

Microwave remote sensing of soil moisture

Z. Bob Su

*International Institute
for Geo-Information Science and Earth Observation (ITC)*
Enschede,
The Netherlands

email: B_Su@ITC.NL
<http://WWW.ITC.NL>

(With contributions from R. van der Velde and C. Prigent)



Purpose of this lecture

- An introduction of the physical processes in retrieval of soil moisture
- A review of the state-of-the-art remote sensing techniques used for retrieving soil moisture fields from active and passive microwave systems
- A list of potential data/information providers of soil moisture



Physical processes in retrieval of soil moisture (1)



- Two basic approaches: passive microwave (MW) and active MW remote sensing
- In passive MW methods, the natural thermal emission of land surface (or brightness temperature) is measured at microwave wavelengths, using a radiometer.
- In active MW methods, a microwave pulse is sent and received. The power of the received signal is compared to that which was sent to determine the backscattering coefficient of the surface.
- Both methods provide information on the surface reflectivity.
- The surface reflectivity R_{σ}^p is the integral of the surface scattering coefficient over all scattering directions.

Physical processes in retrieval of soil moisture (2)



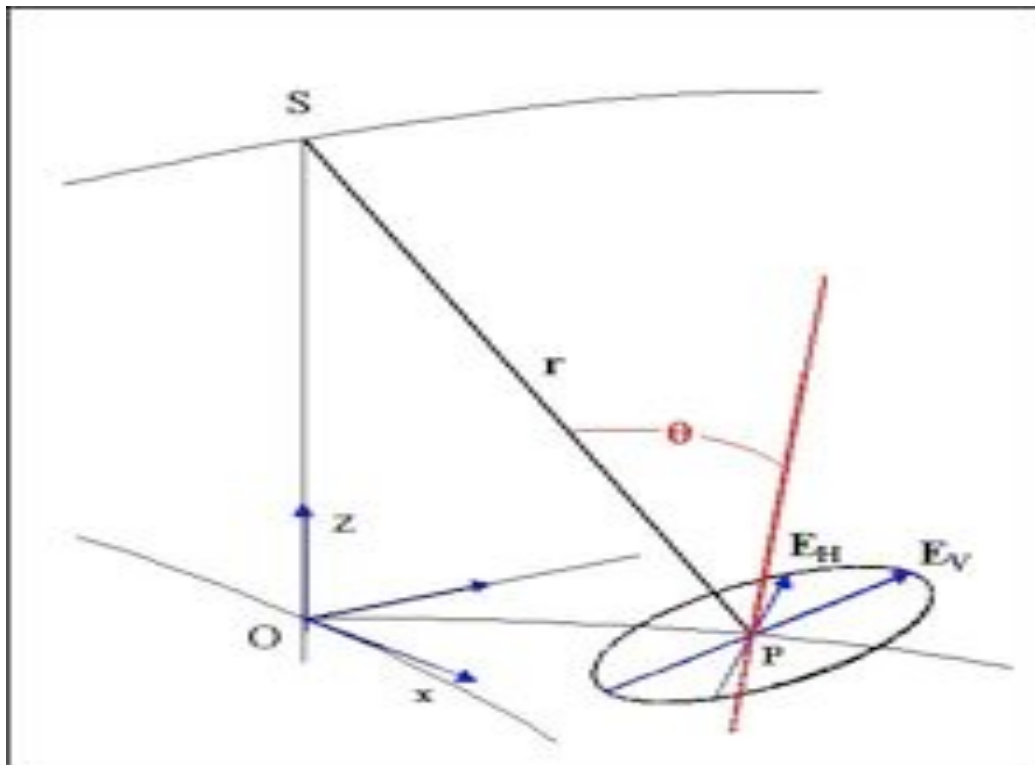
- The basic reason microwave remote sensing is capable of providing soil moisture information is that there is a large difference between the dielectric constants of water (~80) and the soil particles (~4).
- The Fresnel reflection equations (Ulaby *et al.*, 1986) predict the surface reflection coefficient (R_0^p) as a function of dielectric constant (ϵ_r) and the viewing angle (θ), based on the polarization of the sensor (p=horizontal-H or vertical-V).

$$R_0^H = \left| \frac{\cos \theta - (\epsilon_r - \sin^2 \theta)^{\frac{1}{2}}}{\cos \theta + (\epsilon_r - \sin^2 \theta)^{\frac{1}{2}}} \right|^2 \quad R_0^V = \left| \frac{\epsilon_r \cos \theta - (\epsilon_r - \sin^2 \theta)^{\frac{1}{2}}}{\epsilon_r \cos \theta + (\epsilon_r - \sin^2 \theta)^{\frac{1}{2}}} \right|^2$$

- From the reflection coefficient, the dielectric constant of the soil can be estimated. The dielectric constant of soil is a composite of the values of its components: air, soil particles, and water (bound and free water).

Physical processes in retrieval of soil moisture (3)

- Instantaneous up-welling radiation is described by electric fields E_H and E_V for horizontal and vertical polarizations. The horizontal field component is perpendicular to the plane defined by the nadir line SO and line of sight SP lines, while the vertical component lies in this plane.



(Source: SMOS level 2 processor Soil moisture ATBD)

Physical processes in retrieval of soil moisture (4)

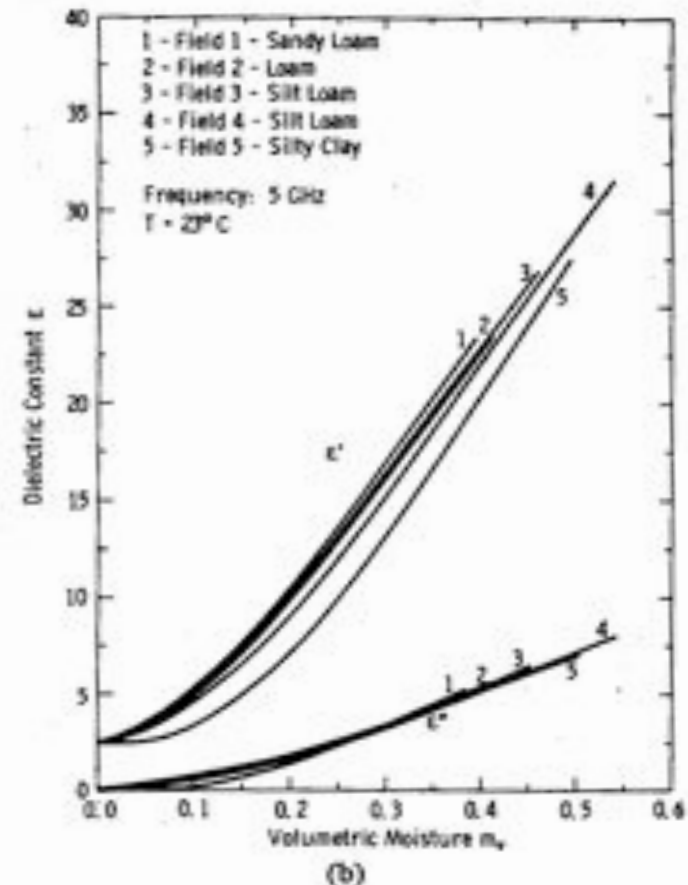
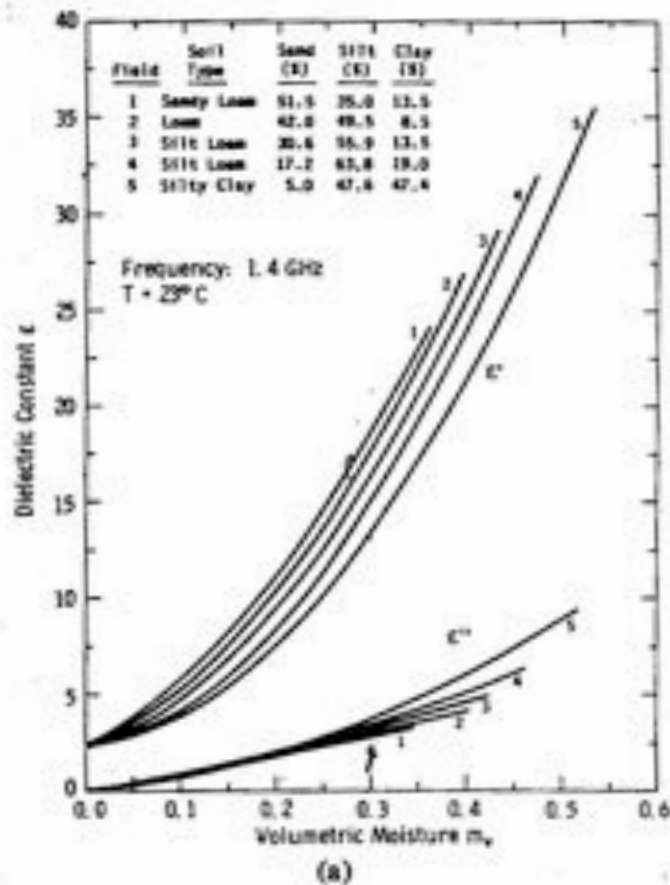


- At MW frequency, the Planck's law can be approximated by the Rayleigh-Jeans relationship, i.e. that brightness temperature and radiances are directly proportional.
- The observed brightness temperature (T_B^p) of a surface is equal to its emissivity (ϵ_s) multiplied by its physical temperature (T_s).
- The observed emissivity is equal to 1 minus the reflectivity, which provides the link in the Fresnel equations to soil moisture.
- Surface variables such as temperature, soil moisture, roughness, vegetation, etc... enter the general radiative transfer equation through their effects on surface reflectivity R_o^p and surface brightness temperature T_B^p :
- For bare soil surfaces, T_s reduces to a weighted sum of soil temperatures at subsurface levels accounting for the penetration depth (λ/e).

Physical processes in retrieval of soil moisture (5)



- On the basis of an estimate of the mixture dielectric constant derived from the Fresnel equations and soil texture information, volumetric soil moisture can be estimated (*Hallikainen et al. 1985*).



