Uncertainty analysis for satellite derived sensible heat fluxes and scintillometer measurements over Savannah environment and comparison to mesoscale meteorological simulation results

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ABSTRACT

Three methods for estimating instantaneous sensible heat flux (H) over Savannah environment in West Africa were compared: first, satellite derived estimations using the Surface Energy Balance Algorithm for Land (SEBAL) method [Bastiaanssen, W.G.M., Menenti, M., Feddes, R.A., Holtslag, A.A.M., 1998a. A remote sensing energy balance algorithm for land, SEBAL: 1. Formulation. J. Hydrol. 212–213, 198–212]; secondly, measurements at two test sites in Ghana with a large-aperture scintillometer (LAS); third, high resolution mesoscale meteorological simulations using the MM5 (5th-Generation Penn State/NCAR) mesoscale modelling system. Satellite-derived sensible heat flux was based on seven NOAA-16 AVHRR images that were processed for a 2-week period in December 2001 (dry season) and were compared to LAS-data and MM5 simulation results.

A methodology based on Gaussian Error Propagation is presented to derive uncertainties in satellite derived sensible heat flux due to (a) input data, (b) coefficients to determine leaf area index (LAI) and (c) methodological differences in estimating surface temperature T0. Total computed relative uncertainty in H was 15% for the Tamale test site and 20% for the Ejura site. Uncertainties in instantaneous evapotranspiration λE, however, are much smaller than uncertainties of H. This results due to the same bias in H and Rn/C0. For LAS-data, an uncertainty analysis due to input data was performed which showed relative uncertainty of 8% for the Tamale site and 7% for Ejura. Satellite derived net radiation (\(Rn\)) was underestimated in comparison to ground measurements which finally caused an underestimation of H. Satellite estimates of H using spatially interpolated ground based measurements of net radiation showed good agreement to LAS data.

MM5-computed latent heat flux showed very low values for the entire region. This caused a serious relative MM5-overestimation of sensible heat flux in comparison to LAS and satellite derived estimates.

It could be shown that Gaussian Error Propagation can serve as an essential tool to assess the reliability of satellite derived sensible heat fluxes. The resulting uncertainties give
1. Introduction

West Africa faces the danger of changed water availability due to global climate change and subsequent potential changes in precipitation distributions but also due to rapid land use changes and associated feedbacks to the hydrological cycle. The investigation of the influence of land use change and global climate change on the water availability of West Africa requires the application of numerical models, such as hydroclimatological models. The question remains, how reliable these models reproduce observed water and energy fluxes. Especially in areas with weak infrastructure (limited data availability) like West Africa, remote sensing can be an option to get distributed and areal estimates of heat fluxes. Additionally, remote sensing can be used for validation or comparison to simulation results. Against this background we compared sensible heat flux estimates as derived from (1) remote sensing, (2) large-aperture scintillometer (LAS) measurements, and (3) mesoscale meteorological simulation results.

Remote sensing provides different methods to estimate heat and mass exchanges at the land surface, e.g. (1) the Surface Energy Balance Algorithm for Land (SEBAL, Bastiaanssen et al., 1998a,b), (2) the Surface Energy Balance System (SEBS, Jia et al., 2003) and (3) the method proposed by Ma et al. (2004). The applied AVHRR Hydrological Analysis System (AHAS) (Parodi, 2002) uses SEBAL as final step to estimate sensible and latent heat fluxes. It was selected because the sensible heat flux (H) for the instantaneous time for the satellite overpass can be determined with a minimum amount of additional field measurements. Additionally, the method is validated in a variety of environments, e.g. Ghana, Niger, Spain, Italy, Turkey, Pakistan, India, Sri Lanka, Egypt, and China (Hafeez et al., 2007; Kimura et al., 2007; Mohamed et al., 2004; Bastiaanssen et al., 2002, 1998b; Bastiaanssen and Bos, 1999). NOAA satellite data was chosen because of the daily daytime overpass. Seven NOAA-16 AVHRR images were processed for a 2-week period in December 2001 (dry season) when cloud cover permitted.

Comparisons of sensible heat flux observed from LAS-data to AVHRR-estimates showed good agreement over semi-arid grassland in Mexico (Watts et al., 2000) as well as in the Sri Lanka wet zone (Hemakumara et al., 2003), albeit without providing uncertainty ranges for the estimates. However, only when uncertainty ranges are quantified, the reliability of the method can be assessed and understood in required detail.

While satellites view the land surface just for a part of a second, the computed fluxes in mesoscale meteorological models like MM5 are integrated over tens of seconds (depending on the time step and the horizontal resolution of the model); LAS-data, on the other hand, yield estimates that are integrated over 10 min. The area represented by one pixel in AVHRR-scenes increases from about 1 km x 1 km at nadir to more than 4 km x 4 km at the edge. LAS-data represents H for the path which is defined as the distance between transmitter and receiver (site dependent, in our case between 1040 and 2420 m). MM5-derived heat fluxes, on the other hand, are spatially averaged over 9 km x 9 km in our application.

