. The measurements were acquired as: maize (M) on 4 July 2006, wheat (W) on 5 July 2006, sugar beet (S) on 6 July 2006, and barley (B) on 6 July 2006. The dots represent the mean directional brightness temperature; the error bars represent the RMSE between the measured and modelled brightness temperatures. The green bars represent the vegetation temperature; the brown bars represent the soil temperature. Light colours represent sunlit components and dark colours represent shaded components.

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