# SPATIO-TEMPORAL RAINFALL MAPPING FROM SPACE: SETBACKS AND STRENGTHS

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**ABSTRACT:**

Meteorological forcing is often identified as a major source of error in hydrological modeling. Traditionally, observations are through meteorological network that often yield incomplete and inaccurate process coverages since observations only are at point scale and at fixed intervals. Particularly in distributed hydrological modeling, however, commonly full coverages over space and time at high resolutions are required and boosted the exploration and use of Remote Sensing images. A number of meteorological satellites have been launched over the past decade and application of retrieval products in hydrology is often regarded innovative since a high potential to improve modeling results is claimed. Generally, retrieval products are based only on observations from single channel and single sensors. Nowadays, there is a shift from 'single input-single output' regression type based retrievals towards 'multiple input-multiple output' inversion type retrievals. Despite many efforts, accuracy of rainfall estimates are still considered low and estimates are expected to yield a better accuracy only when averaged over large areas of $0.25^0$X$0.25^0$, $1^0$ X $1^0$ or even larger and for periods of few days or even a month. As such the existing algorithms effectiveness is questionable and they still require much improvement to deliver rainfall estimates at accuracy and resolutions hydrological models require. The objective of this study is to review 'state-of-the art' image based rainfall retrieval algorithms and to demonstrate their setbacks and strengths. Preparing a list of the available algorithms, however, is not the main focus of the study as this already has been presented by other researchers even though recently developed algorithms require revision. In this study, algorithms are categorized into Infrared (IR)-, Microwave (MW)-, and combined IR-MW- based approaches. The physical premise of the algorithms is discussed as well us sources of uncertainties that are categorized into two: those that relate to the complexity of cloud behavior and rainfall dynamics and those that relate to the Top-Down sensing procedure of satellites. This study also looks forward into the potential contribution of the upcoming Global Precipitation Measurement (GPM) mission to further improve hydrological modeling. The Meteosat Second Generation (MSG) and Tropical Rainfall Measurement Mission (TRMM) satellite images are utilized as a case study to formulate the relationships between images based variables and images based indices with surface rainfall observations in the Upper Blue Nile Basin. It is illustrated that the cold cloud duration retrieved from images and the 10.8µm brightness temperatures of cloud tops carry effective information for rainfall retrieval. However, formulation of a single best equation for the Upper Blue Nile basin requires additional information, for instance topographical information.

## 1. INTRODUCTION

The availability of remote sensing images with relatively high resolutions has resulted in an increased utilization of images for a wide range of land surface applications. These applications include rainfall-runoff relations, soil moisture estimations and flood simulations but also meteorological applications such as rainfall estimations. For the latter, the electromagnetic radiation measured by satellite based sensors is converted to reflectance and brightness temperature values that relate to atmospheric properties and variables of interest. Satellites can be in orbit or geostationary and may use a range of spectral bands such as Visible (VIS), Water Vapor (WV), Infrared (IR) and/or Microwave (MW). Currently, the latter are only limited to orbiting satellites. Commonly geostationary satellites produce images at high temporal resolution while earth orbiting satellites, that acquire low temporal resolution images, produce more direct observations on cloud profiles.

Since the late 1960s, a plethora of image based rainfall retrieval algorithms emerged by the demand of various applications to accurately estimate rainfall. Reviews on the available algorithms are given by Barrett and Martin [1991]; Kidder and Vonder Haar [1995]; Petty [1995]; Levizzani et al. [2002] where reviews illustrate a) image based rainfall retrieval procedures are relatively complex and b) algorithms often have poor performance. This mainly attributes to difficulties to capture the spatial-temporal variability of rainfall formation, for instance, that from convective systems, and to limitation of sensors to directly observe variables that govern rainfall formation in cloud systems. In this respect, through remote sensing image commonly only approximate or "proxy" variables are observed that generally only have a weak and indirect relation to rainfall distributions as observed at the land surface. In addition, satellite systems view from the top of the atmosphere downwards to the land surface and not upwards that would intrinsically be a more logical approach for rainfall observations [see Barrett and Beaumont (1994)].

In this study, the physical basis of the rainfall retrieval algorithms is reviewed and the sources of uncertainty within the context of hydrologic applications are discussed. For this, the algorithms are categorized into IR-based, MW-based and combined IR-MW based approaches. The Meteosat Second Generation (MSG) and Tropical Rainfall Measurement Mission (TRMM) satellite images are utilized as a case study to formulate the relationships between images based variables and images based indices with surface rainfall observations in the Upper Blue Nile Basin. For this purpose, rainfall observations of 34 ground based stations in the basin are used.