A review of methods used to retrieve soil moisture



- 1) (Advanced) Synthetic Aperture Radar (SAR/ASAR) method
- 2) Microwave radiometer method
- 3) Wind scatterometer method
- 4) Synthesis

1) SAR / ASAR method



- Space borne SAR systems
- Theoretical and semi-empirical scattering approaches
 - Surface scattering (bare soil, sparse vegetation)
 - Vegetation scattering (theoretical models)
- Empirical approaches (fitting methods)
- Summary

Space borne SAR systems

Table 1. Technical details of SAR sensors

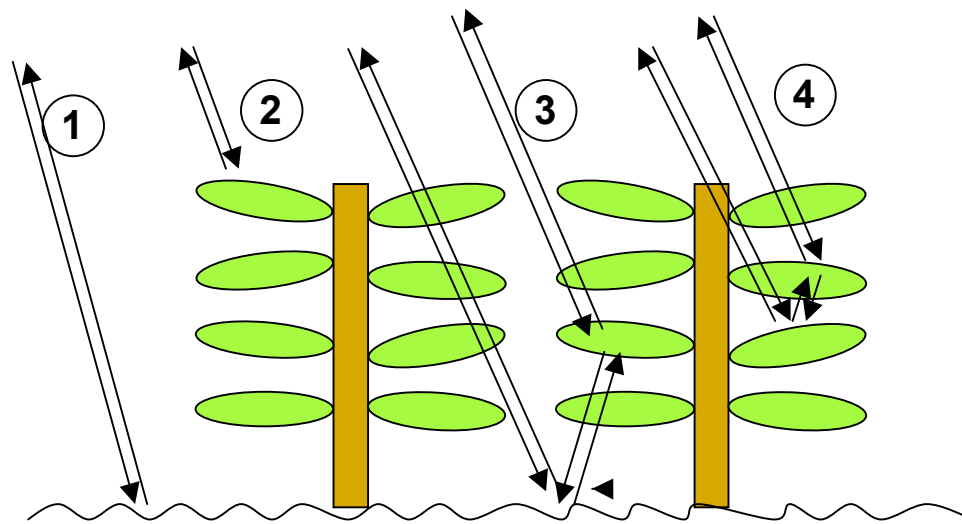
Parameters	ERS-1/2	SIR-C/X-SAR	JERS-1	RadarSat-1	ASAR	RadarSat-2	PALSAR	TerraSar
Platform	satellite	shuttle	satellite	satellite	satellite	satellite	satellite	satellite
Frequency (GHz)	5.3	1.3 (L) 5.0 (C) 10.0 (X)	1.28	5.6	5.3	5.4	1.27	9.65
Polarization	Single (VV)	Full	Single (HH)	Single (HH)	Dual	Full	Full	Full
Altitude (km)	~800	~225	~568	~800	~800	~800	~692	~514
Revisit time (days)	35	NA	44	24	35	24	46	11
Incidence angle (deg)	23°	17°-63°	39°	20-49° ¹	15-45° ¹	20-49° ¹	8-60° ¹	20-45° ¹
Resolution (m)	25	30	18	10-100 ¹	25-75 ¹	3-100 ¹	7-100 ¹	1-16 ¹
Swath (km)	100	90	75	100-500 ¹	100-400 ¹	10-500 ¹	40-350 ¹	5-100 ¹
Launch	1991 (ERS-1) 1994 (ERS-2)	April 1994 Oct. 1994	1992	1995	2002	2005	2005	2005

¹The sensor has a selectable image swath and, therefore, a variable, resolution, incidence angle range and swath width depending on the selected configuration.

Theoretical scattering approaches



- Microwave scattering terms that are typically represented in physical scattering methods



$$\sigma^o = \sigma_{sur}^o + \sigma_{veg}^o + \sigma_{sur-veg}^o + \sigma_{veg-veg}^o$$

Theoretical scattering approaches



- Surface scattering methods usually relate geometric and dielectric properties to a bare soil surface backscatter response.
- The most frequently used theoretical surface scattering methods are originated from the Kirchhoff approaches (Beckmann and Spizzichino, 1963) and the Small Perturbation Method (Rice, 1957), which are both restricted to a limited range of roughness conditions.
- In the Integral Equation Method (IEM) (Fung et al. 1992 and Fung 1994) these two methods are combined to a method valid for a wide range of roughness conditions.
- Interaction between active microwaves and the vegetation layer consists of various scattering terms. In the passive case, brightness temperatures can be modeled using zeroth order approximation of the radiative transfer equation, because higher order emission terms are relatively small. However, among active microwave observations higher order scattering terms (volume scattering) can be responsible for significant amounts of scattering. Therefore, physical methods (Lang and Sidhu 1983 - Turbid medium, Ulaby et al. 1990 - MIMICS, and Karam et al. 1992 - UTA) model the following scattering interactions:
 - Surface scattering;
 - Vegetation scattering;
 - Scattering within the vegetation;
 - Vegetation-surface scattering.

Semi-empirical scattering approaches



- Alternatively, semi-empirical approaches have been developed that use only the variations in the surface height (σ) to describe the surface roughness.
- Oh et al. (1992) found for scatterometer measurements that the depolarization ratio ($\sigma_{vh}^0 / \sigma_{vv}^0$) is very sensitive to soil moisture and based their semi-empirical model on this characteristic.
- Dubois et al. (1995) based a semi-empirical method on only co-polarized observations (σ_{hh}^0 and σ_{vv}^0).
- Semi-empirical backscatter relationships are usually derived from the ground based active microwave data sets as described in Oh et al. (1992) and Wegmuller (1993).

Empirical approaches (fitting methods)



- An example of an empirical change detection method is proposed in Shoshany et al. (2000), who used the Normalized Backscatter Moisture Index (NBMI) as a basis for their soil moisture retrieval algorithm:

$$NBMI = \frac{\sigma_{t1}^o - \sigma_{t2}^o}{\sigma_{t1}^o + \sigma_{t2}^o} \quad sm = a_r \cdot NBMI + b_r$$

- where, σ_{t1}^o σ_{t2}^o and are the backscatter coefficients at different time steps, a_r and b_r are empirical parameters that should be fitted to *in-situ* soil moisture (sm) observations.
- Many empirical relationships have generated accurate soil moisture retrievals but based on extensive calibrations, which limits the applicability of these soil moisture retrieval algorithms to a small area.

1) Summary

- Physical models such as MIMICS require often a detailed parameterization of the vegetation and soil surface layer, which is typically not available.
- Semi-empirical models have frequently generated good results for specific areas, but when these techniques are applied to other locations or other field conditions the accuracy of the soil moisture products decreases significantly.
- Empirical methods that are based on change detection yield often accurate soil moisture results, but are strictly speaking not valid for application that exceed the calibration conditions.
- Currently SAR methods are not able to estimate soil moisture with sufficient accuracy that can be used to assist disaggregating SMOS soil moisture products (from ~50km to ~1km).
- The revisit time of the present and future SAR systems for exactly the same configuration exceeds 15 days. This is often not sufficient for global soil moisture monitoring products.
- Despite these disadvantages of SAR based soil moisture retrieval, the proposed L-band PALSAR instrument onboard the Japanese ALOS satellite offers the opportunity of retrieving soil moisture in a combined passive/active microwave approach.
- The combination of passive and active microwave observations is expected to increase the accuracy of the retrievals and can yield high resolution soil moisture maps.



2) Microwave radiometer method



- Space borne passive microwave sensors
- Passive microwave theory
 - Surface roughness effects on the apparent emissivity
 - Vegetation effects on the apparent emissivity
- Passive microwave soil moisture retrieval algorithms:
 - Jackson et al. (1993)
 - Owe et al. (2001)
 - Bindlish et al. (2003)
 - Wen et al. (2003)

Space borne passive microwave sensors



Table 1. Overview of the antenna specifications of four space borne passive microwave sensors.

Parameter	SMMR	SSM/I	TMI	AMSR/-E
Platform	Nimbus-7	DMSP	TRMM	Aqua and ADEOS
Operational period	1978-1987	1987- now (series)	1997 - now	2002 - now
orbit	Near-polar	Near-polar	Equator	Near-polar
Altitude (km)	955	860	350	705
Incidence angle (deg)	50.3	53.1	52.8	55
Frequencies (GHz)	6.6, 10.7, 18, 21, 37	19.3, 22.3, 37, 85.5	10.7, 19.4, 21.3, 37.0 85.5	6.9, 10.7, 18.7, 23.8, 36.5, 89.0
Polarization	H and V	H and V	H and V, only V at 21.3 GHz	H and V
Swath Width (km)	780	1400	758.5	1445
Foot print size (km)	~140 at 6.6 Ghz ~27 at 37 GHZ	~50 at 19 Ghz ~15 at 85.5 GHz	~38.3 at 10.7 GHz ~4.4 at 85.5 GHz	~ 70 at 6.9 GHz ~ 14 at 89 GHz

Passive microwave theory

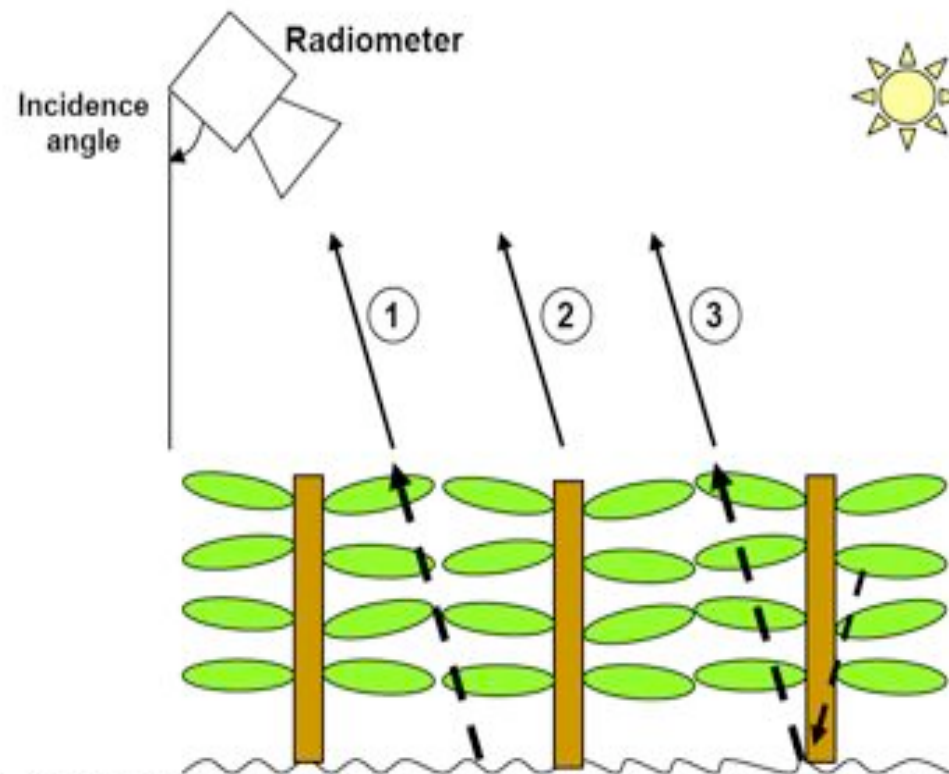


Figure 1. schematic representation of the different microwave emission terms over a vegetated surface.

$$T_B = (e_s \Gamma) T_s + (1 - \omega)(1 - \Gamma) T_c + (1 - e_s)(1 - \omega)(1 - \Gamma) T_c$$

Surface roughness effects



Surface roughness has a positive effect on the surface area and on the apparent emissivity of natural surfaces. Due to an increase in the surface area, the amount of emitted energy scattering increases and higher brightness temperatures are observed under the same soil moisture conditions. Most soil moisture retrieval methods use the empirical model of Choudhury et al. (1979) to correct for these surface roughness effects, which is expressed by:

$$R_s = R_0 \exp(-h \cos^2 \theta) \quad (1)$$

$$h = \sigma^2 k^2$$

Vegetation effects

The effects of vegetation on T_B observations are two-fold: 1) vegetation covers the surface and attenuates the soil surface emission, 2) vegetation emits microwave radiation and is responsible for a contribution of radiated energy to sensor.