The applied software tool AHAS allows user decisions in the computation of intermediate steps, like e.g. the selection of different split-windows techniques for the calculation of surface temperature $T_o$. Additionally, it is very flexible in the final computation of H, e.g. in the wet/dry pixel selection or the selection of the blending height. Here, it is of interest, how the specific decisions influence the final estimation of H. Moreover, the results of satellite derived sensible heat flux estimates depend on the accuracy of radiometric corrected input satellite channels data that determine the accuracy of derived normalized difference vegetation index (NDVI) or soil adjusted vegetation index (SAVI) values. Additionally, the accuracy of the parameterizations and empirical relationships used to derive, e.g. leaf area index (LAI), albedo, roughness length or surface temperature influence the final estimate on H. This work particularly focuses on the quantification of the uncertainty in H due to

- **methodological uncertainty**: estimation of $T_o$,
- **uncertainty in input data**: quality of satellite visible channel input and corresponding NDVI and SAVI values, and
- **uncertainty in empirical coefficients**: model to estimate LAI from SAVI.

It is primarily intended to show the general approach how to assess uncertainty propagation in satellite derived sensible heat flux estimates. This work is constrained to the above mentioned uncertainties rather than performing a complete uncertainty analysis for all parameters or all intermediate steps involved in the procedure to estimate H.

2. Experimental design

2.1. Site description

The presented study was carried out in the central part of West Africa. Three sites in the Ghanaian part of the Volta Basin (Fig. 1, grey shaded) are located in Navrongo (10°55'N, 1°02'W), Tamale (9°29'N, 0°55'W), and Ejura (7°20'N, 1°16'W). Each site is equipped with meteorological stations measuring air temperature, wind velocity and -direction, incoming shortwave radiation, net radiation, precipitation, and ground heat flux. Furthermore, the stations Tamale and Ejura were equipped with LAS.

The three sites show major differences concerning climate, vegetation, soils, land use, and slopes. The climate of the Ghanaian part of the Volta Basin is characterised by high rainfall...
variability and strongly affected by the inter-tropical discontinuity (ITD). The ITD separates Atlantic air masses from desert air masses with humidity of less than 25% (Hayward and Oguntoyinbo, 1987; Leroux, 2001). The climate shows one dry season (November–April) with an annual rainfall ranging from 1100 to 1250 mm. The mean annual temperature lies between 25 and 27 °C (Hayward and Oguntoyinbo, 1987).

2.2. Date description

The meteorological measurements used in this study are part of observations of energy- and water balance in the Volta Basin within the GLOWA-Volta project (http://www.glowa-volta.de). Due to cloud cover in the AVHRR images and data storage problems at the meteorological stations, only seven out of totally 69 satellite scenes for the timeframe 11th November 2001–28th February 2002 could be processed. Satellite scenes applicable to H estimation are shown in Table 1. Wind direction measurements show north-western winds (indicating the Harmattan, which tends to transport dust from the Sahara desert to the Volta Basin). Bushfires occur regularly in Savannah environments during the dry season, which modify atmospheric composition and radiation budget (Crutzen and Andreae, 1990).

LAS-data was not affected by precipitation. The effect of increasing aerosol optical thickness due to bushfires and Harmattan, however, could not be investigated. Although bushfires increased the aerosol load in the air, the amount was not such that the LAS could no longer be operated. Beyrich et al. (2002) proposed a significant reduction in LAS signal intensity if the visibility becomes less than 5 km.

3. Methods applied

3.1. Surface Energy Balance Algorithm for Land

SEBAL requires spatially distributed, visible, near-infrared and thermal-infrared remote sensing data, e.g. NOAA-AVHRR images. Furthermore, meteorological data (temperature, relative humidity, global radiation and wind speed) are taken from stations in Navrongo, Tamale and Ejura.

The SEBAL-method is based on the energy balance equation

\[ R_n = G_0 + H + \lambda_e \]  

(1)

with \( R_n \) net radiation [W m\(^{-2}\)], \( G_0 \) ground heat flux [W m\(^{-2}\)], and \( \lambda_e \) latent heat flux [W m\(^{-2}\)]. Incoming longwave radiation was computed using measurements of air temperature \( T_a \). Outgoing short- and longwave terms were estimated using remotely sensed \( T_0 \), albedo and emissivity. Instantaneous \( R_n \) was computed using ground based incoming shortwave radiation. Surface albedo was estimated using the linear model proposed by Valiente et al. (1995). The surface temperature \( T_0 \) was computed using the technique by Kerr et al. (1992) which takes into consideration fractional vegetation cover. The thermal infrared emissivity was estimated using the NDVI-based method proposed by Van de Griend and Owe (1993). Ground heat flux has been estimated through the approach proposed by Bastiaanssen (1995) taking into account surface temperature and a preliminary (leaf-)surface through NDVI. The approach to estimate sensible heat flux is described in detail in Bastiaanssen et al. (2002, 1998a). This approach will be briefly summarised in the following.

