Satellite Remote Sensing and Applications of Land-Climate Interactions

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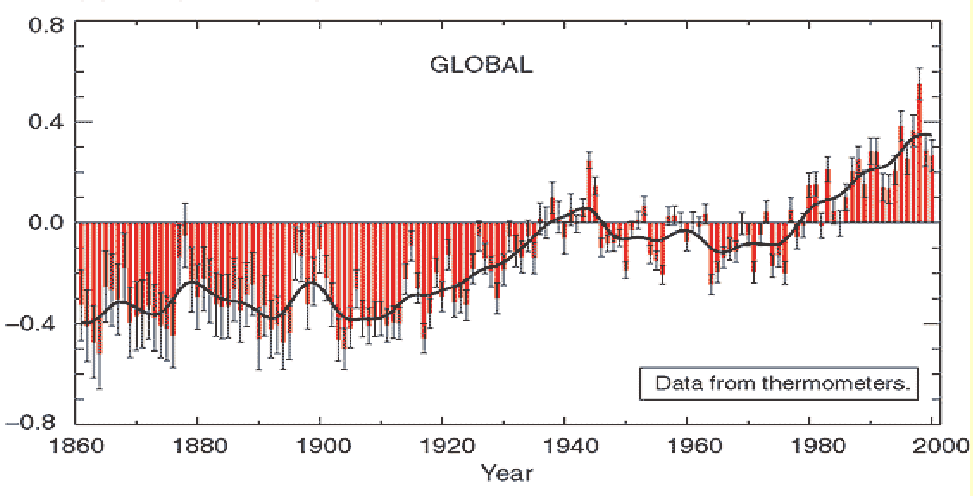
Motivation?

Changes in Climate

- Global mean surface temperature has risen by about 0.6°C over the 20th century, with the largest increase in the past two decades (*IPCC*, 2001).



Global mean surface temperature anomaly relative to 1951-1990

- Global land surface precipitation has increased significantly (by about 2%) over the 20th century (*IPCC*, 2001).

Land and Climate Interactions

- Land and climate are closely coupled.

biogeophysical processes
(water, energy, heat, momentum, carbon exchanges)

climate $\longleftrightarrow$ **land**

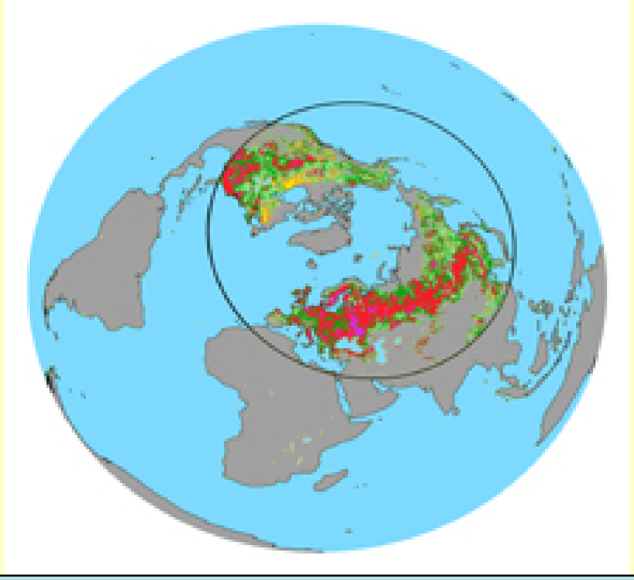
biogeochemical processes
(photosynthesis and respiration)

- Understanding land-climate interactions is crucial to evaluate the future state of climate.

Outline

- **Response of vegetation to climate change**
- **Land surface feedbacks on climate**
- **Improving land-climate interaction modeling**
- **Future work**

Topic I: Response of Vegetation to Climate Change



A hypothesis for warming-enhanced plan growth in the north since 1980s

(Zhou et al., JGR, 2001; 2003a; Kaufmann, Zhou et al., IEEE, 2000; Bogaert, Zhou et al., JGR, 2002)

Have Climate Changes Promoted Northern Vegetation Growth?

Changes in Climate

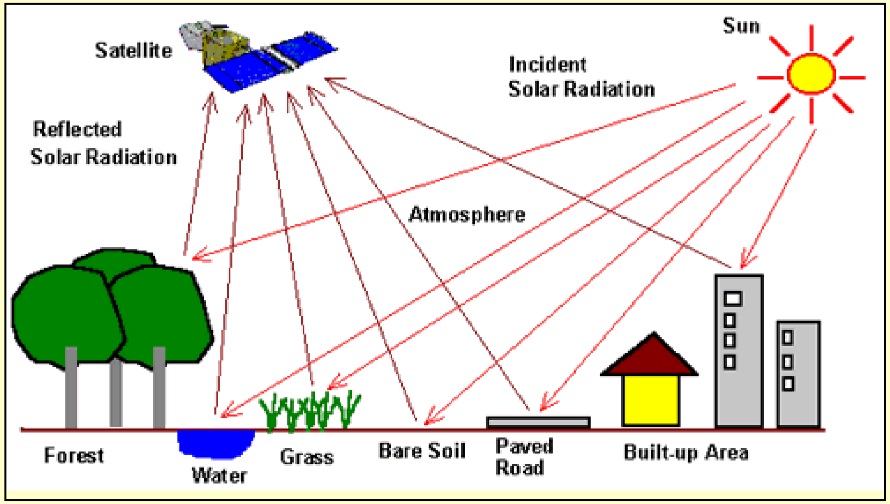
- Pronounced warming in northern high latitudes
- Earlier disappearance of snow in spring
- Increased precipitation in northern high latitudes
- Increased concentration of atmospheric CO_2

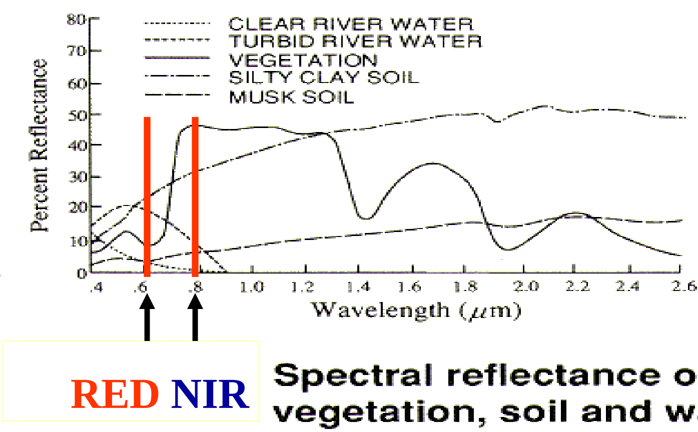
?