A method based on the radiative transfer theory described in Mo et al. (1982)

$$T_B = (e_s \Gamma) T_s + (1 - \omega)(1 - \Gamma) T_c + (1 - e_s)(1 - \omega)(1 - \Gamma) T_c \quad (4)$$

Where, e_s is the smooth surface emissivity (equals $1 - R_s$), ω is the single scattering albedo, Γ is the transmissivity of the vegetation layer, T_s and T_c are the soil surface and canopy temperature, respectively. The first term on right hand side of equation 4 represents the emission contribution from the soil corrected for the energy absorbed by the vegetation layer (1). The second component on the right side is direct microwave emission from the vegetation layer (2). The third term quantifies the vegetation emitted radiation traveling via the soil surface to sensor (3). These three terms are illustrated in figure 1.

Passive microwave soil moisture retrieval algorithms

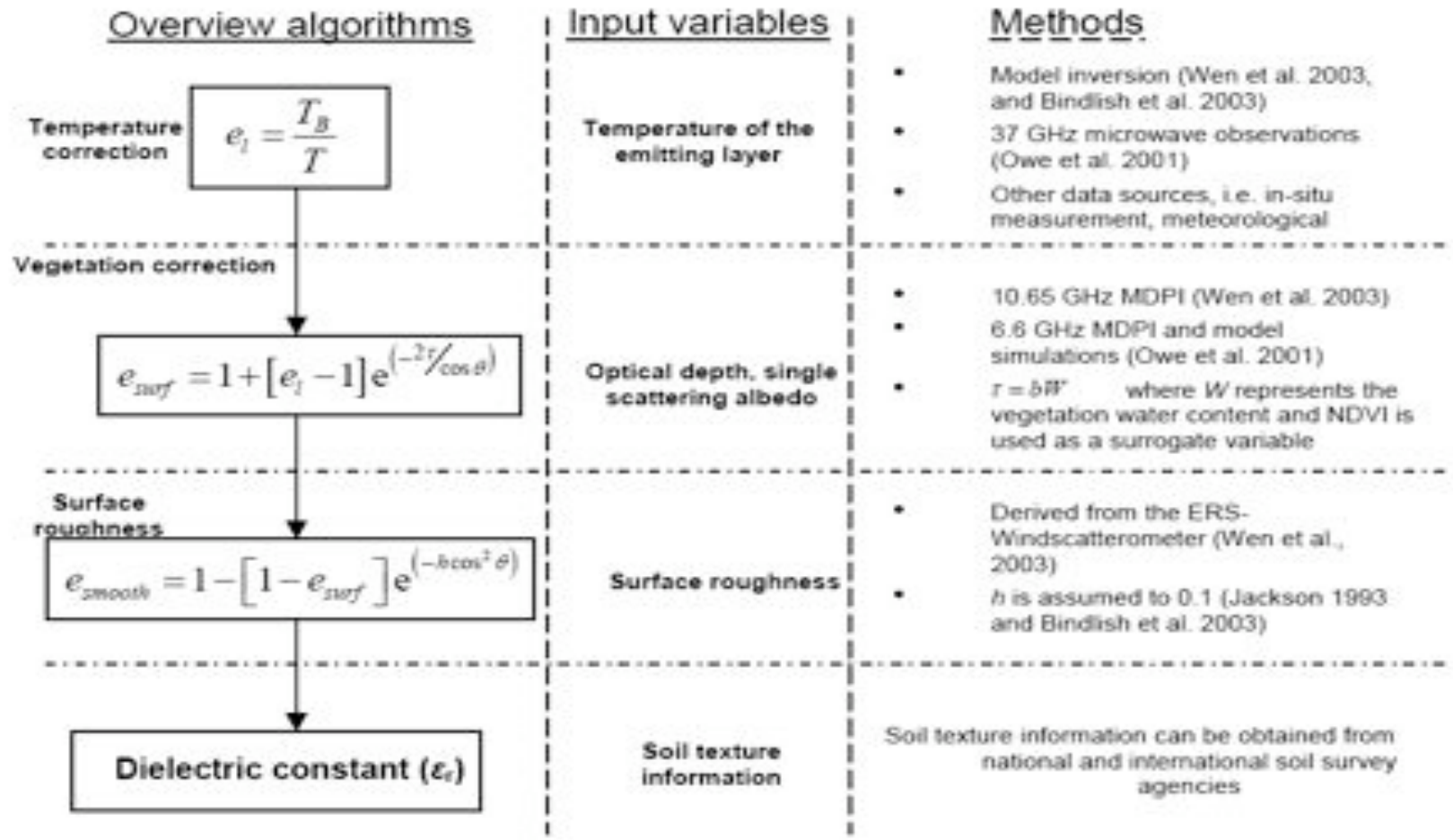
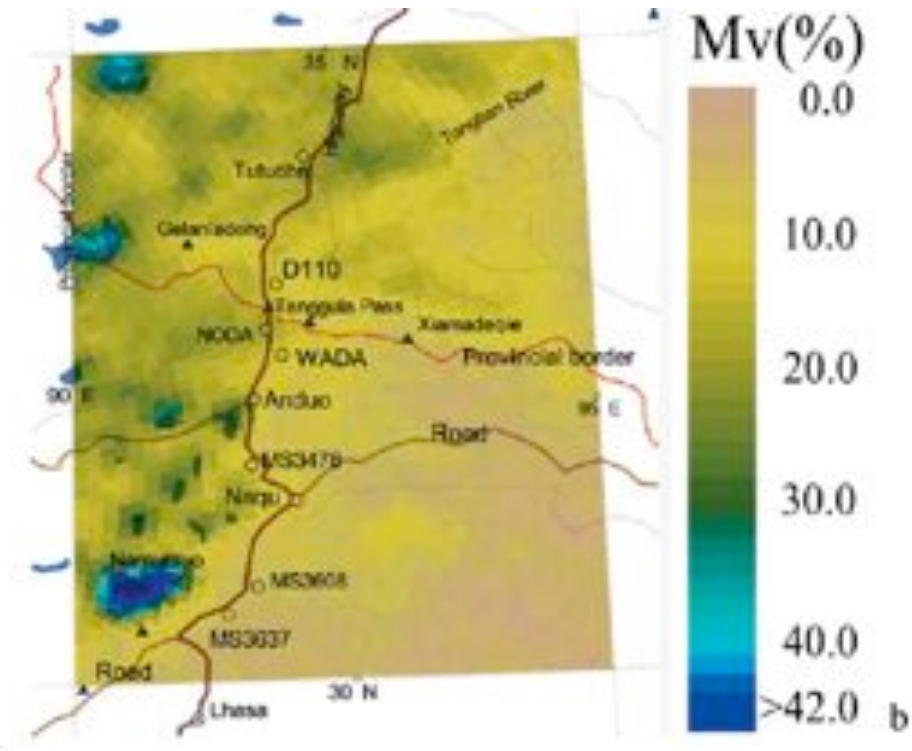
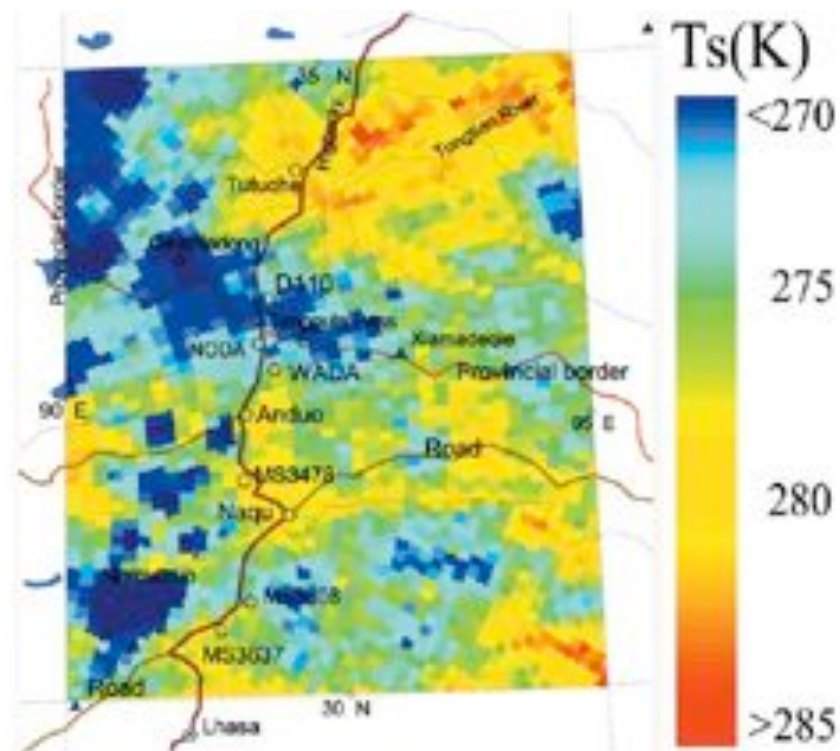


Figure 2. Overview of the difference between the various passive microwave soil moisture retrieval methods.