The user has to select two pixels in the satellite image: one completely wet pixel for which \( H \approx 0 \) and the temperature difference between \( T_0 \) and near surface air temperature \( T_a \) equals 0 (\( \Delta T \approx 0 \)) holds; additionally, a completely dry pixel has to be selected for which \( H = R_n - G_0 \) holds. These pixels are used to determine \( \Delta T \) for every pixel in the satellite image using an image-dependent linear regression:

\[ \Delta T = a + bT_0 \quad [K] \]  

(2)

Thus, \( H \) can be calculated using:

\[ H = \frac{\rho \varepsilon P \Delta T}{r_{ah}} \quad [W m^{-2}] \]  

(3)

where \( \rho \) [kg m\(^{-3}\)] is the moist air density, \( \varepsilon \) [J kg\(^{-1}\)] is the specific heat at constant pressure, and \( r_{ah} \) [s m\(^{-1}\)] is the near surface aerodynamic resistance to heat transport. SEBAL is based on an iterative process considering atmospheric stability and buoyancy effects according to the Monin-Obukhov

Table 1 – NOAA-16 overpasses used to estimate input uncertainties for red and near infrared channels

<table>
<thead>
<tr>
<th>Date</th>
<th>Start time of scene (UTC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>01/12/04</td>
<td>14:12</td>
</tr>
<tr>
<td>01/12/05</td>
<td>14:02</td>
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<tr>
<td>01/12/07</td>
<td>13:41</td>
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<tr>
<td>01/12/13</td>
<td>14:17</td>
</tr>
<tr>
<td>01/12/14</td>
<td>14:06</td>
</tr>
<tr>
<td>01/12/15</td>
<td>13:56</td>
</tr>
<tr>
<td>01/12/16</td>
<td>13:45</td>
</tr>
</tbody>
</table>
similarity theory, estimating \( r_{anm} \), friction velocity \( u_f \), stability correction functions and sensible heat flux \( H \). Finally, evapotranspiration \( \lambda_E \) can be computed as remainder term of the energy balance.

There is no absolute method for the user to select wet/dry pixels in satellite data. The risk exists that pixels containing bushfires are selected as driest pixel and picture elements containing clouds as wettest pixel. For the dry pixel selection, the AVHRR bushfire product has been used to avoid biomass burning pixels. The wettest pixel is usually shallow water. In the spatial subsets used, there are different pixels in the Volta reservoir with varying surface temperatures. For wet pixel selection, an irrigated area with rice fields was used near Ejura.

3.2. Large aperture scintillometer

The LAS consists of a transmitter emitting electromagnetic radiation towards a receiver. The distance between both can be chosen up to 5000 m for a beam diameter of 0.15 m. In our case the distance varies between 2035 and 2420 m for the different sites. It is installed at a certain height above the surface. The emitted radiation is scattered by the turbulent medium in the path. The variance of intensity of received radiation is proportional to the structure parameter of the refractive index of air, \( C_T^2 \) (Hill, 1992). At the wavelength used (940 nm) the refractive index mainly depends on temperature, except when the Bowen ratio \( \beta \) is much smaller than one. The structure parameter \( C_T^2 \) of temperature can directly be deduced from \( C_T^2 \)-measurements assuming perfect correlation of the fluctuations in temperature and humidity (Wesely, 1976; Kohsiek, 1982; Moene, 2003):

\[
C_T^2 = C_n^2 \left( \frac{T}{A_T} \right)^2 (1 + 0.031 \beta^{-1})^{-2} \left[ K^2 \text{ m}^{-2/3} \right]
\]

The factor involving the Bowen ratio is the correction term for the influence of humidity fluctuations. \( T \) is the mean air temperature [K], and \( A_T \) equals \( T \left( \frac{d m}{d T} \right) \) [-] which depends mainly on the wavelength of the radiation used and to a lesser extent on temperature, pressure and humidity.

In order to derive the sensible heat flux from \( C_T^2 \), Monin-Obukhov Similarity Theory (MOST) relationships for \( C_T^2 \) are needed in combination with an estimate for the friction velocity (based on mean wind speed \( u \), roughness length \( z_0 \) and MOST):

\[
\frac{\Delta z}{z_0} = f_{\text{tr}} \left( \frac{z - d}{L} \right)
\]

To solve for the sensible heat flux from \( C_T^2 \) and mean wind speed, an iterative procedure (combining (5a) and (5b)) is needed. But generally, the Bowen ratio needed for Eq. (4) is unknown as well. The Bowen ratio can be derived from the energy balance equation (Eq. (1)), measured net radiation, soil heat flux and LAS-derived sensible heat flux. Since the latter depends on the Bowen ratio, an extra iterative procedure is needed. Details on this procedure can be found in Meijninger et al. (2002). In the present study, the similarity relationships by De Bruin et al. (1993) have been used.