Changes in Vegetation

- Increased productivity through:
  - ➢ enhanced photosynthesis
  - ➢ enhanced nutrient availability

Satellite Remote Sensing of Vegetation





Spectral reflectance of vegetation, soil and water

Greenness Index:

Normalized Difference Vegetation Index (NDVI)

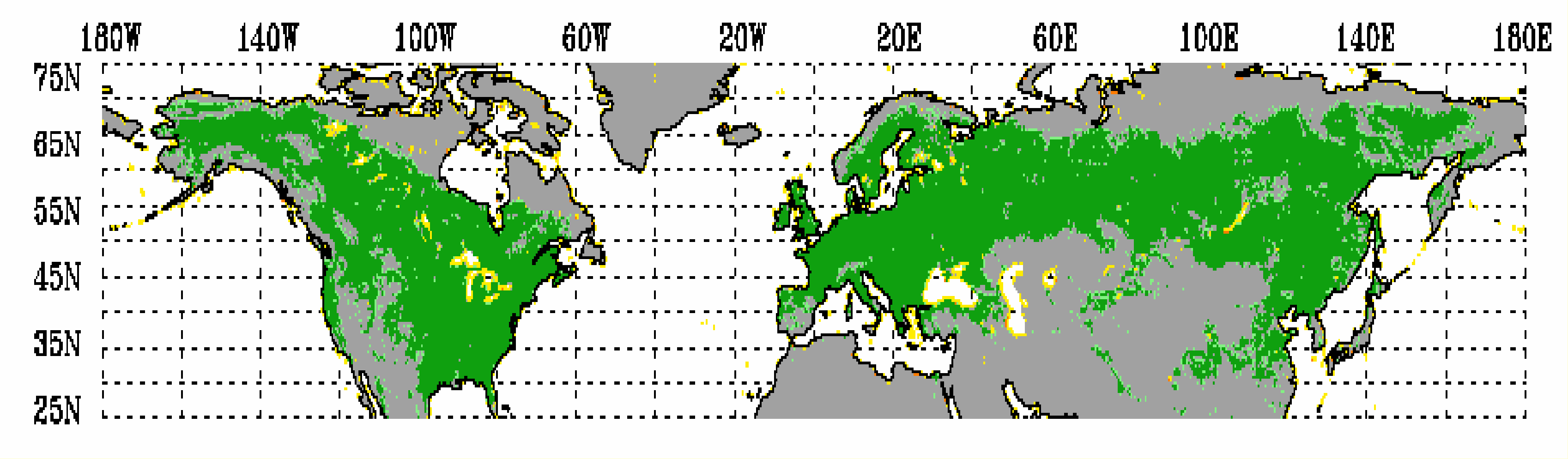
NDVI=(NIR-RED)/(NIR+RED)

Data

- GIMMS 15-day composite 8 km **NDVI** from 1981 to 1999
- Observed monthly land surface climate data (1981-1999)
  - NOAA **precipitation**: 2.5°x2.5°
  - GISS **temperature**: 2°x2°
- A **land cover** map at 8 km resolution

Study Region

- Vegetated pixels between April to October
  - ➢ minimize the non-vegetation solar zenith angle effects (e.g., satellite drift and changeover)
  - ➢ reduce the non-vegetation background contribution (e.g., snow and bare soils)

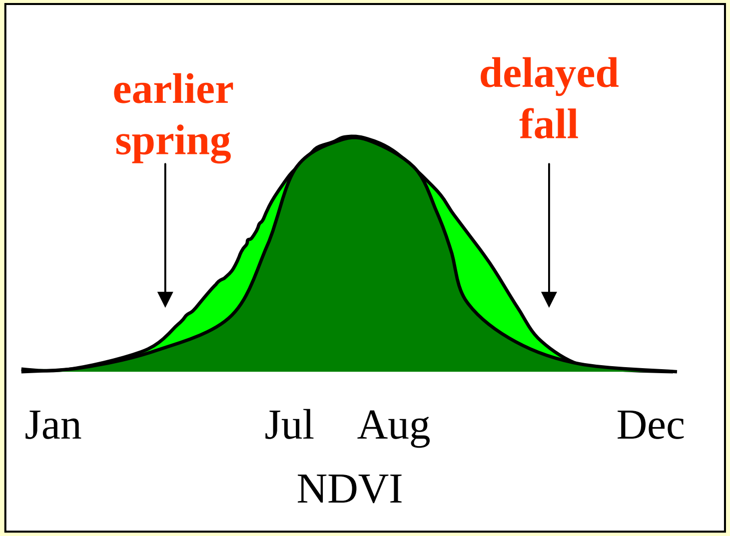


Map of vegetated pixels at 8 km resolution

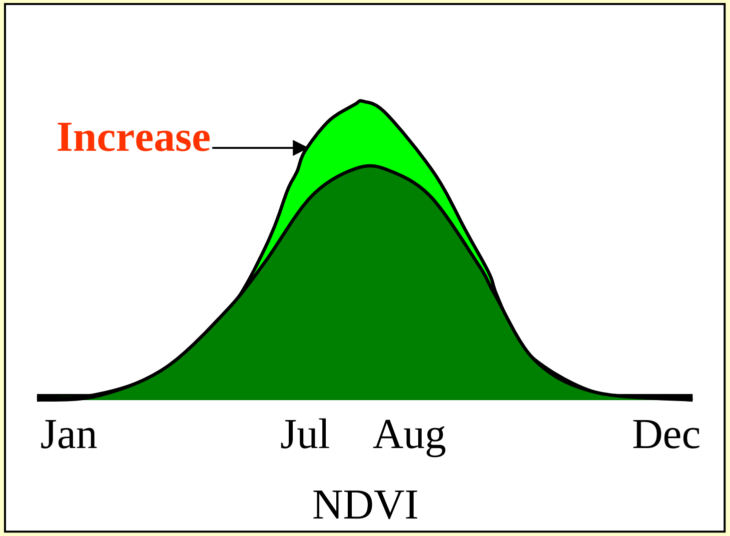
Changes in Vegetation Activity

- Changes in vegetation photosynthetic activity can be characterized by
  - changes in growing season duration
  - changes in NDVI magnitude