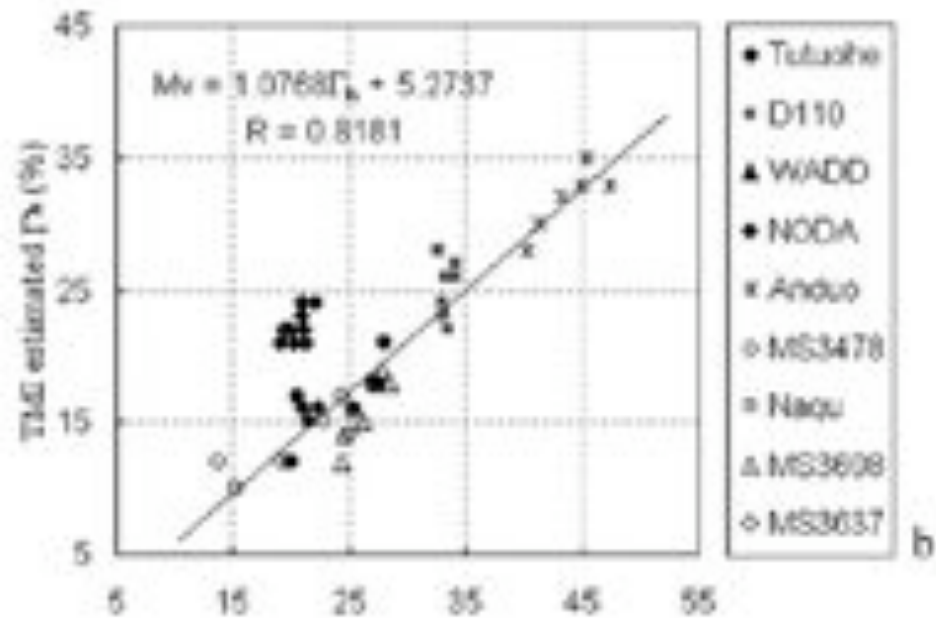
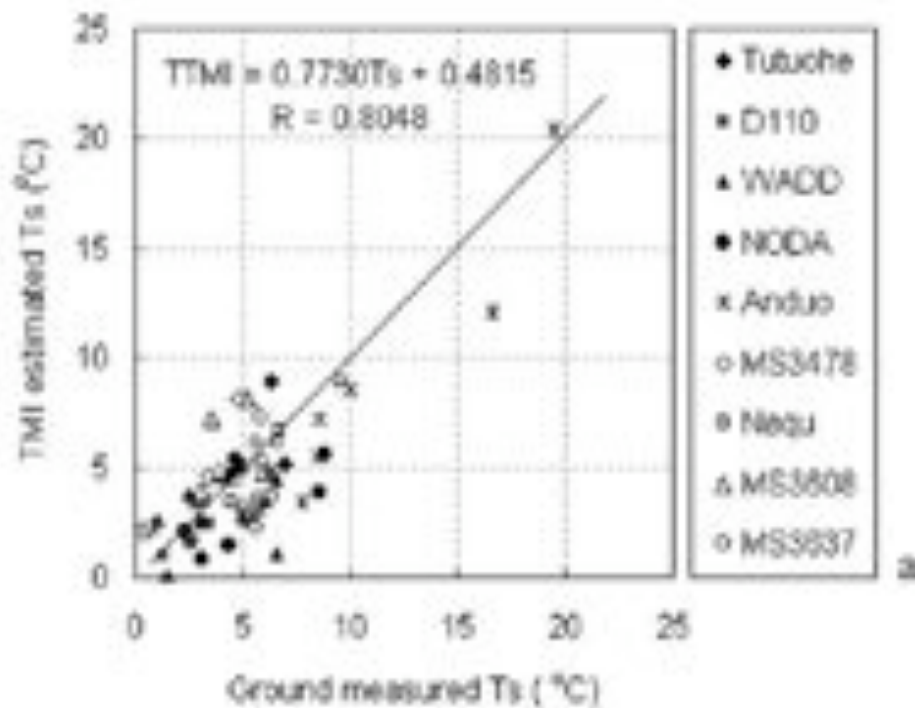
Retrieved land surface temperature and soil moisture from TRMM/TMI data compared to GAME/Tibet in-situ data

(Wen, Su, Ma, 2003, JGR)



Retrieved land surface temperature and soil moisture from TRMM/TMI data compared to GAME/Tibet in-situ data

(Wen, Su, Ma, 2003, JGR)



2) Summary

- Four soil moisture retrieval algorithms using passive microwave observations have been discussed: Jackson et al. (1993), Bindlish et al. (2003), Owe et al. (2001) and Wen et al. (2003). Each of these methods performs equally under similar vegetation conditions with the adjustment of a few parameters and is capable of retrieving soil moisture with accuracy in the order of 3-5 Vol.-% (Hurkmans et al. 2003).
- Preferably, the optical depth is estimated from the radiometer observations itself. Owe et al. use, the *NPDI* to invert the dielectric constant and the optical depth, simultaneously. However, retrieving two variables from one observation might lead to non-unique solutions. The method proposed by Wen et al. (2003) is more promising. It uses the *NPDI* of a bare soil surface and of a vegetated surface to retrieve the optical depth. The only difficulty in applying this technique is to find a SMOS footprint (~25 km), which is only influenced by bare soil radiation.



2) Summary (cont.)

- As a surface emission model, the one proposed by Wang and Choudhury (1981) is physically more adequate, because it accounts for depolarization effects caused by surface scattering. A disadvantage is that both H- and V-polarized Fresnel reflectivity's need to be solved requiring two observations. This might cause difficulties, because the MIRAS instrument is proposed to be a dual polarized radiometer and has, thus, potentially three independent observations: T_{bh} , T_{bv} and $NPDI$. A soil moisture retrieval algorithm including the Wang and Choudhury surface emission model has four unknowns: the temperature of the emitting layer, the optical depth and the H- and V-polarized reflectivity.
- Alternatively, the surface emission model of Choudhury et al. (1979) requires only one independent observation. This would leave one brightness observation for the estimation of the temperature of the emitting layer, but previous studies have shown the difficulty of relating low frequency observations to the temperature of the emitting layer because of their dependence to change in soil moisture (De Jeu and Owe 2001).
- For a future SMOS soil moisture retrieval algorithm it would be more beneficial to use a physically based surface emission model and estimate the temperature of the emitting layer from other data sources. Several other data sources are available, such as in-situ measuring networks, meteorological model predictions and remote sensing observations.



Combined passive and active soil moisture retrieval

- The theoretical algorithm for passive and active microwave soil moisture retrieval proposed by O'Neill et al. (1996) is from a physical point of view the most suitable method to combine radiometer and SAR observations into one soil moisture retrieval algorithm. However, the scattering model used in this algorithm requires several canopy parameters that are a-priori not known and can not be derived from other satellite observations.
- Njoku et al. (2002) uses a physically based radiative transfer approach for passive microwave observations and applies a change detection method for the SAR measurements. With the availability of both SMOS and PALSAR sensors this methodology can be applied on a large scale. However, global soil moisture monitoring applications are not feasible, because the revisit time of the PALSAR is 44 days.

3) Wind scatterometer method



- Both Synthetic Aperture Radar (SAR) and scatterometer are active instruments on board satellites that measure the backscattering signal.
 - SAR
 - High spatial resolution
 - Compatible with land surface variability
 - Very low time sampling of a given region
 - Scatterometer
 - Low spatial resolution
 - Initially designed for ocean observation
 - Global coverage in a few days
 - Long time operation rather recent, as compared to radiometers

Spaceborne Scatterometers

Comparative Operating Characteristics of Spaceborne Scatterometers

	SASS (Seasat)	ESCAT (ERS-1/2)	NSCAT (ADEOS-I)	Seawinds (QuikSCAT/ADEOS-II)
Time Period	July - September 1978	January 1992 - present. Scatterometer Climate Record Pathfinder (SCP) data are only available through January 2001.	September 1996 - June 1997	July 1999 - present
Frequency	14.6 GHz (Ku band)	5.3 GHz (C band)	14.0 GHz (Ku band)	13.4 GHz (Ku band)
Antenna Azimuth Orientations	Four fixed	Three fixed	Six fixed	1 m diameter rotating dish that produces two spot beams, sweeping in a circular pattern
Polarizations	V-H, V-H	V Only	V, V-H, V	V-Outer/H-inner
Beam Resolution	Fixed Doppler	Range Gate	Variable Doppler	Pencil-Beam
Resolution	50/100 km	25/50 km	25/50 km	25 x 6 km
Swath width	750 km	500 km	600 km	1400 km/1800 km
Incidence Angle	0 - 70°	18 - 59°	17 - 60°	46 - 54°
Orbit	Sun-synchronous 810 km altitude 106° inclination	Sun-synchronous 780 km altitude 98.52° inclination	Sun-synchronous 805 km altitude 98.7° inclination	Sun-synchronous 803 km altitude 98.6° inclination
Coverage During a 24-hour Period	Variable	< 41%	78%	92%



(from NSIDC)

The Advanced SCATterometers (ASCAT) on board METOP

- ERS successor, C-band, 25km resolution, 82% of the globe in 1 day



Scatterometer Sensitivity to Soil Moisture

Sensitive to:

- **vegetation**
- **soil roughness**
- **soil moisture**
- **not to surface temperature**

(Schmugge et al. 2002; Du et al., 2000)