## 2. PHYSICAL BASIS FOR RAINFALL RETRIEVAL

The most commonly utilized parts of the electromagnetic wave spectrum for rainfall retrieval are the thermal IR and the MW channels. These channels carry complementary information that caused development of combined IR-MW based approaches. Although the VIS and the WV channels are not utilized frequently, these channels have a potential to generate additional and complementary information on cloud characteristics. Nowadays, there is a growing interest to combine observations from various channels and sensors for rainfall retrieval.

### 2.1 Infrared based approaches

In the IR-based approaches, the cloud top temperature is commonly used as a key variable to infer rainfall rates although such temperature only is to be seen as a proxy variable. The effectiveness of cloud top temperatures for rainfall retrieval purpose is based on the premise that relatively cold clouds are to be associated with high and thick clouds that are assumed to produce relatively high rainfall rates; see figure 1. The figure also shows the IR observations are available at high temporal resolution (here 15 minutes) that is from geostationary satellite.

Rainfall retrieval procedures that apply cloud top IR brightness temperatures can be based on indexing cloud systems, bi-spectral analysis, tracking life history, and cloud model. Cloud indexing [see Todd et al. (1995); Adler et al. (1993); and Liming Xu et al. (1999)] apply indices that are retrieved from images or from synoptic observations where indices include cloud type as defined by image texture, cloud area, and cold cloud duration (CCD). The physical premise for the bi-spectral algorithms [see Lovejoy and Austin, (1979); Tsonis et al. (1996); and Tsintikidis et al. (1999)] is that cloud systems which do not produce rain can be identified from observations in the VIS channel while cloud systems that produce rain can be identified from observations in the IR channel. Cloud life history procedures [see Griffith and Woodley (1978); Levizzani et al (2002); Negri et al. (1984) and Vicente and Scofield (1996)] assume that rainfall rates increase from zero to a maximum for cloud growth phases while rates decrease for cloud dissipation phases. In cloud model approaches generally some coarse scale cloud physics is introduced for the retrieval procedure. A well known example is the Convective Stratiform Technique (CST) [see Adler and Negri (1988); Anagnostou et al. (1999); Reudenbach et al. (2001)].

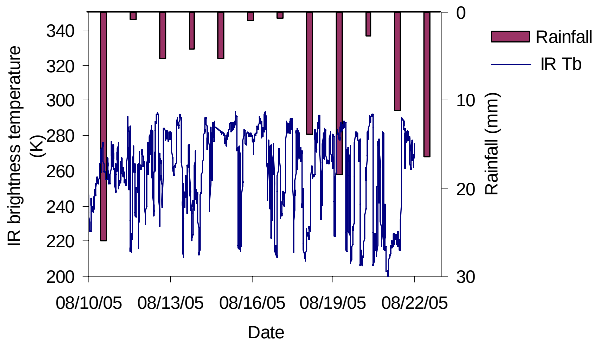



Figure 1: Observed IR brightness temperature (Tb) and daily rainfall (D/Berhan station, Ethiopia)

### 2.2 Microwave channel based approaches

In MW approaches, observations provide information on the entire cloud profile generally through the proxy variable brightness temperature that has to be seen as an integrated variable over a cloud depth. MW based approaches are based on the concept that emitted radiation in the microwave frequencies is affected by atmospheric hydrometeors such as cloud and precipitation droplets that cause augmentation of radiation due to emission and attenuation of radiation due to absorption and scattering. Information from MW channels is much more direct as compared to information from IR channels although in MW approaches rainfall at the land surface cannot be retrieved directly. Commonly, in meteorology, orbiting satellites carry MW channels where images become available at resolutions of once or twice per day.

Wilheit et al. [1994] classified the MW rainfall retrieval algorithms as described in the first Precipitation Inter-comparison Project (PIP-1) into: mostly empirical, mostly physical and highly physical, see table 1. It was stated that the classification is arbitrary and even the mostly empirical algorithms could be considered more physically based than the IR based algorithms.

Table 1: Classification of algorithms for the microwave channel based rainfall retrieval approaches

| **Type of algorithm** | **Remarks** |
|---|---|
| Empirical | Observe the anomalous depression of short wave brightness temperature by frozen precipitation aloft and translate it into surface rain rate. |
| Mostly empirical | Use radiative transfer models to select brightness temperatures or functions of brightness temperatures to regress against ground truth. |
| Mostly physical | Arbitrary distribution of hydrometeors is used as an input to radiative transfer models. The output of the model is compared to observed brightness temperatures to infer rain rate.<br>The problem here is lack of information on details that are important for microwave radiative transfer models, for e.g. scattering by ice. |
| Highly physical | Uses storm scale hydrodynamic models including hydrometeor microphysics to generate the hydrometeor profile input to the radiative transfer models. Accuracy depends on the appropriateness of initial conditions and the realism of the hydrometeors produced. |