3.3. The mesoscale meteorological model MM5

The meteorological simulations were performed using the 5th-Generation Penn State/NCAR Mesoscale Model (MM5, Grell et al., 1994) in non-hydrostatic mode (Dudhia, 1993). National Centre for Environmental Prediction (NCEP) reanalysis data (National Centre for Environmental Prediction, USA) in 2.5° × 2.5° resolution provided the boundary and initial conditions for MM5 (including soil temperature and -moisture). A three-domain-system (Fig. 2) with horizontal resolution of 81 km × 81 km, 27 km × 27 km and 9 km × 9 km was used. All domains were run with a 4-week spin-up time. Four-dimensional data assimilation (FDDA) was applied for domain 1 allowing inclusion of upper air measurements (radiosonde observations). Twenty-six vertical layers were used with terrain following coordinates extending up to 30 mb at the model top (around 21 km). MM5 includes the Oregon State University Land Surface Model (OSU-LSM, Chen and Dudhia, 2001) accounting for feedback mechanisms between soil, vegetation, and planetary boundary layer. The OSU-LSM calculates the surface and subsurface water and energy balance and yields \( C_{so}, H \) and \( \lambda_E \). Elevation, land use and soil type data were taken from NCAR data archives, as well as from data sets compiled from partners within the GLOWA-Volta project.

The optimal MM5-configuration for precipitation computation in the Volta Basin of West Africa was investigated by Kunzmann and Jung (2003). We used the same configuration in this study. Convective parameterisation according to Grell et al. (1991), microphysics according to Reisner et al. (1998), and the cloud-radiation-scheme according to Dudhia (1993) were chosen. Additionally, the RRTM longwave scheme (Mlawer et al., 1997) was used. It must be noted that the radiation schemes in MM5 do not account for atmospherically radiation interaction with atmospheric aerosols. MM5 is applied to West Africa to investigate the influence of soil-moisture and land use change on precipitation in the Volta Basin (Kunzmann and Jung, 2007) and for climate change simulations (Neumann et al., 2007).

3.4. Uncertainty analysis for satellite derived sensible heat flux

In order to assess the reliability of the satellite-derived \( H \)-estimates, an uncertainty analysis based on Gaussian Error Propagation was performed. The uncertainty of the \( H \)-estimate is expressed as standard deviation (or second moment) \( \sigma \), which is calculated in first order accuracy. In case of two independent variables \( x_1 \) and \( x_2 \), determining the dependent
3.4.1. Uncertainty of $H$ due to six different methods to estimate surface temperature $T_0$ from satellite data

Table 2 shows the methods after Becker and Li (1990), Vidal (1991), Kerr et al. (1992), Ottle and Vidal-Madjar (1992), Ulivieri et al. (1994) and Coll and Caselles (1997) which have been used to compute mean surface temperature and standard deviation from AVHRR data on 13th December 2001. In a first step, $\hat{H}$ was computed using mean $T_0$. To compute the gradient $\partial H/\partial T_0$, it was necessary to alter mean $T_0$ (in this case 5%) and repeat the computation of $H$ finally obtaining the secant approximation via $\partial H/\partial T_0 \approx (H(1.05 T_0) - H(T_0))/(0.05 T_0)$.

To check out the stability of the gradient, the computation has been repeated using altered mean $T_0$ by 3%. It is stressed that the computed uncertainties in $H$ only depend on the computation of intermediate steps (net radiation and ground heat flux) as the final SEBAL-algorithm is independent of the applied temperature differences due to the internal calibration (Eq. (2)).

3.4.2. Uncertainty of $H$ due to uncertainties in the vegetation indices NDVI and SAVI

NDVI and SAVI are connected to the final $H$ estimation via the computation of surface roughness, ground heat flux, and displacement height. The uncertainty analysis for radiometrically corrected AVHRR-channels in the visible and near-infrared region needed satellite images over a few days. Surface reflectance at an Earth location should be constant over a short period of time (e.g. 1 week). However, surface reflectance changes in different scenes due to geometric distortion, differing satellite overflight path, clouds and shadows aroused by clouds, and differing quality of pre-processing (e.g. radiometric correction). Four satellite images with good geometrical accordance (4, 5, 13, and 14th of December 2001) have been used to compute mean NDVI and mean SAVI (which are the only generated products from atmospherically corrected satellite data) and standard deviation (input uncertainties). Therefore, effects due to scale differences between the seven images are included, because the satellite does not look at the

<table>
<thead>
<tr>
<th>Author</th>
<th>Split window algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Becker and Li (1990)</td>
<td>$T_0 + 1.274 + (1 + 0.15616 \frac{1}{T_0} - 0.482 \frac{1}{T_0^2}) \frac{T_0 - T_5}{50 \frac{1}{T_0} - 300 \frac{1}{T_5}} + (6.26 + 3.98 \frac{1}{T_0} + 38.33 \frac{1}{T_5}) \frac{T_0 - T_5}{T_0}$</td>
</tr>
<tr>
<td>Vidal (1991)</td>
<td>$T_0 = 2.4 + 3.6 T_4 - 2.6 T_5 + 3.1 + 3.1 T_4 - 2.1 T_5$</td>
</tr>
<tr>
<td>Kerr et al. (1992)</td>
<td>$T_0 = C_0 T_5 + (1 - C_0) T_4$</td>
</tr>
<tr>
<td>Ottle and Vidal-Madjar (1992)</td>
<td>$T_0, T_5$ of a totally vegetated surface; $T_4, T_5$ of bare soil; $C_0$, fractional vegetation cover</td>
</tr>
<tr>
<td>Ulivieri et al. (1994)</td>
<td>$c_1 T_4 + c_2 T_5 + c_3$</td>
</tr>
<tr>
<td>Coll and Caselles (1997)</td>
<td>$c_4$, $c_5$ and $c_6$ are empirical coefficients tabulated for several emissivity combinations</td>
</tr>
</tbody>
</table>