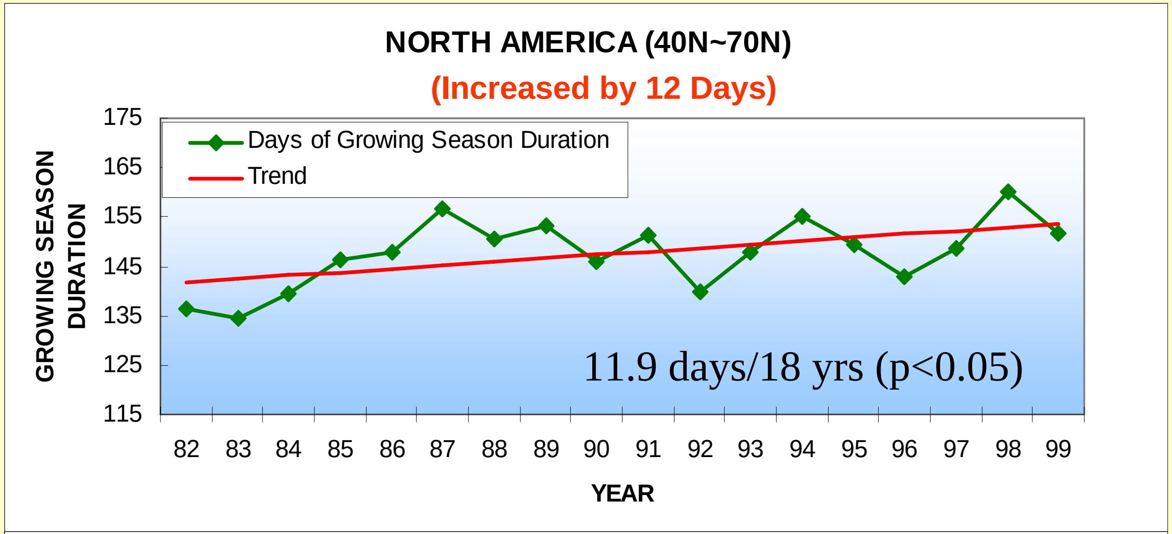
Longer growing season

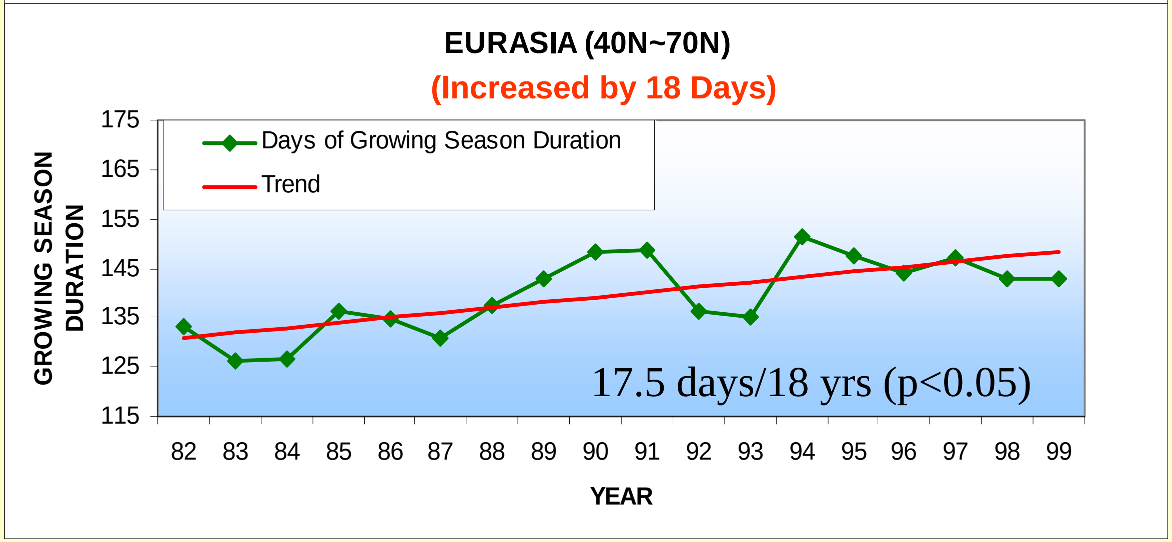


Increases in NDVI magnitude

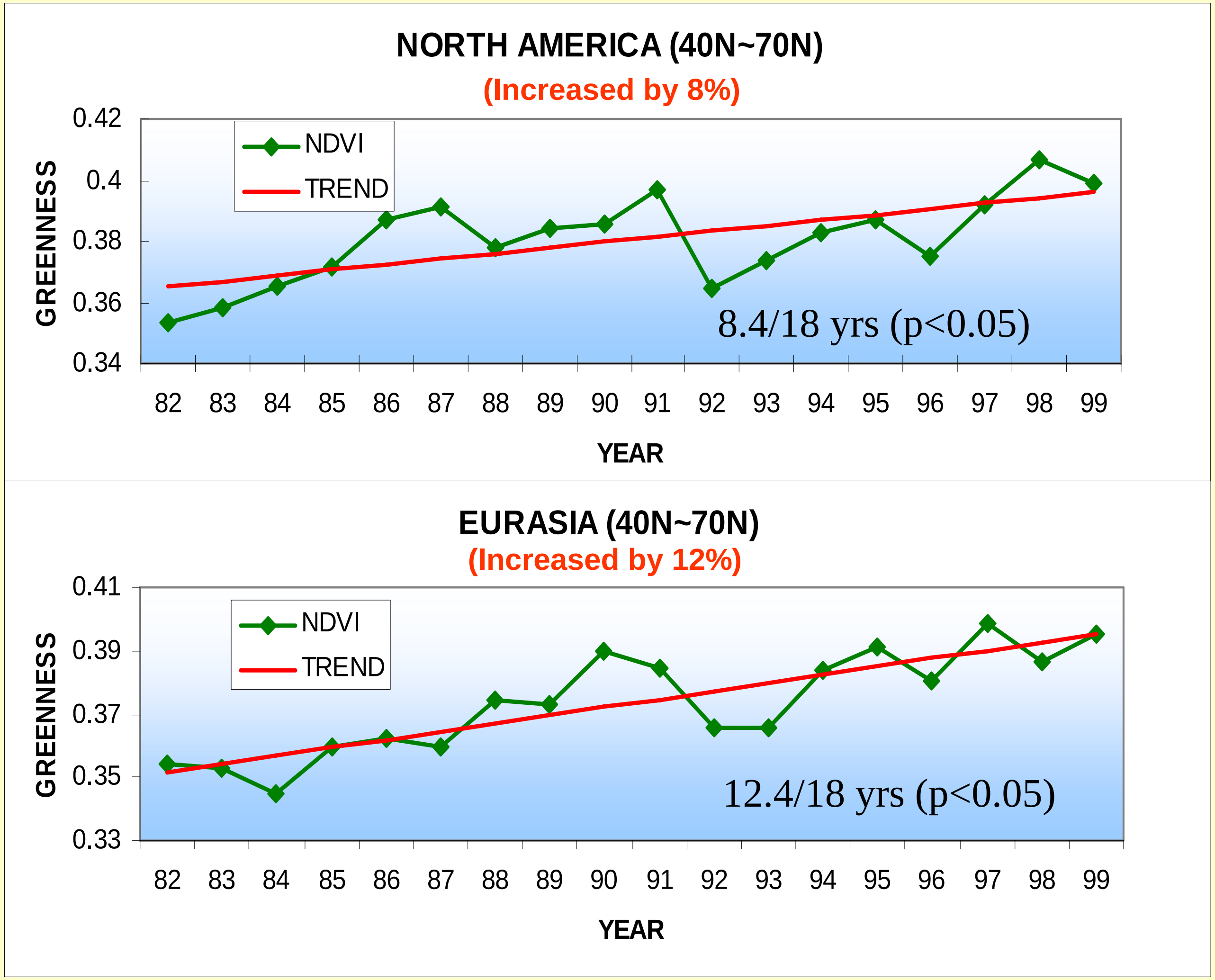


Lengthening in Growing Season