The physically based approaches are expected to be more applicable under various climatic settings without much adjustment than that required for the empirical algorithms. The Authors of this article also share this idea. Therefore, the procedure for the MW based empirical algorithms is not discussed in this paper. However, the general procedure for most of the physically based algorithms is outlined hereafter. By these algorithms, first a cloud model is applied to simulate cloud microphysical properties. The simulation outputs then serve as inputs to a radiative transfer model that is used to develop a cloud-radiation database. The objective is to associate vectors of multi-frequency brightness temperature ($T_B$) values to each of the profile sets that represent the state of the atmosphere. The next step, which is an inversion procedure, is to retrieve liquid/ice water content profiles from the cloud-radiation database based on observed brightness temperature ($T_B$) values.

### 2.3 Combined IR-MW approaches

The need to improve the performance of IR- and MW-based rainfall retrieval approaches resulted in the development of combined approaches that benefit from the strengths of both data sources. Such algorithms combine and benefit from the availability of IR images at high temporal resolutions with MW images that carry the relatively direct information on cloud and rainfall characteristics. This has resulted in the emergence of several algorithms such as multi-variate probability matching and variance constrained multiple regression [see Marzano et al (2004, 2005)]; statistical regression [see Miller et al. (2001)] but also algorithms based on Artificial Neural Networks (ANN) [see Hsu et al. (1997, 1999); Sorooshian et. al. (2000), and Hong et. al. (2005)] . Figure 2 shows the ANN structure as developed for the PERSIAN algorithm.

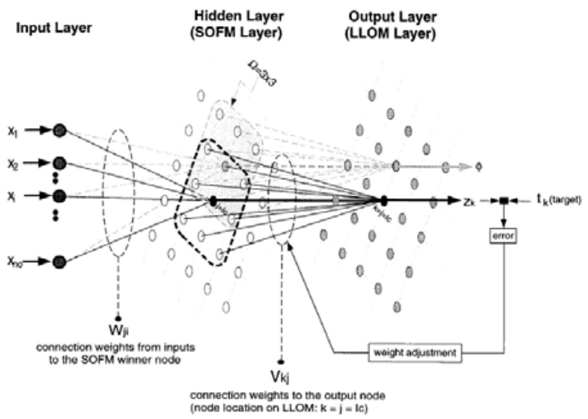
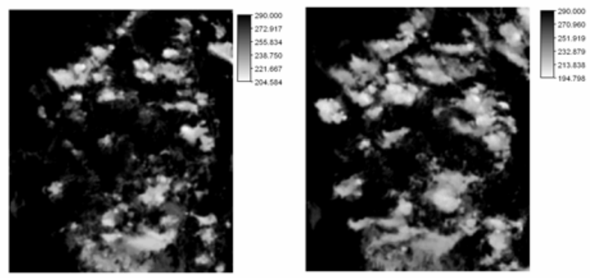



Figure 2: The modified counter propagation ANN [Hsu et al. (1999)]. $x_1$, $x_2 \ldots x_n$ etc refer to satellite image derived variables.

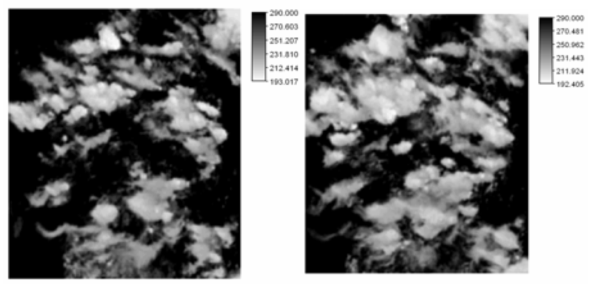
## 3. ISSUES RELATED TO RAINFALL RETRIEVALS

### 3.1 Rainfall dynamics

Characteristics and complexity of rainfall dynamics as well as limitation of satellite based sensors to observe cloud behavior at scales relevant for rainfall formation, to a large extent, contribute to the rainfall retrieval approaches poor performance. The wide range of spatial and temporal scales of the cloud dynamics and rainfall formation introduces complexity that cause that rainfall retrievals from images are uncertain with respect to location, extent and intensity. The regional and seasonal dependence of the rainfall formation also causes uncertainty although to a different scale. For instance, an algorithm verified for observations at the start of a rainy season, when convective cells dominate, can have a significant bias when tested for the middle of the rainy season or for other regions for which other factors such as advection of humid air may dominate. As such it is also necessary to evaluate the effectiveness of seasonal and geographic location based relationship between image based proxy variables and observed surface rainfall rates [see Todd et al. (1995)]. Clouds often do not simply grow or dissipate without splitting or merging with the surrounding clouds, see figure 3. This also adds complexity to rainfall retrieval processing such as, for instance, the life-history methods which track the clouds over space and time.



a) 10:00 UTC b) 11:00 UTC



c) 11:30 UTC d) 12:30 UTC

Figure 3: Growth of clouds as observed for the Upper Blue Nile basin on August 22, 2005 by MSG. Note: values are brightness temperatures (K) for the 10.8 μm channel and the white color indicates relatively thick and high clouds.