variable $H(x_1, x_2)$, the uncertainty (standard deviation $\sigma_H$) of $H$ is determined by (e.g. Papoulis, 1991):

$$\sigma_H = \left( \frac{\partial H}{\partial x_1} \right)^2 \sigma_{x_1}^2 + \left( \frac{\partial H}{\partial x_2} \right)^2 \sigma_{x_2}^2$$

(6)

with $\sigma_{x_1}$ and $\sigma_{x_2}$ being the uncertainties (standard deviations). In case of more than two independent variables, Eq. (6) is adjusted accordingly. The uncertainty analysis was accomplished on a pixel base using two-dimensional fields of $\sigma_x$.

To quantify the effect of model caused variance in $H$, uncertainty analysis has been investigated for the following three potential sources of uncertainties, representing methodological uncertainty, uncertainty in input data and uncertainty in empirical constants.

Fig. 2 – Three-domain system used for MM5-derived sensible heat fluxes.

<table>
<thead>
<tr>
<th>Author</th>
<th>Split window algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Becker and Li (1990)</td>
<td>$T_0 + 1.8(T_4 - T_5) + 48(1 - \gamma) - 75 \Delta e$</td>
</tr>
<tr>
<td>Vidal (1991)</td>
<td>$T_0 + 1.347 T_4 + 0.39(T_4 - T_5)(T_4 - T_5) + 0.56 \alpha(1 - \gamma) - \beta \Delta e$</td>
</tr>
<tr>
<td>Kerr et al. (1992)</td>
<td>$T_0 = C_0 T_5 + (1 - C_0) T_4$</td>
</tr>
<tr>
<td>Ottle and Vidal-Madjar (1992)</td>
<td>$c_4$, $c_5$ and $c_6$ are empirical coefficients tabulated for several emissivity combinations</td>
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</tr>
<tr>
<td>Coll and Caselles (1997)</td>
<td>$T_0, T_5$ of a totally vegetated surface; $T_4, T_5$ of bare soil; $C_0$, fractional vegetation cover</td>
</tr>
</tbody>
</table>
same scene at a constant angle. The final uncertainty analysis, again, is based on the scene 13th December 2001. The computation of uncertainty in \( H \) due to atmospherically corrected input data needs to be investigated using the standard deviation of the vegetation indices instead of using the \( \sigma \) of input data (which is much higher) because of the normalisation during the processing of vegetation indices.

### 3.4.3. Uncertainty of \( H \) due to the values of the empirical coefficients for estimation of LAI

In the computation of sensible heat fluxes, the leaf area index is used to estimate displacement height and finally roughness length \( z_{0m} \). Van Leeuwen et al. (1997) proposed a method to estimate LAI (\( L \)) from SAVI (\( S \)) for Savannah environment through a linear regression using vegetation-species dependent coefficients:

\[
L = \frac{S - c_1}{c_2} \quad [\text{m}^2 \text{m}^{-2}]
\]

with \( c_1 = 0.14 \), \( c_2 = 0.3 \) for bush- and grassland. These empirical coefficients, however, are dependent on time (e.g. point of time in vegetation period) and space. Since the area under investigation does not cover only a single vegetation type, but various different types, the uncertainty related to the values of the selected coefficients has to be quantified. Furthermore, AVHRR-data has been resampled to a pixel size of \( 1 \text{ km} \) the selected coefficients has to be quantified. Furthermore, various different types, the uncertainty related to the values of investigation does not cover only a single vegetation type, but these coefficients on the final estimation of LAI: big differences occur in relative uncertainty between areas with SAVI > 0.14 (\( U_r \) commonly less than 4%) and areas with SAVI < 0.14 (\( U_r > 14 \), reaching 38%). This occurs due to the fact that \( c_1 \) in Eq. (7) equals 0.14; consequently, LAI is computed to be zero if SAVI \( \leq \) c1. This propagates to \( z_{0m} = 0 \) because the displacement height equals the vegetation height. Therefore, the impact of the uncertainty in these coefficients on the final estimation of \( H \) is investigated, using mean values and standard deviations of \( c_1 \) and \( c_2 \) (Table 3).