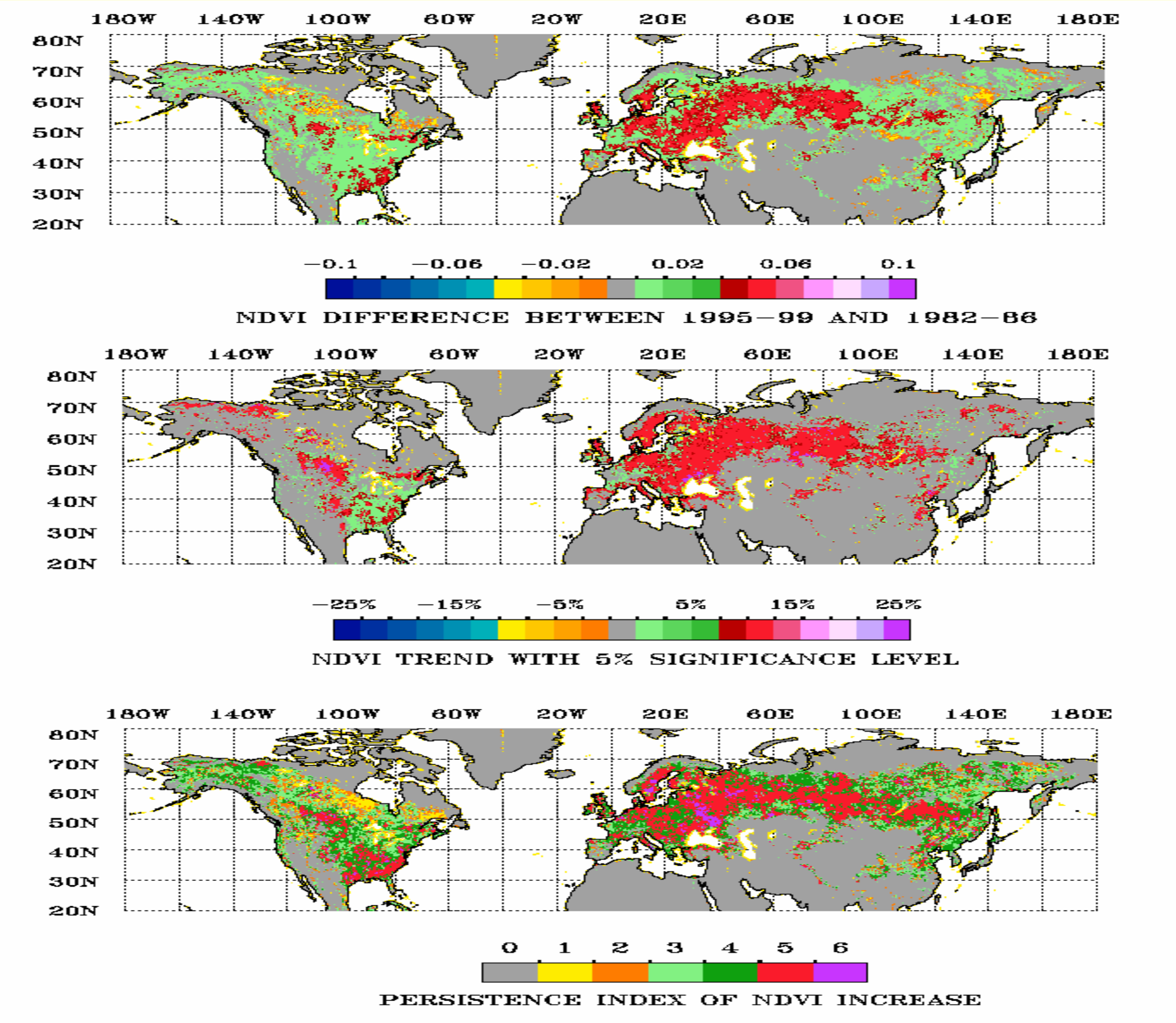




Increase in NDVI Magnitude

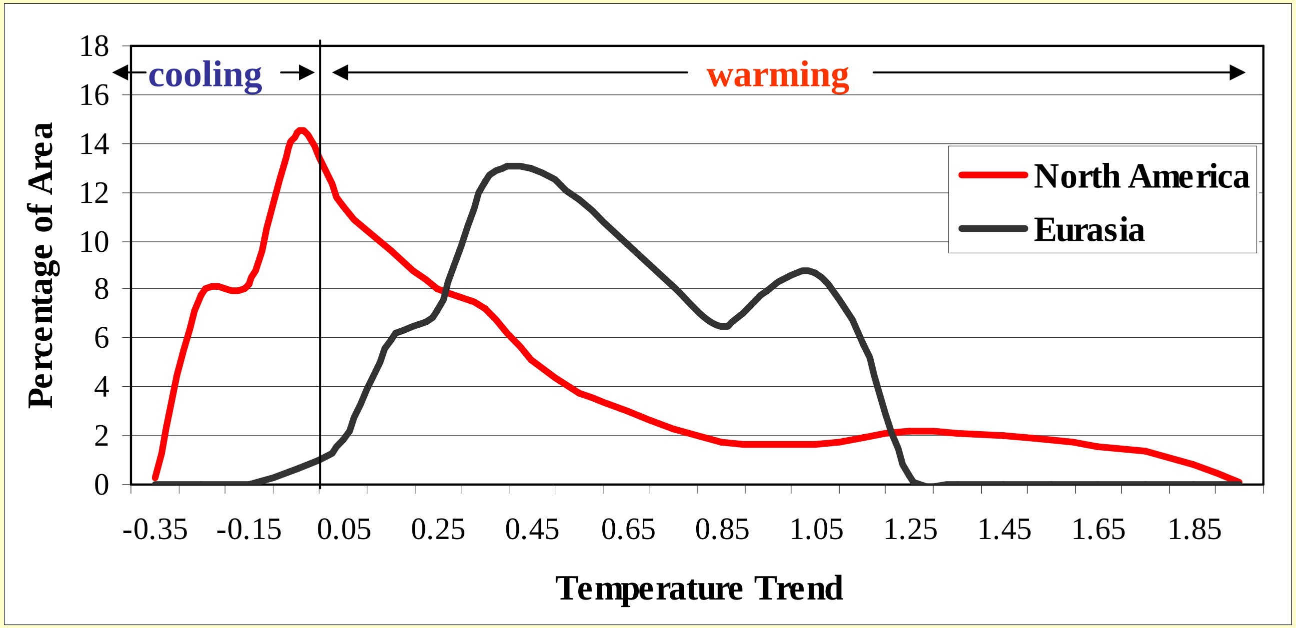


Spatial Patterns of Greening

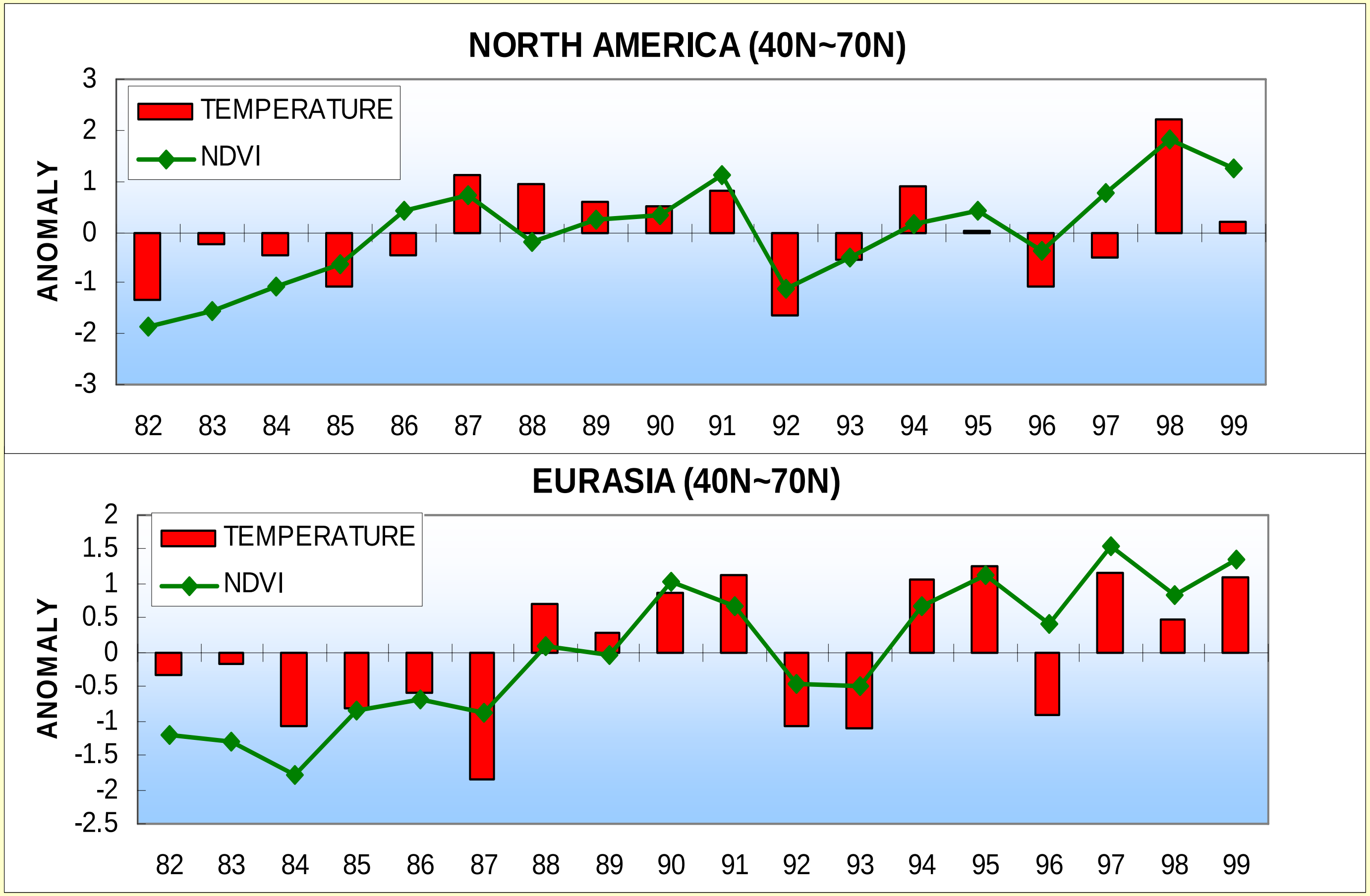


Continental Differences in Warming

- The greatest warming occurred during winter and spring.
- Eurasia has an overall warming while North America has smaller warming or cooling trends.