The significant difference in the amount and pattern of rainfall from the two major cloud types that produce rainfall, i.e. convective and stratiform clouds, requires studying these cloud types differently. Such practice based on remote sensing observations is an ongoing research topic. Passive MW remote sensing is considered better than IR remote sensing to identify convective and stratiform precipitation. Figure 4 shows convective rainfall cells embedded in stratiform clouds as retrieved from TRMM images. However, the distinction between the two precipitation systems is non-unique but also low image resolutions introduce additional difficulty. For instance, Hong et al [1999] showed that the area covered by convective/stratiform clouds change as the spatial resolutions of the images change. Although stratiform precipitation always occur more frequently than convective precipitation, mixed rainfall areas increase gradually as the resolution decreases.

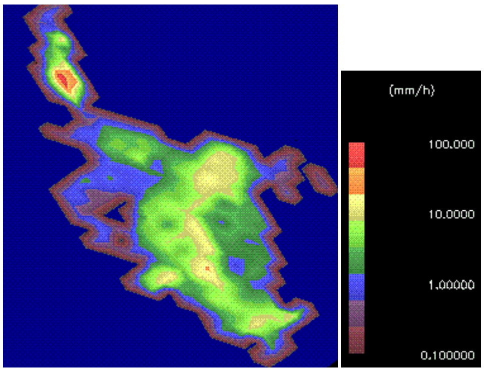
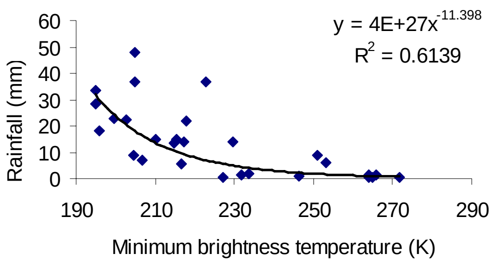



Figure 4: Rainfall rate in the Upper Blue Nile basin from TRMM PR observations August 27, 2005. (Source: TRMM online data access)

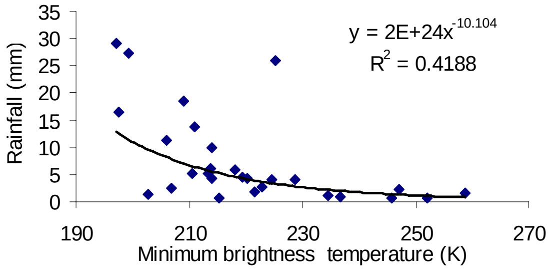
### 3.2 The top-down observation

The most logical way to observe rainfall is upwards from the earth's surface to the cloud system instead of downwards from the satellite orbits to the cloud systems. This difference in view point introduces uncertainties to all the available satellite image based rainfall estimation algorithms.

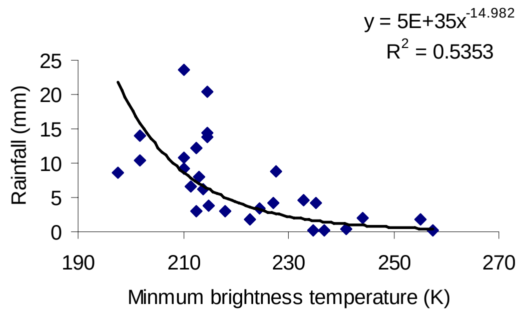
**IR-based approaches:** IR-based approaches are based on observations of cloud top surfaces since radiation, in this part of the electromagnetic wave spectrum, does not penetrate deep into the clouds. This makes rainfall retrieval 'inferential' in a sense that rainfall is inferred from cloud top temperatures. Figure 1 proves that the relation between cloud top temperature and daily rainfall depth is weak and often it is the case that not all cold clouds produce rain while also rain does not always fall from cold clouds. Thus, this indirect approach often results in poor accuracy of pixel based rainfall estimates. In literature, it is stated that rainfall estimates often require aggregation over a coarse spatial domain, for instance larger than $1^0X1^0$ and low temporal resolutions of days to improve accuracy, such as, applied for the GPI method. In addition, the detection of false rainfall signals from cold clouds that do not produce rainfall and the difficulties with warm rain that is to be associated to stratus clouds cause inaccuracies and thus uncertainties in the approaches. Images in the visible channel provide useful information on cirrus clouds since these clouds are less bright compared to clouds that produce rain. However, these images are only available during day time and are affected by the position of the sun and thus require geometric corrections.




a) For D/Sina meteorological station.




b) For D/Birhan meteorological station.