### 3.5. Uncertainty analysis for LAS-derived sensible heat flux

Eqs. (4) and (5) allow for the determination of the sensible heat flux from LAS data. Measurement uncertainties, however, impact the final \( H \)-estimation. Table 4 shows the assumed standard deviations for the nine variables \( x_i \) required for the estimation of \( H \). The resulting standard deviation of \( H \) according to Gaussian Error Propagation in turn is obtained by

\[
\sigma_H^2 = \sum_{i=1}^{9} \left( \frac{\partial H}{\partial x_i} \right)^2 \sigma_{x_i}^2 + \left( \frac{H_{\text{H}} - H_{\text{S}}} {2} \right)^2 \left[ (\text{W m}^{-2})^2 \right]
\]

where is again obtained by a secant approximation and \( H_{\text{H}} \) and \( H_{\text{S}} \) are sensible heat fluxes computed with the commonly used MOST functions of Hill et al. (1992) and De Bruin et al. (1993), respectively. The last term in Eq. (8) takes into account the uncertainty in the similarity relationships used to link the sensible heat flux to \( C_T^2 \).

### 4. Results

#### 4.1. Uncertainty analysis

Uncertainty in \( H \) due to the selection of different split-window methods to estimate \( T_0 \) was investigated (Fig. 3). The resulting relative uncertainty (\( U_r \)) in \( H/(\text{H} \times 100) \) was about 10% for each of the three sites. It could be shown that the spatial pattern of relative uncertainty is related to surface temperature: the higher \( T_0 \) the higher is the uncertainty of \( H \). The highest uncertainties arise in pixels with thin clouds where surface reflectance shines through (north western part of the scene).

Only changing surface temperatures without recomputation of \( C_0 \) and \( R_n \) would not effect the final \( H \) estimates, due to the internal calibration in SEBAL given in Eq. (2): the coefficients \( a \) and \( b \) would be unchanged. The simulated uncertainties in \( C_0 \) and \( R_n \), which are estimated from AVHRR data as weak functions of \( T_0 \) propagate finally to \( H \) uncertainties.

Estimation of \( C_0 \), \( R_n \), and \( \lambda_E \) uncertainties have been performed based on the standard deviation, resulting from different \( T_0 \) simulations. These are shown in Table 5. The effect of varying \( T_0 \) on \( \lambda_E \) is small because latent heat flux is computed as residual of the energy balance.

The uncertainty in \( H \) due to input data (atmospherically corrected satellite channels red and infrared) is shown in Fig. 4. The spatial pattern is related to the pattern of LAI: big differences occur in relative uncertainty between areas with SAVI > 0.14 (\( U_r \) commonly less than 4%) and areas with SAVI < 0.14 (\( U_r > 14 \), reaching 38%). This occurs due to the fact that \( c_1 \) in Eq. (7) equals 0.14; consequently, LAI is computed to be zero if SAVI \( \leq \) c1. This propagates to \( z_{0m} = 0 \) because the displacement height equals the vegetation height. Therefore,

### Table 3 – Coefficients to estimate LAI (after Van Leeuwen et al., 1997)

<table>
<thead>
<tr>
<th>Vegetation Type</th>
<th>( c_1 )</th>
<th>( c_2 )</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bush and grassland</td>
<td>0.138</td>
<td>0.128</td>
<td>0.122</td>
<td>0.0126</td>
</tr>
<tr>
<td>Grassland</td>
<td>0.138</td>
<td>0.349</td>
<td>0.469</td>
<td>0.0852</td>
</tr>
<tr>
<td>Millet</td>
<td>0.284</td>
<td>0.35</td>
<td>0.35</td>
<td></td>
</tr>
</tbody>
</table>

### Table 4 – Tolerances used to estimate uncertainties in LAS-data

<table>
<thead>
<tr>
<th>Quantity ( x_i )</th>
<th>Unit</th>
<th>Assumed standard deviation ( \sigma(x_i) )</th>
</tr>
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<tbody>
<tr>
<td>Temperature</td>
<td>K</td>
<td>0.1 K</td>
</tr>
<tr>
<td>Wind speed</td>
<td>m s(^{-1})</td>
<td>0.5%</td>
</tr>
<tr>
<td>Atmospheric pressure</td>
<td>Pa</td>
<td>100 Pa</td>
</tr>
<tr>
<td>Bowen ratio*</td>
<td>–</td>
<td></td>
</tr>
<tr>
<td>Path length</td>
<td>m</td>
<td>0.5%</td>
</tr>
<tr>
<td>Path height</td>
<td>m</td>
<td>0.5 m</td>
</tr>
<tr>
<td>Height of wind speed measurement</td>
<td>m</td>
<td>0.1 m</td>
</tr>
<tr>
<td>( C_T^2 )</td>
<td>K(^2) m(^{-2/3})</td>
<td>0.5%</td>
</tr>
</tbody>
</table>

* The Bowen ratio is determined iteratively from a combination of the expressions for \( H \), the energy balance equation and observations of structure parameter of the refractive index, net radiation and soil heat flux.
the quality of input data and atmospheric correction in the visible and near-infrared region (which is used to compute SAVI) is very important for Savannah environment. Nevertheless, uncertainty in satellite derived $H$ due to atmospherically corrected satellite channels is about 2% and therefore negligible at the Tamale and Ejura site.