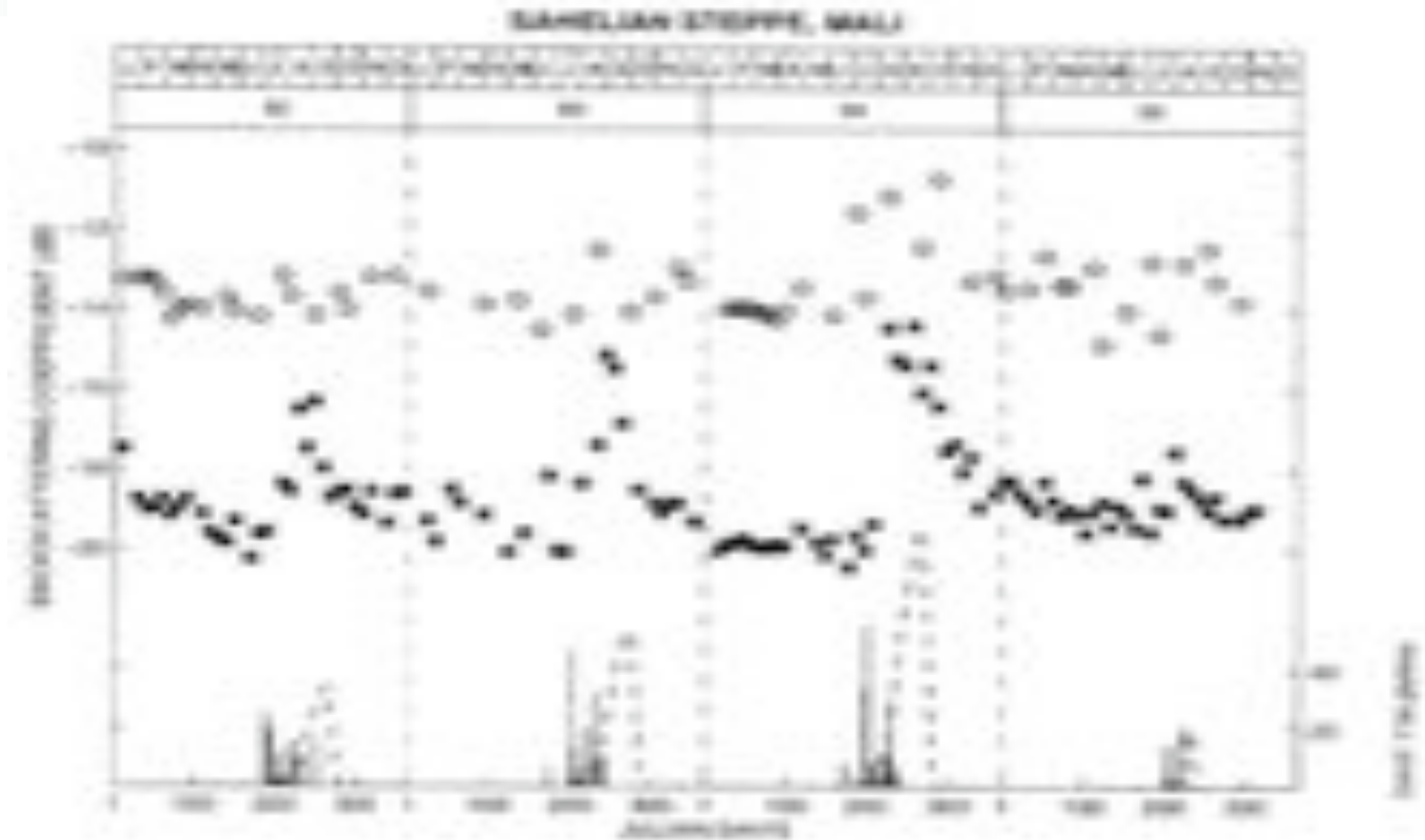
Depends on the observing angle

Satellite scatterometer observes the Earth with different angles:

- **each location not often seen with the exact same angle**
- **models developed to account for angle dependence**

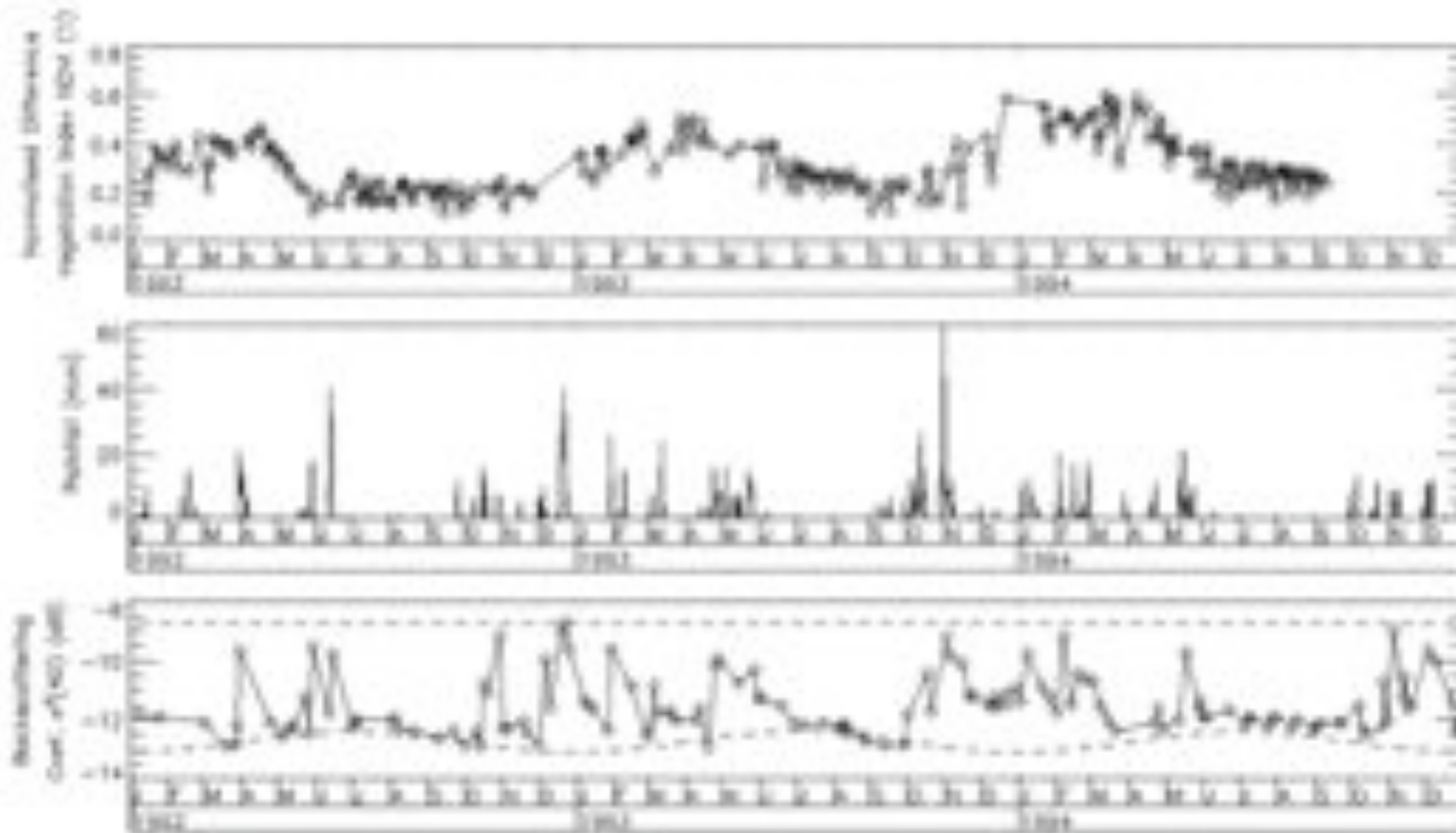


Scatterometer Sensitivity to Soil Moisture



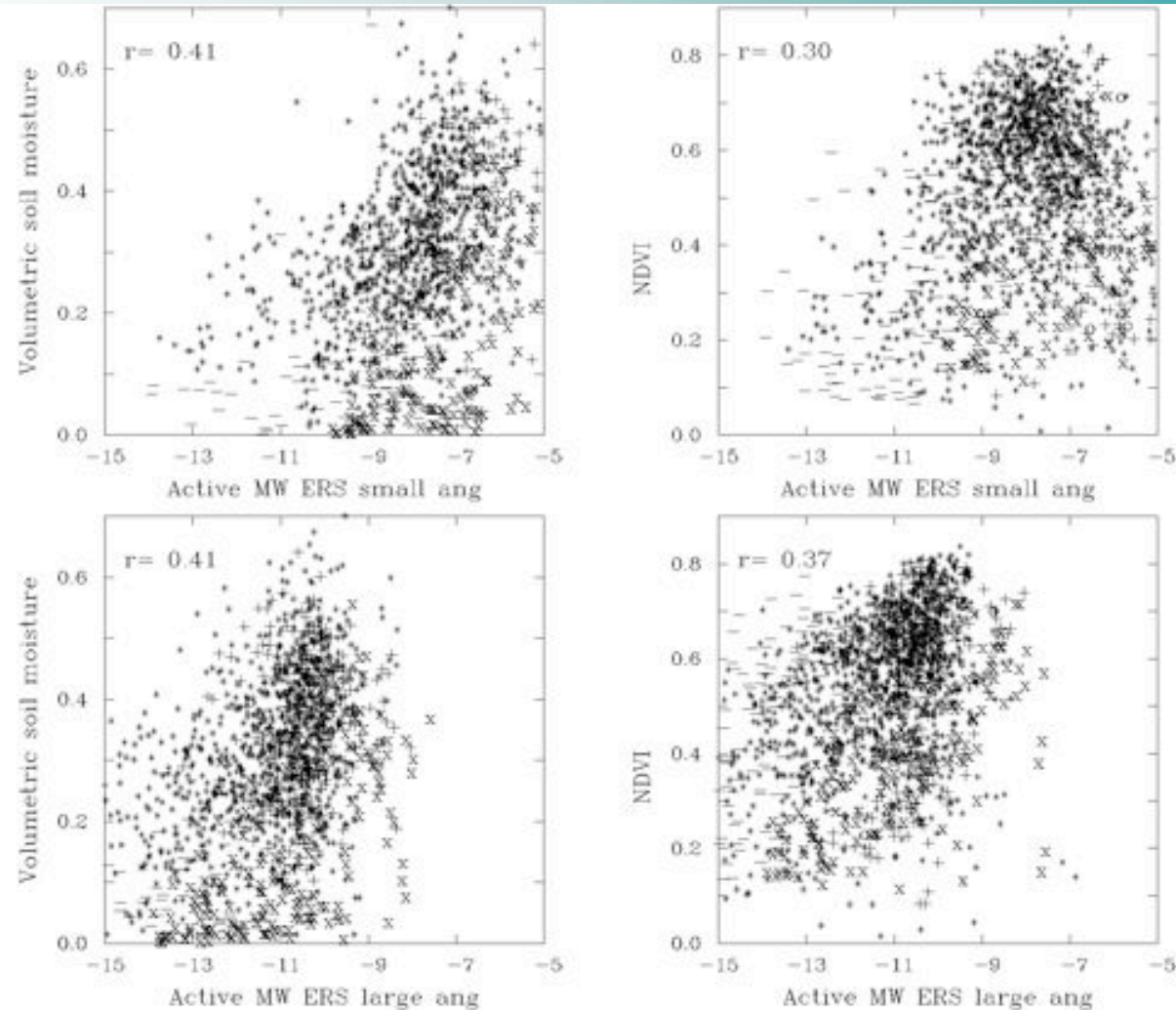
Temporal variation of the 10-day averaged backscattering at 20° (o) and 45° (*) incidence angle, for the northern Gourma (01/1992-12/1995). Rainfall (bars) and the green biomass (dotted line) also indicated (Frison et al., 1998)