Positive NDVI-Temperature Correlation



Statistical Results at Continental Scale

y	x	Is there a statistically meaningful relation?		
		$y = \beta_0 + \beta_1 x + \varepsilon$	$y = \beta_0 + \beta_1 x + \beta_2 \text{time} + \varepsilon$	$\Delta y = \beta_0 + \beta_1 \Delta x + \varepsilon$
EA NDVI	EA T	**yes**	**yes**	**yes**
NA NDVI	NA T	**yes**	**yes**	**yes**
EA NDVI	NA T	**no**	**no**	**no**
NA NDVI	EA T	**no**	**no**	**no**

Note: T – Temperature; EA – Eurasia; NA – North America

Model NDVI at Regional Scale

$$\begin{aligned}\mathrm{NDVI}_{\mathrm{summer}} = {} & \beta_{11} T_{\mathrm{winter}} + \beta_{12} T^2_{\mathrm{winter}} + \beta_{21} T_{\mathrm{spring}} + \beta_{22} T^2_{\mathrm{spring}} + \beta_{31} T_{\mathrm{summer}} \\ & + \beta_{32} T^2_{\mathrm{summer}} + \beta_{41} P_{\mathrm{winter}} + \beta_{42} P^2_{\mathrm{winter}} + \beta_{51} P_{\mathrm{spring}} + \beta_{52} P^2_{\mathrm{spring}} \\ & + \beta_{61} P_{\mathrm{summer}} + \beta_{62} P^2_{\mathrm{summer}} + \beta_{7} \mathrm{SZA}_{\mathrm{summer}} + \beta_{8} \mathrm{AOD}_{\mathrm{summer}} \\ & + \alpha_{\mathrm{summer}} + \varepsilon\end{aligned}$$

- Panel data analysis: data aggregated into 2°x 2° boxes by seasons and vegetation types: 1430 boxes

- T and P represented by a quadratic specification (a physiological optimum) with effects for earlier seasons.

- SZA and AOD used to separate non-vegetation effects.

- βs estimated using statistical techniques from econometrics.

Statistical Results at Regional Scale

variables	Is there a statistically meaningful relationship?	R^2
T	**yes**	**largest**
P	**yes**	**small**
AOD	**yes**	**small**
SZA	**yes**	**smallest**

Note: T - Temperature; P - Precipitation; AOD - Stratospheric aerosol optical depth; SZA - Solar zenith angle

Conclusions

- **Eurasia** is **photosynthetically more vigorous** than **North America** during the past two decades:
  - **Eurasia** has a **higher** percentage of vegetated pixels (61% vs. 30%) showing a **larger** increase in the NDVI magnitude (12% vs. 8%) and a **longer** active growing season (18 vs. 12 days) than **North America**.
- There is a **statistically meaningful relationship** between changes in satellite measured **NDVI** and those in observed surface air **temperature** at continental and regional scales.
- These results suggest a hypothesis for **warming-enhanced plant growth** in the north since 1980s.

(Zhou et al., JGR, 2001; 2003a)

Topic II: Land Surface Feedbacks on Climate

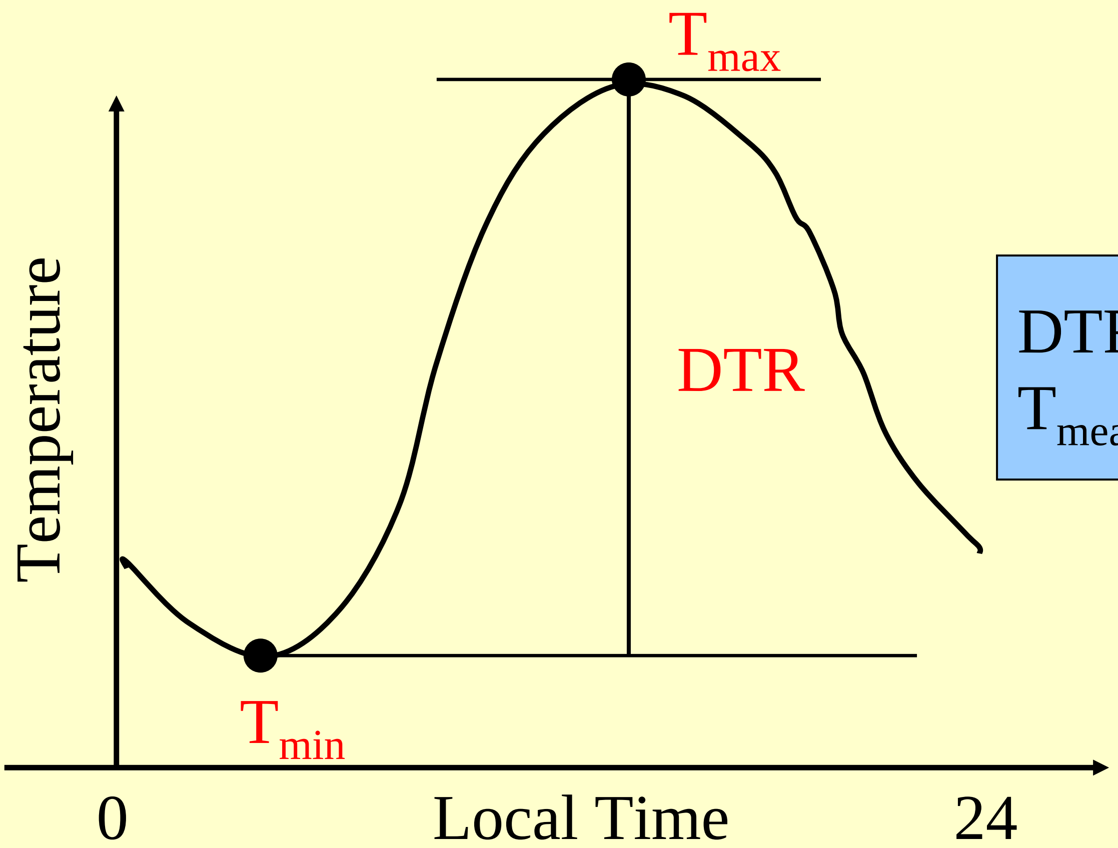
climate ← **land**

A hypothesis for impacts of drought and vegetation removal on climate over semi-arid regions