In the next step, the uncertainty in $H$ due to the incorrectness of empirical constants is investigated. Due to the sensitivity of the uncertainty with respect to SAVI (as seen above), we choose the coefficients to estimate LAI in Eq. (7) for this part of the uncertainty analysis. The relative uncertainty in $H$ due to the selection of the coefficients used to estimate LAI (Fig. 5) was computed to be 4% in Tamale, and 8% in Ejura. The same effect of SAVI as in the uncertainty analysis of input data could be observed: in regions where SAVI $\sim c_{1}$ mean, relative uncertainty reached very high values up to 100%.

It could be shown that satellite derived $H$ highly depends on NDVI and SAVI, resulting from atmospherically corrected input data, the correctness of the used empirical relationships and on the methods used for the computation of intermediate steps. Total relative uncertainty in $H$ provided by the investigated uncertainty computations was 15% for Tamale and 20% for the Ejura site. It is obvious that uncertainty can reach much higher values in regions with SAVI $\sim c_{1}$.

Different values of $H$ are obtained depending on empirical formulae used to compute dependent parameters such as $T_0$, LAI, etc. The resulting uncertainty ranges (as they were derived from the Gaussian Error Propagation) show that other sources of data assessment, especially observations of heat fluxes or measurements of surface temperatures, are important tools for the validation of satellite derived heat fluxes to finally ensure reliable estimates.

4.2. Comparison satellite-derived vs. LAS-derived sensible heat flux

An estimation of $R_n$ from satellite data using computed incoming and outgoing radiation terms led to an under-

Table 5 – Uncertainty propagation due to input uncertainties ($\sigma T_0$) calculated from six different split-window algorithms

<table>
<thead>
<tr>
<th>3 Pixel × 3 pixel</th>
<th>$T_0$ [°C]</th>
<th>$G_0$ [W m$^{-2}$]</th>
<th>$R_n$ [W m$^{-2}$]</th>
<th>$H$ [W m$^{-2}$]</th>
<th>$\lambda_E$ [W m$^{-2}$]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Abs</td>
<td>$\sigma T_0$</td>
<td>Abs</td>
<td>$\sigma G_0$</td>
<td>Abs</td>
</tr>
<tr>
<td>Ejura</td>
<td>41.55</td>
<td>2.23</td>
<td>58.7</td>
<td>0.25</td>
<td>311.8</td>
</tr>
<tr>
<td>Tamale</td>
<td>49.15</td>
<td>2.33</td>
<td>55</td>
<td>1.4</td>
<td>222.2</td>
</tr>
<tr>
<td>Navrongo</td>
<td>49.65</td>
<td>2.15</td>
<td>52.3</td>
<td>1</td>
<td>243.6</td>
</tr>
</tbody>
</table>
estimation of $R_n$ in comparison to ground-based measurements (Fig. 6). Incoming shortwave radiation was taken from ground-based measurements. One possible incorrectness may be found in the outgoing longwave radiation due to the fact that in the hot Savannah environment the measurements in the thermal satellite channels are in saturation over large areas. Furthermore, the correctness of $R_n$ is additionally limited by high aerosol optical thickness (as a consequence of the Harmattan and bushfires) which in turn limits the correctness of derived surface emissivity and albedo.

The result is an underestimation of sensible heat flux obtained with AHAS due to the dependence of the $\Delta T$-calculation for the dry pixel on $R_n$. A comparison of AHAS-estimated $H$ (3 pixel $\times$ 3 pixel) to LAS shows a root mean square error (RMSE) of 39 W m$^{-2}$ for Tamale and 104 W m$^{-2}$ for Ejura (Fig. 7).

The horizontal bars show the computed uncertainty in $H$, the vertical bars represent uncertainty in LAS. It becomes evident that relative uncertainties in LAS-data are much smaller (8% for Tamale, 7% for the Ejura site) than uncertainties in the satellite based approach. The weak result for the Ejura site may be explained by hilly terrain as shadowed areas are a source for misinterpretation in remote sensing. Furthermore, the land surface and vegetation parameterisation fitted better in case of the Tamale region than for the Ejura site.

To overcome the weak satellite derived estimates of $R_n$, measured $R_n$ values from Navrongo, Tamale and Ejura were interpolated using inverse distance weighting. An estimation of $H$ (Fig. 8) with the station-interpolated $R_n$ showed good accordance to LAS-data with a RMSE of 25 W m$^{-2}$ for the Tamale site (Fig. 9). For the Ejura region, RMSE improved to 82 W m$^{-2}$.

Fig. 10 shows the results of $H$-computation from LAS-data in the timeframe 4–7th and 13–16th December 2001 combined with ground-based measurements of net radiation and measurements of ground heat flux. The sensible heat flux is only shown for daytime because the computation requires stable atmospheric conditions. The curves are typical for cloudless sky conditions. Furthermore, the fast rise of sensible heat flux in the morning and the fast decrease in the afternoon under cloudless dry season conditions can be found which

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Fig. 5 – Relative uncertainty in sensible heat flux $H$ [%] due to uncertainty in coefficients to estimate LAI.

Fig. 6 – Comparison of AHAS-estimated $R_n$ to ground-based measurements.

Fig. 7 – Comparison of AHAS-estimated $H$ to LAS for the sites Tamale and Ejura.