Scatterometer Sensitivity to Soil Moisture



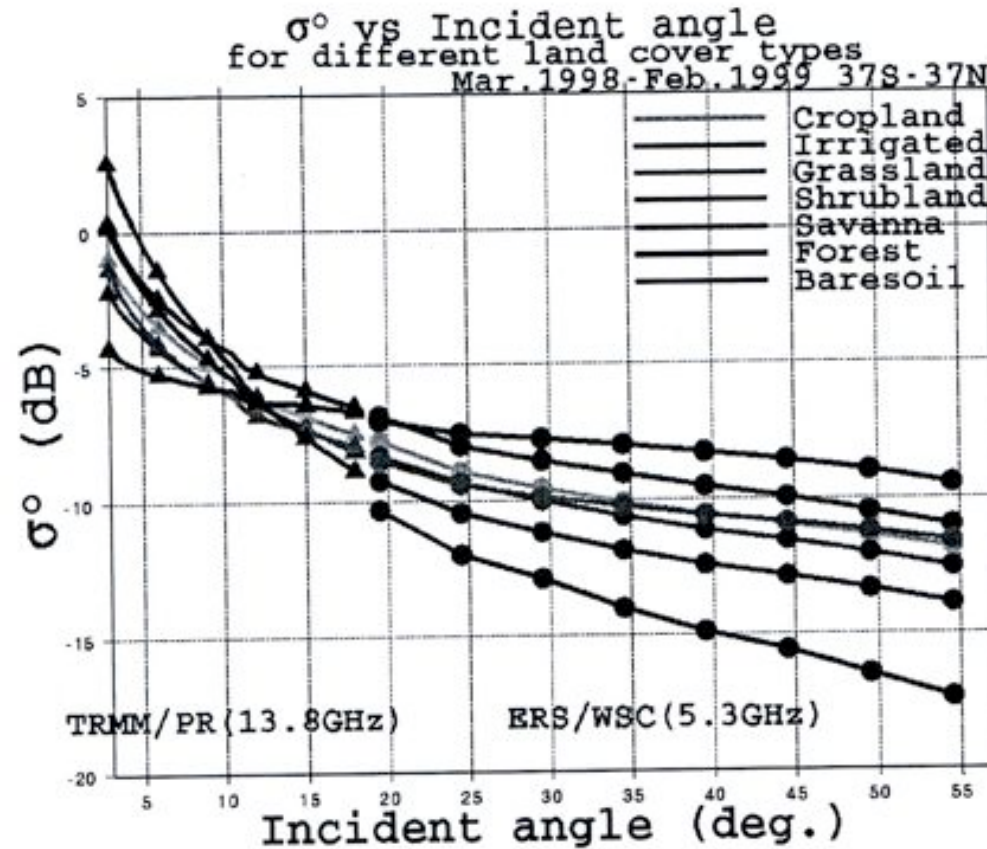
Temporal evolution of the NDVI, rainfall observations, and the normalized backscattering coefficient at 40° over an agricultural region in southern Portugal (Wagner et al., 1999b)

Scatterometer Sensitivity to Soil Moisture



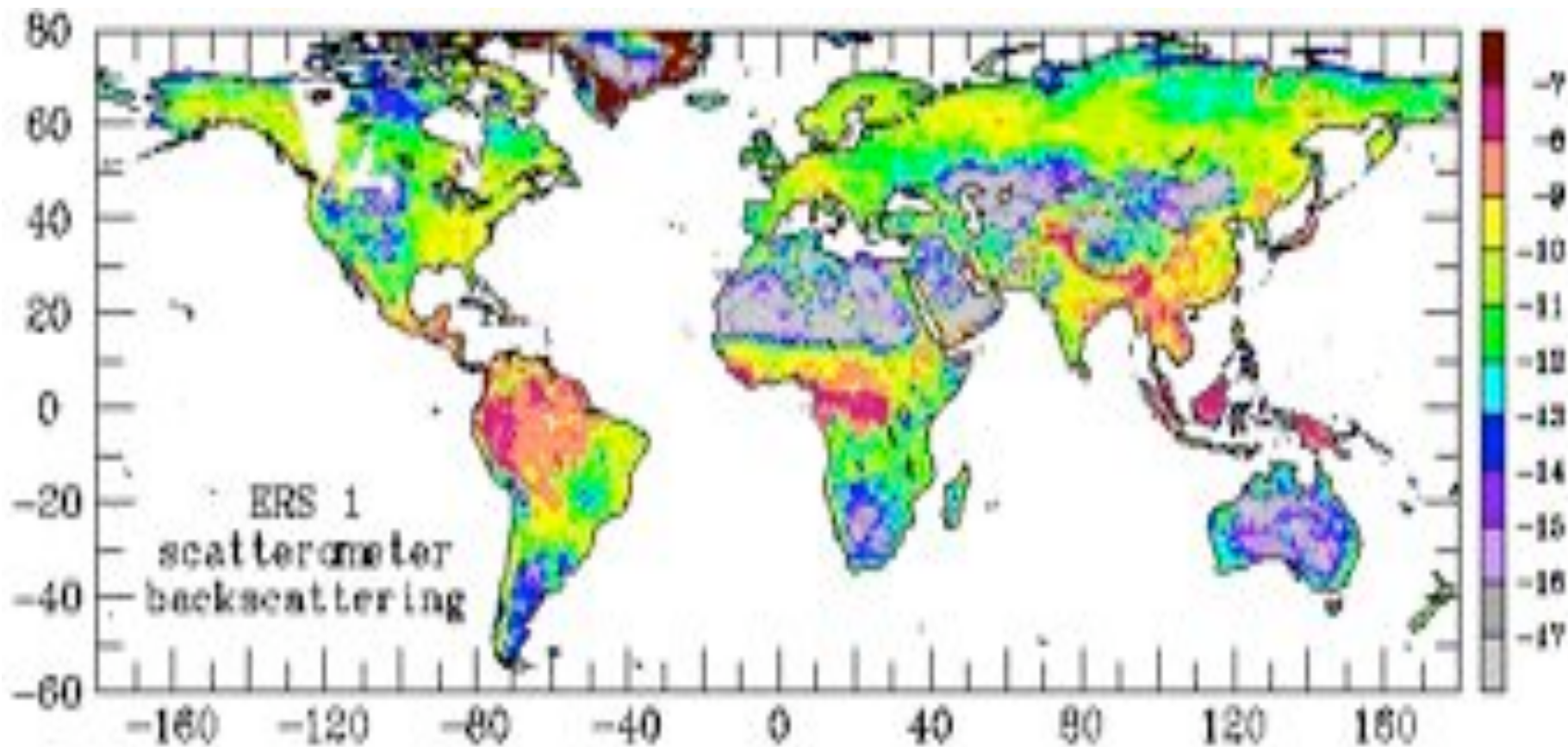
ERS observations versus in situ soil moisture (left) and NDVI (right) for 1993-1994 on a monthly basis. Upper panels for angles $< 30^\circ$, lower panels for angles $> 30^\circ$. Symbols: + Illinois, o Iowa, * Russia, x India, - Mongolia (Prigent et al., 2005)

Scatterometer Sensitivity to Soil Moisture



Annual average of the backscattering coefficient observed by TRMM/PR and ERS for different land cover (Seto et al., 2003)

Scatterometer Sensitivity to Soil Moisture



Monthly mean ERS backscattering coefficient (dB) measured by the 3 antennas and linearly interpolated at 45° for July 1992

Scatterometer Sensitivity to Soil Moisture



From literature review:

- clear sensitivity to soil moisture
- vegetation impact also very important

- depending on the authors and their objectives, one sensitivity or the other emphasized...

- relative contributions strongly depend on environment and difficult to separate

Soil Moisture Retrieval Methods



Physical algorithms based on radiative transfer calculations

- more or less complex radiative transfer
- locally calibrated
- significant amount of ancillary information
- local application
- extension questionable

Pulliainen et al. (1998): Boreal forest in Europe

Woodhouse and Hoekman (2000): Sahel and Spain

Jarlan et al. (2002): Sahel

Grippa and Woodhouse (2002): Niger and Sweden

Soil Moisture Retrieval Methods

Detection change methods

- **multiple sources of variability at a global scale**
- **locally, reduced number of variability**
- **variation in vegetation accounted for by ancillary information**
 - **different sensitivity at different angle (Wagner et al., 1999)**
 - **NDVI observations (Wen and Su, 2003)**

Extensive work from Wagner et al.