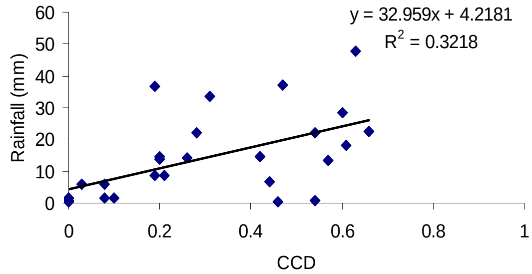



c) For Adet meteorological station.

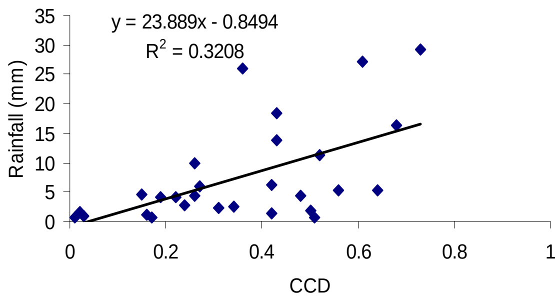
Figure 5: Daily Rainfall vs. daily minimum IR brightness temperature observations for August, 2005.

Figure 5 and 6 illustrate that both Tmin and CCD carry relevant information that could be related to daily rainfall amount. As it is shown in figure 5, power law relationship between daily rainfall and daily minimum brightness temperature (Tmin) observations can be established. Although the $R^2$ value, also known as the coefficient of determination that ranges between 0 and 1, is not very low, the relationship between the two variables is not very strong. Also the observed scattering indicates that the relation is non unique since single brightness temperatures can be related to unequal daily rainfall depths. Nevertheless, the minimum brightness temperature is indicative towards daily rainfall amounts. For instance, for the considered stations, Tmin of less than 210 K is most likely associated to a rainfall amount higher than 10 mm while Tmin of greater than 230 K corresponds to a rainfall amount of lower than 5 mm.

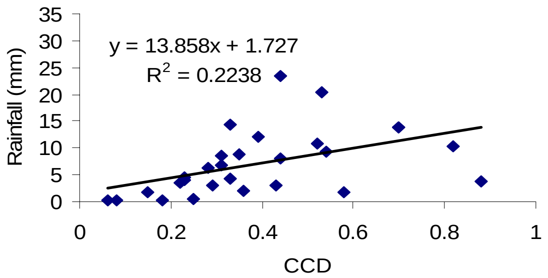
The Cold Cloud Duration (CCD) is used as one of the indices for retrieval of daily rainfall amounts from images. A major limitation with the CCD is that rainfall amount is related only to the cloud duration. However, such assumptions could fail when convective clouds of high rainfall intensity occur over a short period of time. In addition, results from this approach, similar to other IR based approaches, are affected by the applied temperature threshold that varies with season and geographic position. In this study, the CCD values are computed based on a brightness temperature threshold of 160 K. It should however be understood that the threshold is affected by many factors and also changes over meso-scale spatial domains and season. However, several cloud indexing approaches use a constant threshold. Figure 6 shows the $R^2$ value is low when the relationship between observed daily rainfall and CCD values is established for combined observations from six stations than that when the relationship is based on observations from single station. Such could partly indicate the effect of geographic position on the relationship between satellite observations and surface rainfall.



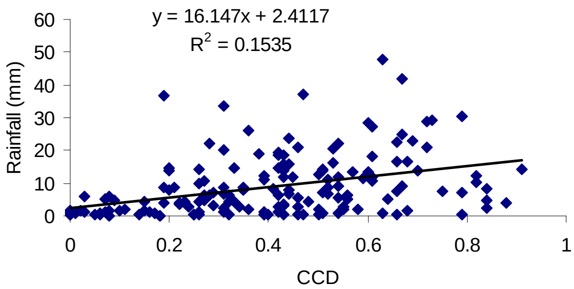

a) D/Sina




b) D/Birhan




c) Adet




d) Six stations in the Upper Blue Nile Basin

Figure 6: Observed daily rainfall vs. daily CCD

Table 2 shows the least square based regression equations and performance indicators for rainfall estimation based on Tmin and/or CCD as explanatory variables. The performance of the applied regression equations is evaluated in terms of the Relative Error (RE), Root mean Square Error (RMSE) and the Relative variance (Rvar). RE is the ratio of the absolute error to the average of the observed data while Rvar is the ratio of the variance of the estimates to that of the observations. The desired value for RE is close to zero and that for Rvar is close to one. As it is shown in table 2 the errors of the estimates are relatively high and are about half of the averages of the observations. For the stations at D/Birhan and D/Sina, the Rvar and the RMSE become closer to the desired value when the estimates are based on both Tmin and CCD as compared to when only one of the two variables is considered. For the station at Adet, although the Rvar becomes closer to one when only Tmin is used, the RMSE becomes lower when both Tmin and CCD are used.