(*Zhou et al., PNAS, 2007; Zhou et al., JGR, 2007*)

Diurnal Cycle of Surface Air Temperature

- Maximum/minimum temperature (T_{max}/T_{min}), diurnal temperature range (DTR), and mean temperature (T_{mean})



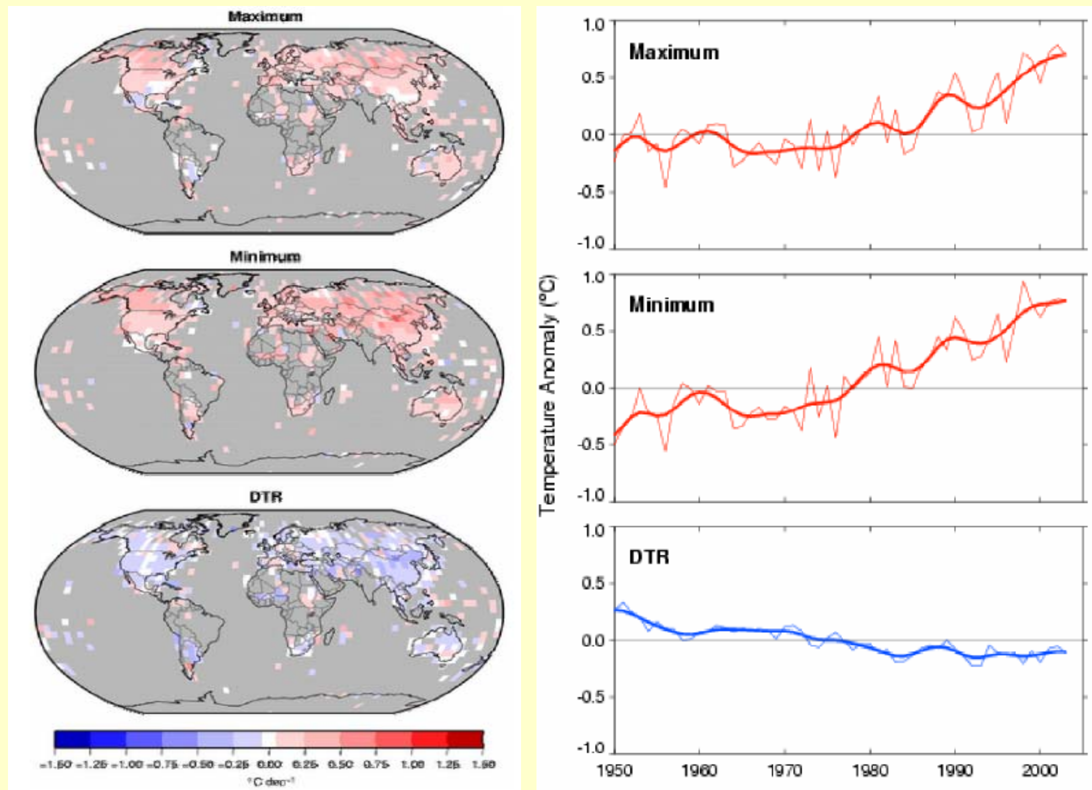
$DTR=T_{max}-T_{min}$
$T_{mean}=(T_{max}+T_{min})/2$

Global Warming vs DTR Reduction

- T_{min} warms much faster than T_{max} $\rightarrow$ $T_{mean}\uparrow$ and DTR$\downarrow$
- DTR trends are a signal connected to global warming

$DTR=T_{max}-T_{min}$

$T_{mean}=(T_{max}+T_{min})/2$

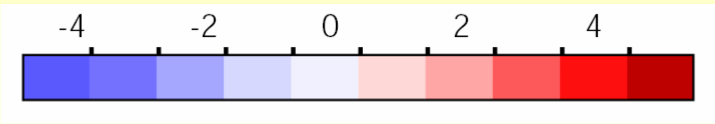


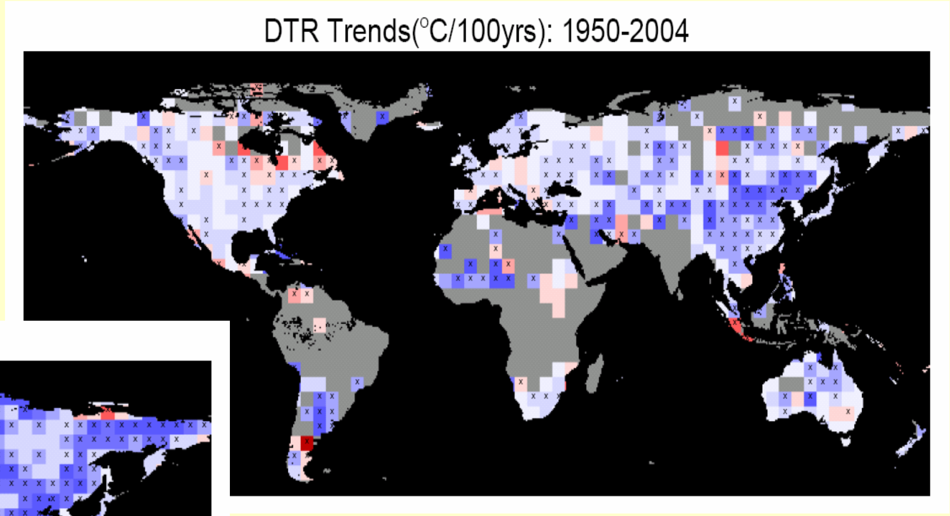
Trend and time series of annual T_{max},T_{min}, and DTR for 1950-2004