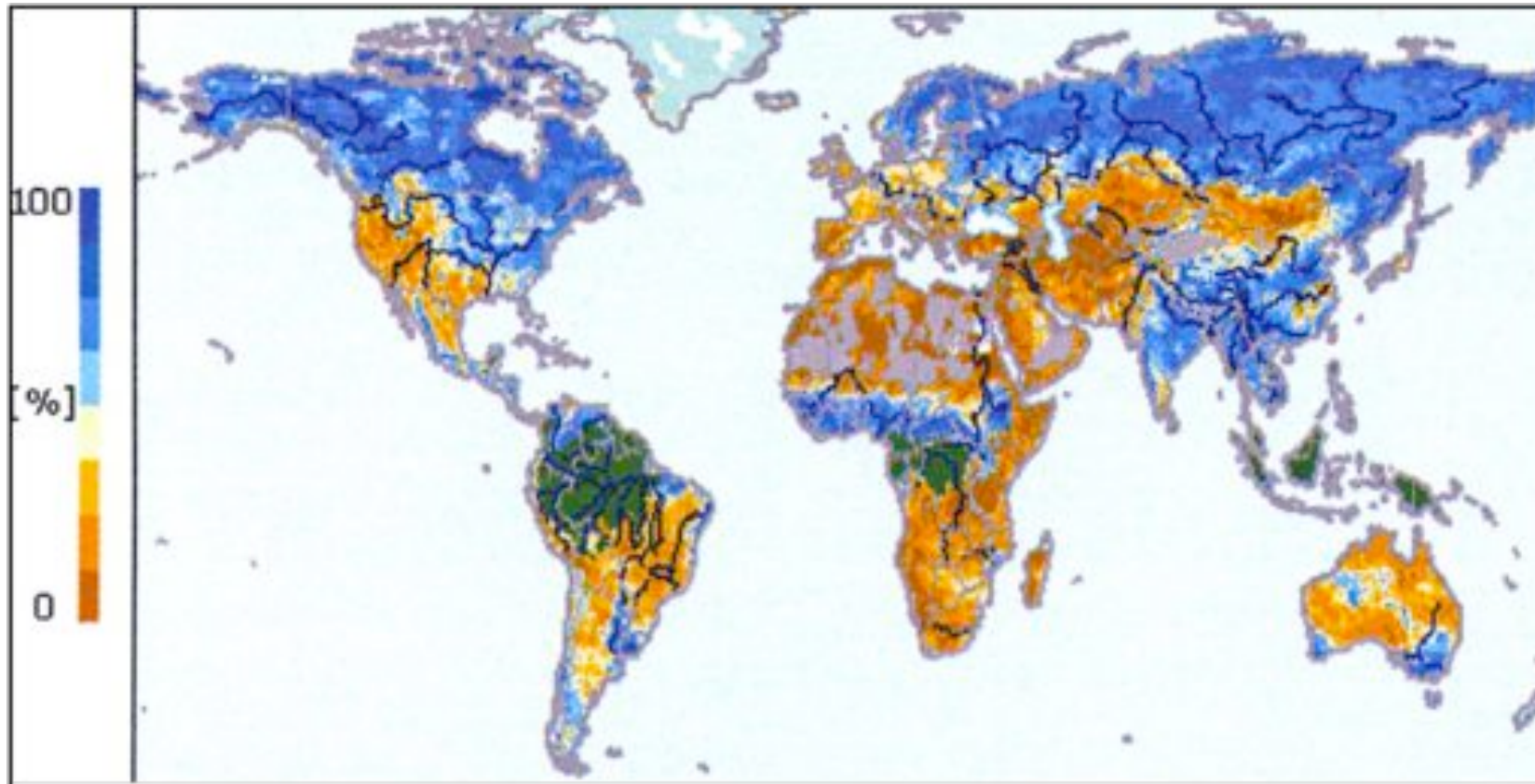
- **for a given location, soil moisture principal source of variability**
- **vegetation taken into account by the slope parameters**
- **min (dry) and max (saturated) scattering values to define the soil moisture index**
- **9 years of soil moisture index**
- **compared to precipitation and to model outputs**

See also Wen and Su (2003):

- **vegetation, soil moisture, roughness have different time variations**
- **NDVI observations to estimate vegetation contribution**

Soil Moisture Retrieval Methodologies

Detection change methods



Example of global soil moisture index, Wagner et al.

Limitations:

- can be valuable at a local basis
- qualitative estimate, unless calibrated locally
- for comparison from an area to the next, comparison of moisture index impossible

3) Summary



ERS scatterometer provides the only long time record.

Sensitivity to soil moisture...but also to vegetation and roughness

Two types of methods developed:

**physically-based methods (complex, local)
detection change (global, index only)**

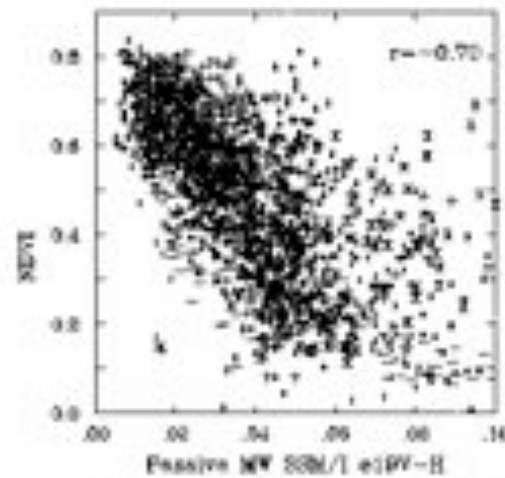
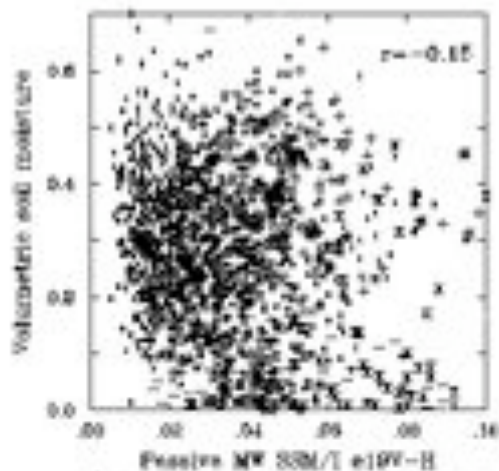
Limited use of the synergy with other instruments so far

Recent work to combine scatterometer data (ERS), radiometer observations (SSM/I), NDVI, and Ts diurnal cycle amplitude (Prigent et al., Aires et al., JGR, 2005)

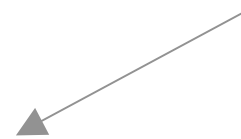
Combined use of scatterometer and other satellite data

First, systematic and objective analysis of collocated satellite data and in situ soil moisture measures for 2 years:

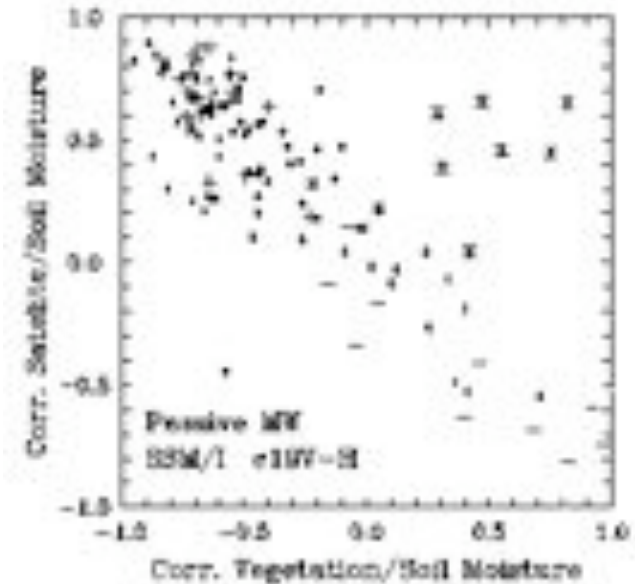
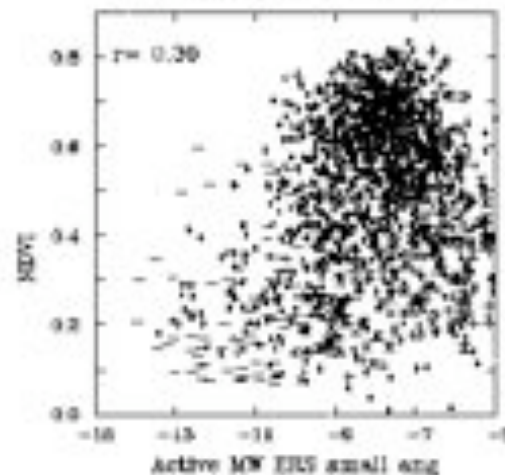
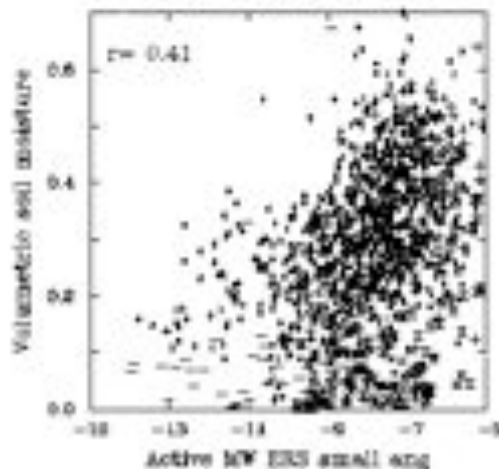
- satellite data: MW emissivities, MW σ^0 , TIR Ts cycle, NDVI
- Global Soil Moisture Data Bank (Robock et al., BAMS, 2000)



Lower correlation between satellite observations and soil moisture than with vegetation



Correlation satellite / soil moisture related to correlation vegetation / soil moisture



Combined use of scatterometer and other satellite data

Second, find a method that uses all information sources, even the soil moisture and vegetation link at global scale



- SSM/I MW
- TIR Ts Ampl.
- ERS σ^0
- NDVI

Statistical model



(Neural Network)

Soil Moisture

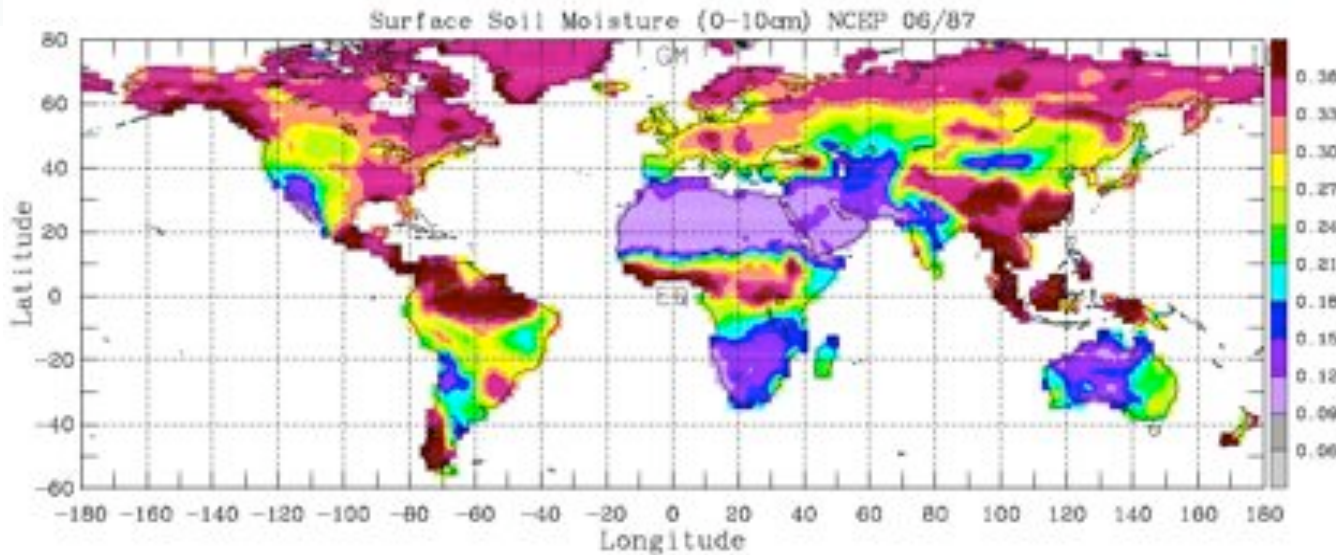
Advantages of this method:

- Does not depend on radiative transfer codes that can be questionable globally
- Data-fusion of multi-spectral satellite observations
- Nonlinear model \Rightarrow situation-dependent (important for global scale)

Applications:

- Consistency checking method: Check the consistency of model output with satellite observations
- Variational assimilation applications: Define a link between observations and model (link coherent with model); additional constraint to the model: spatial and temporal coherency with satellite observations

Combined use of scatterometer and other satellite data



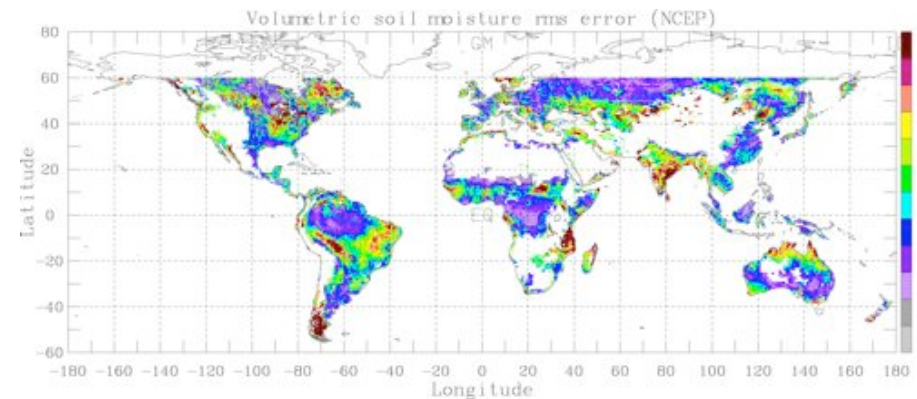
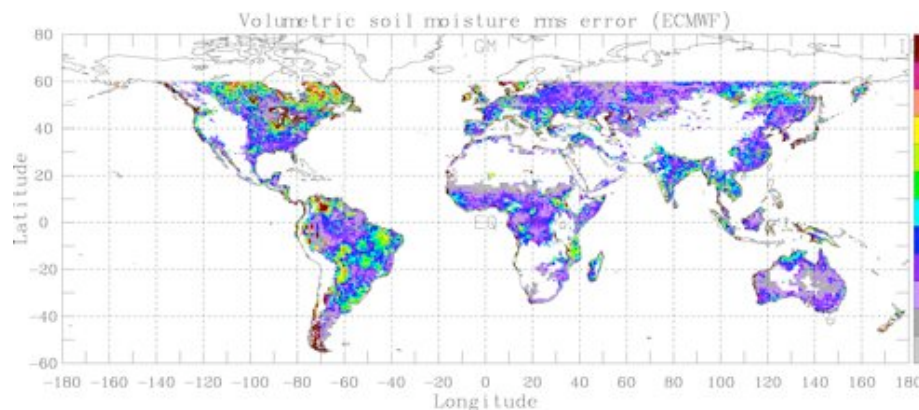
(NCEP)

Consistency checking between model outputs and satellite observations

ECMWF

RMS error statistics

NCEP



Synthesis



The European Space Agency (ESA) has planned to launch an L-band passive microwave instrument designed to measure Soil Moisture and Ocean Salinity (SMOS), with which it is expected to retrieve soil moisture at high accuracies. In anticipation to the SMOS data availability, existing methods for estimation of soil moisture are reviewed. With the increasing number of operational earth observation satellites, the focus on synergistic approaches is steadily growing. Signatures and retrieved entities from different sensor types are additive in many cases and combination of such entities may lead to significant improvements of the retrieval of soil moisture and related parameters.

SAR/ASAR: Conclusions

- Physical, semi-empirical and empirical methods have been discussed for soil moisture retrieval from SAR observations.
- Physical models such as MIMICS (Ulaby et al. 1990) require often a detailed parameterization of the vegetation and soil surface layer, which is typically not available.
- Soil moisture applications that use semi-empirical models have frequently generated good results for specific areas, but when these techniques are applied to other locations or other field conditions the accuracy of the soil moisture products decreases significantly.
- Empirical methods that are based change detection yield often accurate soil moisture results, but are strictly speaking not valid for application that exceed the calibration conditions.
- Thus, currently SAR methods are not able to estimate soil moisture with sufficient accuracy that can be used to assist disaggregating SMOS soil moisture products.
- Further, the revisit time of the present and future SAR systems for exactly the same configuration exceeds 15 days. This is often not sufficient for global soil moisture monitoring products.
- Despite these disadvantages of SAR based soil moisture retrieval, the proposed L-band PALSAR instrument onboard the Japanese ALOS satellite offers the opportunity of retrieving soil moisture in a combined passive/active microwave approach.
- The combination of passive and active microwave observations is expected to increase the accuracy of the retrievals and can yield high resolution soil moisture maps.



Microwave radiometer methods: Conclusions

- Four soil moisture retrieval algorithms using passive microwave observations have been discussed: Jackson et al. (1993), Bindlish et al. (2003), Owe et al. (2001) and Wen et al. (2003). Each of these methods performs equally under similar vegetation conditions with the adjustment of a few parameters and is capable of retrieving soil moisture with accuracy in the order of 3-5 Vol.-% (Hurkmans et al. 2003).
- The Jackson algorithm uses a physically based methodology, but requires several additional data sources for operational applications, such as temperature of the emitting layer, optical depth and vegetation cover. The dependency to these different ancillary data sets has been partly resolved by Bindlish et al (2003). However, the retrieval of the optical depth is related to the *NDVI*, which is not desirable. The *NDVI* is sensitive to changes in *W*, but not to dry biomass. Thus, for tree-type vegetation cover lower *NDVI* values are observed than for tall grass lands, which do not correspond to response of microwaves. Further, the signal of the *NDVI* saturates at intermediate levels of *W* (Jackson et al. 2003).
- Preferably, the optical depth is estimated from the radiometer observations itself. Owe et al. use, the *NPDI* to invert the dielectric constant and the optical depth, simultaneously. However, retrieving two variables from one observation might lead to non-unique solutions. The method proposed by Wen et al. (2003) is more promising. It uses the *NPDI* of a bare soil surface and of a vegetated surface to retrieve the optical depth. The only difficulty in applying this technique is to find a *SMOS* footprint (~15 km), which is only influenced by bare soil radiation.



Microwave radiometer methods: Conclusions



- As a surface emission model, the one proposed by Wang and Choudhury (1981) is physically more adequate, because it accounts for depolarization effects caused by surface scattering. A disadvantage is that both H- and V-polarized Fresnel reflectivity's need to be solved requiring two observations. This might cause difficulties, because the MIRAS instrument is proposed to be a dual polarized radiometer and has, thus, potentially three independent observations: τ , ρ , and $NPDI$. A soil moisture retrieval algorithm including the Wang and Choudhury surface emission model has four unknowns: the temperature of the emitting layer, the optical depth and the H- and V-polarized reflectivity.
- Alternatively, the surface emission model of Choudhury et al. (1979) requires only one independent observation. This would leave one brightness observation for the estimation of the temperature of the emitting layer, but previous studies have shown the difficulty of relating low frequency observations to the temperature of the emitting layer because of their dependence to change in soil moisture (De Jeu and Owe 2001).
- For a future SMOS soil moisture retrieval algorithm it would be more beneficial to use a physically based surface emission model and estimate the temperature of the emitting layer from other data sources. Several other data sources are available, such as in-situ measuring networks, meteorological model predictions and remote sensing observations.

COMBINED ACTIVE AND PASSIVE METHODS: CONCLUSIONS



- The theoretical algorithm for passive and active microwave soil moisture retrieval proposed by O'Neill et al. (1996) is from a physical point of view the most suitable method to combine radiometer and SAR observations into one soil moisture retrieval algorithm. However, the scattering model used in this algorithm requires several canopy parameters that are a-priori not known and can not be derived from other satellite observations.
- Njoku et al. (2002) uses a physically based radiative transfer approach for passive microwave observations and applies a change detection method for the SAR measurements. With the availability of both SMOS and PALSAR sensors this methodology can be applied on a large scale. However, global soil moisture monitoring applications are not feasible, because the revisit time of the PALSAR is 44 days.

Wind scatterometer method: Conclusion



- The wind scatterometers have characteristics that are very valuable for long term monitoring of global land surface parameters: they cover the globe with a spatial resolution and sampling rates that are fully compatible with regional to global applications. In addition, they have a very high instrumental stability that is adequate for the analysis of long time series.
- The backscattering coefficients are sensitive to several factors, surface roughness, vegetation and soil moisture essentially, their respective contribution varying with the environment. The contributions from the vegetation and the soil moisture are complicated and their separation is not trivial.
- Two different approaches have been attempted to retrieve soil moisture information from wind scatterometer data, the physically-based methods and the empirical change detection technique.
- The modeling approach makes it possible to better understand the measurement processes. However, it can be difficult to implement even on a regional scale: it requires ancillary information that are not always available and / or specific calibration for each environment.
- The detection change schemes have demonstrated the sensitivity of scatterometer measurements to variations in surface soil moisture at a given location. External information like the NDVI or the analysis of multiple angle observations helps subtract the vegetation contribution from the signal. These methods provide soil moisture indexes for a given location but, contrary to the modeling approach, they cannot directly estimate quantitative soil moisture information, unless they are calibrated using external data sources.
- Recent developments include the use of multi-satellite information and land surface model outputs to better constrain the problem. For example, Prigent et al. [2005] and Aires et al. [2005] combine land surface model outputs and a suite of satellite data from the visible to the microwave on a global basis over two years, to derive soil moisture estimates. The satellite data include: ERS scatterometer data at low and high angles, passive microwave emissivities calculated from SSM/I, thermal infrared information derived from the available geostationary satellites and the AVHRR visible and near-infrared reflectances. Using multi-satellite information clearly helps separate the contributions from the vegetation and the soil and makes it possible to derive a soil moisture estimate with a theoretical error within 5%