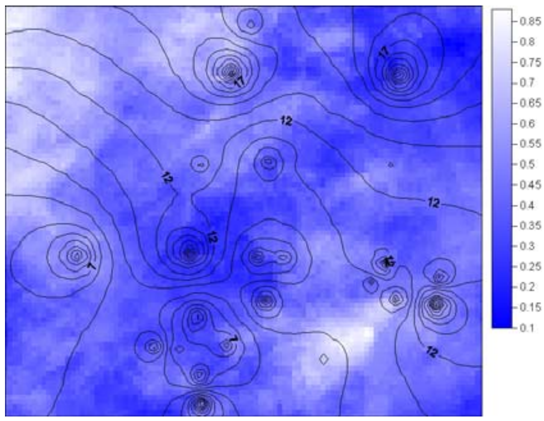


Figure 7: Contour map of observed daily rainfall (mm) overlain on CCD (in fraction of a day) map for August 13, 2005.

Table 2: Performance assessment of rainfall retreival equations

| Station | Equation | RE | RMSE | Rvar |
|---|---|---|---|---|
| D/Birhan | 23.889*CCD-0.8494 | 0.66 | 6.82 | 0.32 |
| | $2*10^{24}*Tmin^{-10.104}$ | 0.55 | 7.00 | 0.16 |
| | 35.28+15.55*CCD-0.15*Tmin | 0.64 | 6.59 | 0.37 |
| D/Sina | 32.959*CCD+4.2181 | 0.56 | 10.74 | 0.32 |
| | $4*10^{27}*Tmin^{-11.398}$ | 0.48 | 10.25 | 0.54 |
| | 72.82+16.81*CCD-0.3*Tmin | 0.57 | 9.92 | 0.61 |
| Adet | 13.858*CCD+1.727 | 0.53 | 5.28 | 0.22 |
| | $5*10^{35}*Tmin^{-14.962}$ | 0.53 | 5.58 | 0.71 |
| | 54.72+3.42*CCD-0.22*Tmin | 0.48 | 4.60 | 0.41 |
| Six stations | 16.147*CCD + 2.4117 | 0.71 | 9.59 | 0.02 |
| | $6*10^{22}*Tmin^{-9.4653}$ | 0.64 | 9.30 | 0.11 |
| | 44.56+6.95*CCD-0.18*Tmin | 0.68 | 8.10 | 0.22 |
| | 30.64+12.66*CCD-0.19*Tmin+0.006*Elv | 0.62 | 7.44 | 0.34 |

Hydrological modeling requires spatial rainfall inputs at the scale of model elements. This requires formulation of a single relationship that is applicable to all elements that makeup the land surface model domain. Table 3 shows such equations for the Upper Blue Nile catchment based on rainfall observations for the month of August 2005 from six stations. The performance indicators values in table 3 illustrate that formulation of a single best equation for the entire spatial domain requires additional explanatory variables such as for instance elevation (Elv.) in order to yield better performance.

Table 3: Performance assessment of a single best rainfall retrieval equation

| Equations | RE | RMSE | Rvar |
|---|---|---|---|
| 44.56+6.95*CCD-0.18*Tmin | D/Birhan | | |
| | 0.68 | 6.79 | 0.22 |
| | D/Sina | | |
| | 0.62 | 12.17 | 0.18 |
| | Adet | | |
| | 0.52 | 4.8 | 0.39 |
| 30.64+12.66*CCD-0.19*Tmin+0.0056*Elv | D/Birhan | | |
| | 0.68 | 6.69 | 0.36 |
| | D/Sina | | |
| | 0.54 | 10.68 | 0.27 |
| | Adet | | |
| | 0.55 | 5.07 | 0.69 |

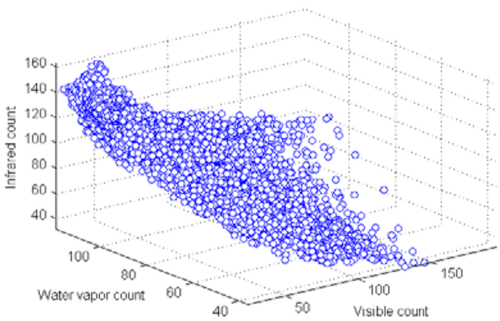


Figure 8: MSG observations for August 15, 2006 at 12:00 UTC (observations are presented in eight bit counts)