Fig. 8 – Comparison of AHAS-estimated $H$ to LAS for the sites Tamale and Ejura.
clarifies the need of good time accordance when comparing different methods.

4.3. Comparison satellite-derived vs. MM5-computed sensible heat flux

A comparison of satellite derived $H$ (18 pixel × 18 pixel) to MM5 simulation results (2 pixel × 2 pixel) showed a RMSE of 167 W m$^{-2}$ for Tamale and 120 W m$^{-2}$ for Navrongo (Fig. 11). A reason for the disagreement between MM5 and satellite estimates is the fact that the OSU-LSM causes too much drying out in the four soil layers. The consequence is that MM5-computed latent heat flux is less than 10 W m$^{-2}$ in December 2001 at the Tamale site. Fig. 12 shows the spatial pattern of $H$ for 13 December 2001, 14:00 UTC. Due to the unequal spatial patterns in $H$ computed with MM5 and AHAS (Fig. 8), a pixel-based comparison and corresponding RMSE calculation did not seem to be reasonable. Another reason for this shortcoming is the fact that the patterns of the computed $H$-estimates follow the pattern of the land use types which are connected to fixed physical values (e.g. albedo, emissivity) used in MM5. Fig. 13 shows $H$, $R_n$, $\lambda_E$ and $G_0$ computed with MM5 for the timeframe 4–7th and 13–16th December 2001 from 2-h output data. It becomes evident that in the heat flux computations in MM5 there is only little day-to-day variation in the diurnal cycle of the fluxes under the given meteorological situation. The initial soil moisture in MM5 leads to daily $\lambda_E$-maxima up to 390 W m$^{-2}$ in the first days for the Tamale site which then decrease in the absence of rainfall to daily maxima of less than 10 W m$^{-2}$ (about 20 W m$^{-2}$ for Navrongo) after the 4 week spin-up time. This weakness in the OSU-LSM results in very low values of $\lambda_E$ and causes too high values of $H$.

Fig. 9 – Comparison of AHAS-estimated sensible heat flux $H$ (using ground-based net radiation $R_n$) to LAS-data.

Fig. 10 – Ground-based measurement of $H$, $R_n$ and $G_0$ [W m$^{-2}$] in 10 min resolution (DOY338: 1.12.2001).

Fig. 8 – AHAS-estimated $H$ using AVHRR-16 (13 December 2001).
5. Summary and conclusion

Three methods for retrieving sensible heat flux ($H$) were compared over the northern part of Ghana in December 2001 (dry season). SEBAL was applied with NOAA-AVHRR images. It provides maps of surface energy fluxes at a $1\text{ km}^2$ resolution. LAS were operated over three heterogeneous land surfaces in Navrongo, Tamale, and Ejura. MM5 simulations provided maps of energy fluxes for the entire Volta Basin at a resolution of $9\text{ km}^2$.

In order to assess the reliability of the satellite-derived $H$-estimates, an uncertainty analysis using Gaussian Error Propagation was performed. The uncertainty of different methods to determine surface temperature, visible satellite channel input and corresponding NDVI and SAVI values, and empirically determined coefficients to estimate LAI on the final $H$-estimation was investigated. The computed total relative uncertainty in $H$ was 15% for the Tamale and 20% for the Ejura site without concerning the effect of the selection of wet and dry pixel in SEBAL. In the computation of the $T_0$-dependent uncertainty in $H$, it could be shown that the uncertainties in $\lambda_E$ are small because $H$ is biased the same as $R_n - G$. For LAS-data, the average relative uncertainty was much smaller (Tamale 8%, Ejura 7%).

A comparison of ground measured net radiation to satellite estimations showed an underestimation in the remote sensing method which causes an underestimation of satellite derived $H$ in comparison to LAS-data. The estimated sensible heat flux from satellite data for the Tamale site using interpolated ground measured $R_n$ compared well to measurements using LAS with a RMSE of 20 W m$^{-2}$. A comparison of MM5-computed $R_n$ to ground based measurements showed an overestimation in MM5 for the whole region while $\lambda_E$-computations showed unrealistic low values. This causes a relative overestimation of $H$ in comparison to LAS and satellite estimates. The poor result of $\lambda_E$-estimations shows the importance of soil moisture in MM5. Furthermore, the importance of good land use data could be shown. The MM5-results could be improved assimilating land use classification derived from remote sensing data in MM5.

The results are constraint by the following facts: (1) short period of time in dry season due to constraints of data availability of cloud free satellite images, LAS data, and meteorological data, (2) missing validation of intermediate AHAS processing steps with ground data (like, e.g. roughness length estimations through wind profile measurements).

It could be shown that uncertainty analysis based on Gaussian error propagation is an essential tool to assess the
quality and reliability of satellite sensible heat flux estimates. Furthermore, it is a tool to identify model sensitive parameters and therefore applicable in validation procedures. The necessity of ground based observations, e.g. \( R_n \)-measurements and LAS for the validation of the \( H \)-estimates could be shown. The weak performance of the mesoscale meteorological model SVAT scheme in reproducing heat fluxes shows the necessity to validate mesoscale models not solely through precipitation rather than additionally through heat flux measurements.

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