In Figure 8, the dots refer to combinations of VIS, IR and WV counts. The relatively small scatter allows identification of a general trend. This explains that additional and effective information is carried by the VIS and WV observations. The IR observations are mainly indicative of the cloud temperatures that relate to cloud top height whereas the VIS and WV observations are indicative to, respectively, the cloud thickness and the mass of water stored in the cloud. In the same figure, the WV count is associated to different combinations of VIS and IR counts. It is shown that combinations of all counts are non-unique and as such various combinations can be identified. In our opinion, this implies that also rainfall retrievals cannot be seen as very reliable but instead such retrievals must be interpreted as being very uncertain.

**MW-based approaches:** Characteristic to most MW-based approaches is that observations commonly are from orbiting satellites and thus only 1 or 2 images become available on a daily basis. Obviously, this very poor temporal resolution restricts cloud tracking over time and across space that introduces much error and uncertainty in retrieval procedures. Performance of Passive MW rainfall retrieval algorithms also is affected by assumptions that are weak but that are necessary in the retrieval procedure. For instance, the assumption that rainfall is homogeneously distributed over pixel elements of relatively large scale is weak and is often termed and referenced to as the beam filling problem [see Kummerow (1998)]. Since observations are affected by radiation from sources such as land surfaces and large water surfaces, a distinction is commonly made between the algorithms for ocean and land surfaces. For oceans, the low and uniform emissivity of the water surface allows the change in brightness temperature ($T_B$) due to the presence of precipitation drops to be easily detected. As such, algorithms for water surfaces depend on the emission mode at frequencies lower than 20 GHz. However, observations over the land surface are affected by the highly variable land surface emissivity and as a result retrievals are mainly based on the scattering process as observed by frequencies higher than 60 GHz. It is shown in figure 9 that the 85 GHz channel gives information only on properties of snow and graupel. It is the backscattering by large ice and graupel that has a major effect on modulating $T_B$'s at large frequencies. However, the brightness temperatures appear to be strongly related to liquid precipitation processes due to the high correlation between ice mixing ratios and rain rates. This introduces uncertainties in the presence of clouds that produce relatively few, if any, ice above the freezing level, for instance the collision-coalescence produced rainfall [see Petty (1995)]. Thus retrieval algorithms based on emission are expected to give the most direct estimate on surface rainfall rates while the scattering based algorithms provide relatively indirect estimates.

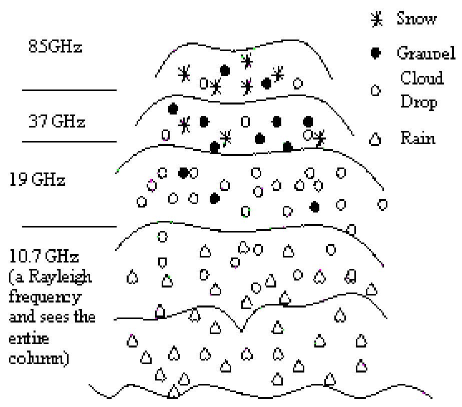


Figure 9: Relationship between observations from passive MW frequencies and cloud phases [Modified after Mugnai et al. (1992) Cited in Barrett and Beaumont (1994)].

**Combined approaches:** The premise of combined IR-MW based approaches is that retrieval algorithms benefit from both the high temporal resolution of IR observations from geostationary satellite and the relatively direct nature of MW observations from the low earth orbiting satellites. These approaches, however, demand spatially and temporally coincident data from the two data sources which is rarely the case. Consequently, this leads to displacements in position of retrieved rainfall distributions over space that often is referred to as satellite-ground misregistration. One of the research challenges to these approaches is which method to use for the integration of observations from different sources. Miller et al. [2001] concluded that a simple regression leads to a bias due to a dominance of the zero and light rainfall observations. The use of ANN has obtained research attention; however, the non-unique relation between remote sensing observations and rainfall observations poses challenge to a simple neural network [see Bellerby et al. (2000)].

## 4. CHALLENGES FOR IMPROVEMENT

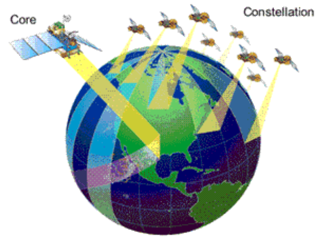
The physical basis of satellite image based rainfall retreival approaches is presented. It is shown that the approaches have major limitations since relations between observations and surface rainfall rates are indirect. The limitations are also due to the complexity of the rainfall dynamics and its variability with season and location. Because of poor performance, retrieval procedures that use single channel and single sensor observations are not sufficient for hydrological applications. A further research is required to evaluate the effectiveness of multi-channel and multi-sensor based rainfall retrieval procedures. Remote sensing techniques such as segmentation and classification can be helpful to identify the different types of raining clouds.

### 4.1 The Global Precipitation Measurement (GPM) mission

NASA and JAXA conceived a new mission called the Global Precipitation Measurement (GPM) mission for the year 2010 as a result of the success of TRMM mission [see Smith et al. (2004)]. The mission is anticipated to improve precipitation observation from space by providing accurate measurements, increased sampling frequency, increased spatial resolution and better coverage of the earth compared to the present precipitation observation era. The core satellite of the GPM mission will carry Dual frequency Precipitation Radar (DPR) and a multi-channel passive microwave rain radiometer called the GPM Microwave Imager (GMI), see figure 10.

In addition to the core satellite, eight satellites in constellation are expected to carry a variety of multi-channel passive MW radiometers. The DPR provides measurements that are sensitive to fluctuations in rain drop size distributions while the high resolution MW radiometers mitigate heterogeneous beam filling problem of the current passive MW measurements. The GPM satellites will also provide unprecedented sampling frequency of eight observations per day. Clearly it is expected that, this increased sampling frequency will result in an improvement of the combined IR-MW based rainfall retrievals by the large number of MW observations per day.

In addition, observations from the European Global Precipitation Measurement (EGPM) mission [see Mugnai et al. (2004)] will serve as a calibration standard for: (1) the light/warm/drizzle rainfall portions of the liquid spectrum (2) the domains pole ward of the 65 degrees parallel beyond which the GPM core satellites does not measure, and (3) light to moderate snowfall which will not be detectable by the DPR.

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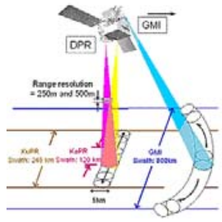


b)

Figure 10: (a) Constellation of GPM satellites (b) and GPM Microwave Imager (GMI) and Dual frequency Precipitation Radar (DFR) beam structure and footprint.
**(**source: **http://gpm.gsfc.nasa.gov)**

### 4.2 Cloud models

The water content that precipitates at the cloud bottoms is one of the outputs from cloud models. The model-simulated cloud water content can be related to surface rainfall rates through equations that describe for instance the evaporation and fall velocity of the water drops. Inputs to cloud models are, among others, hydrometeor and temperature profiles through the cloud layers. As outlined in the previous sections, among image based variables are IR brightness temperatures that are indicative of cloud heights. Georgakakos and Bras [1984] developed a one-dimensional (1D) cloud model that utilizes cloud top IR brightness temperatures as its inputs for rainfall forecasting. French and Krajewski [1994] and Andrieu et al. [2003] revised the 1D model so that it uses ground based radar observations of cloud water content as inputs. Further research challenges are to evaluate the effectiveness of the approach for geographic positions where radar observations are unavailable and to revise the equations so that WV and MW brightness temperatures serve as model inputs. Such improvements are expected to enhance the performance of the 1D model for rainfall simulations.

### 4.3 Scale issues

Common to all the rainfall retrieval approaches is also the scale issue. Up-scaling and downscaling of the ground observations and satellite rain estimates for calibration and verification purposes introduces uncertainty. The temporal and spatial resolutions of the geostationary IR images and the orbiting MW images are not equal and as such combining the information from these images requires collocation of the data in both time and space. This problem also prevails when multi-spectral MW images from the low earth orbiting satellites alone are used. This requires de-convolution of the low frequency images.

To the hydrologic community, an important research challenge is to quantify scaling effects due to sampling, retrieval and assimilation of satellite rainfall retrieval into hydrologic models. In recent literature, such issues have gained attention [see Astin [1997]; Bellerby and Sun [2005]; Lee and Anagnostou [2004].

## 5. CONCLUSION

The physical basis of images based rainfall retrieval approaches and the reason for the poor performance of the approaches are discussed. The poor accuracy of the rainfall retrievals to a large extent is explained by the non-unique relationship between the satellite observations and the surface rainfall rates. A simple case study on the Upper Blue Nile basin showed that the daily CCD and Tmin carry effective information on rainfall production in cloud systems that land surface rainfall rates can be retrieved. The idea that a single best relation based only on CCD and Tmin for the entire Blue Nile is found questionable and inclusion of additional variables such as for instance elevation data is suggested. To be more conclusive, however, further study based on data from several stations is required. Development and evaluation of the effectiveness of a 'Multiple input-multiple output' type approach is regarded a challenging research topic however, such an approach is expected to improve the accuracy of retrievals. It is recommended to introduce physics into the estimation algorithms by using cloud models. This is expected to overcome the major limitation of the black-box approaches.

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