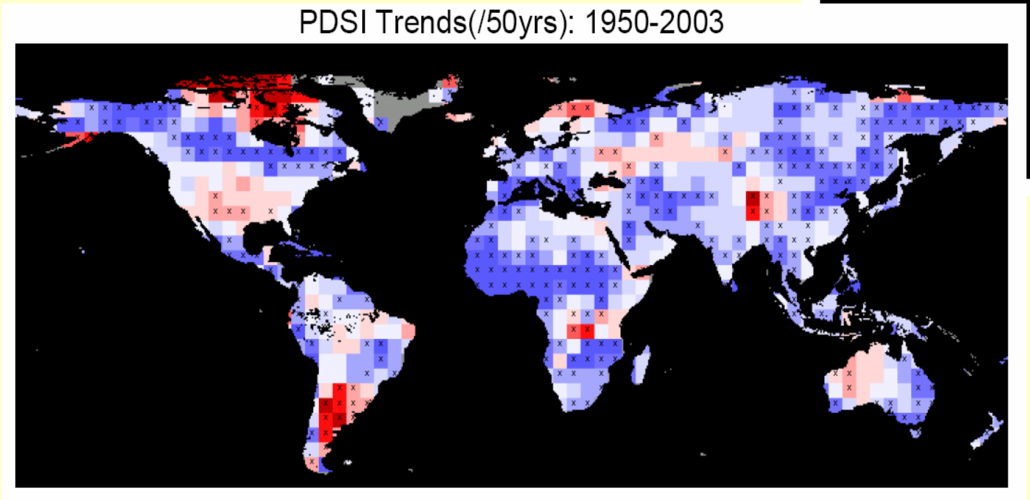
(*Vose et al., 2005*)

Observed DTR Trends: Global View

- DTR declines most over semi-arid regions such as the Sahel and North China where pronounced drought has occurred.







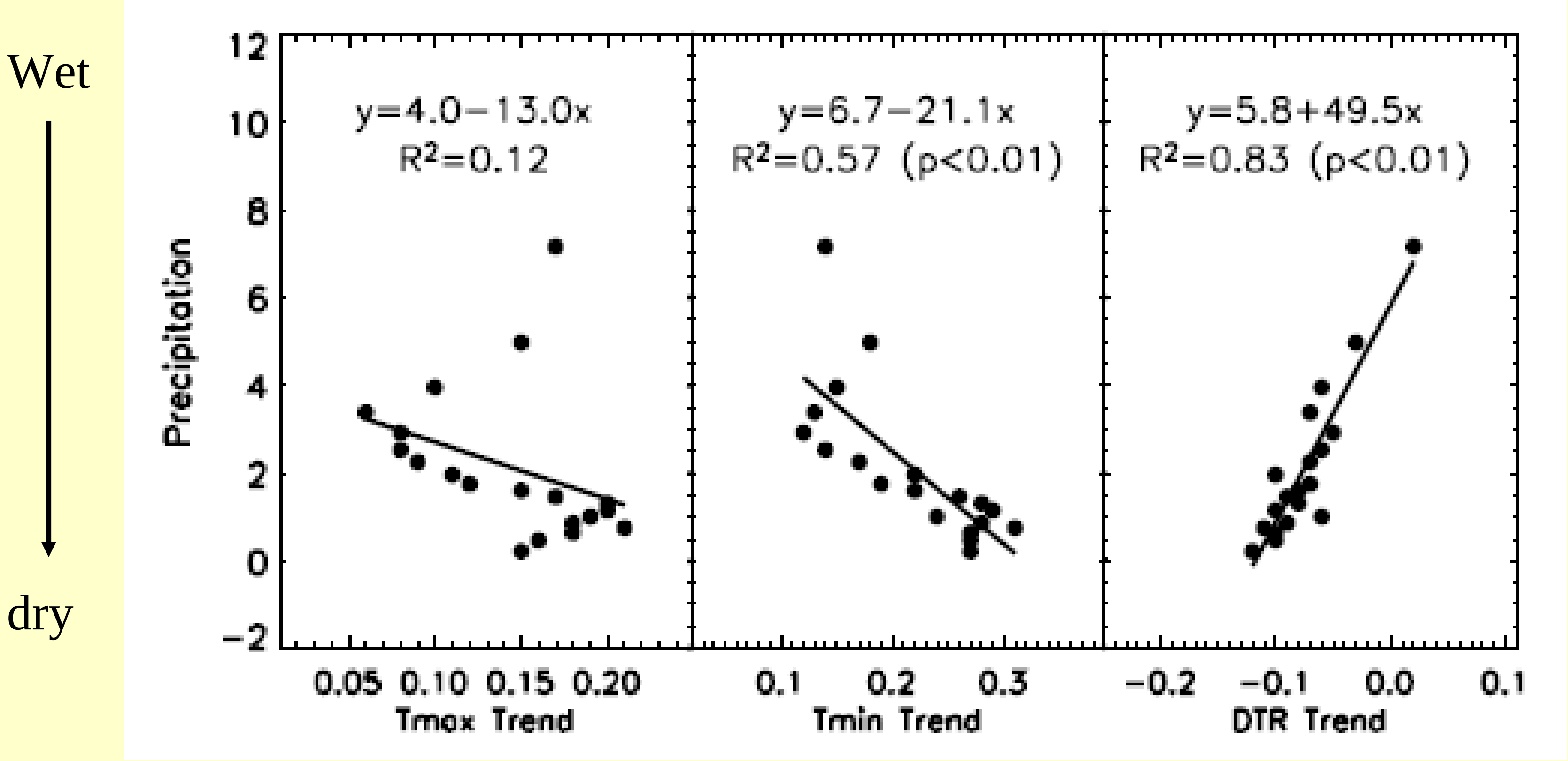
Trends of T_{max}, T_{min}, and DTR averaged over 11 climate regions based on the climatology of rainfall (100mm)

	Rainfall	T_{max} trends	T_{min} Trends	DTR trends
Dry	2.87	0.78	1.54	-0.75
	5.91	0.85	1.71	-0.96
	8.06	1.16	2.04	-0.93
	10.83	1.08	1.89	-0.91
	13.67	1.11	1.81	-0.7
	15.96	0.83	1.52	-0.74
	18.92	0.52	1.11	-0.55
	23.9	0.5	1.02	-0.54
	31.94	0.1	0.82	-0.75
	44.34	0.63	1.07	-0.46
Wet	68.63	0.81	0.9	-0.14

(Data sources: Vose et al., 2005; Chen et al., 2001)

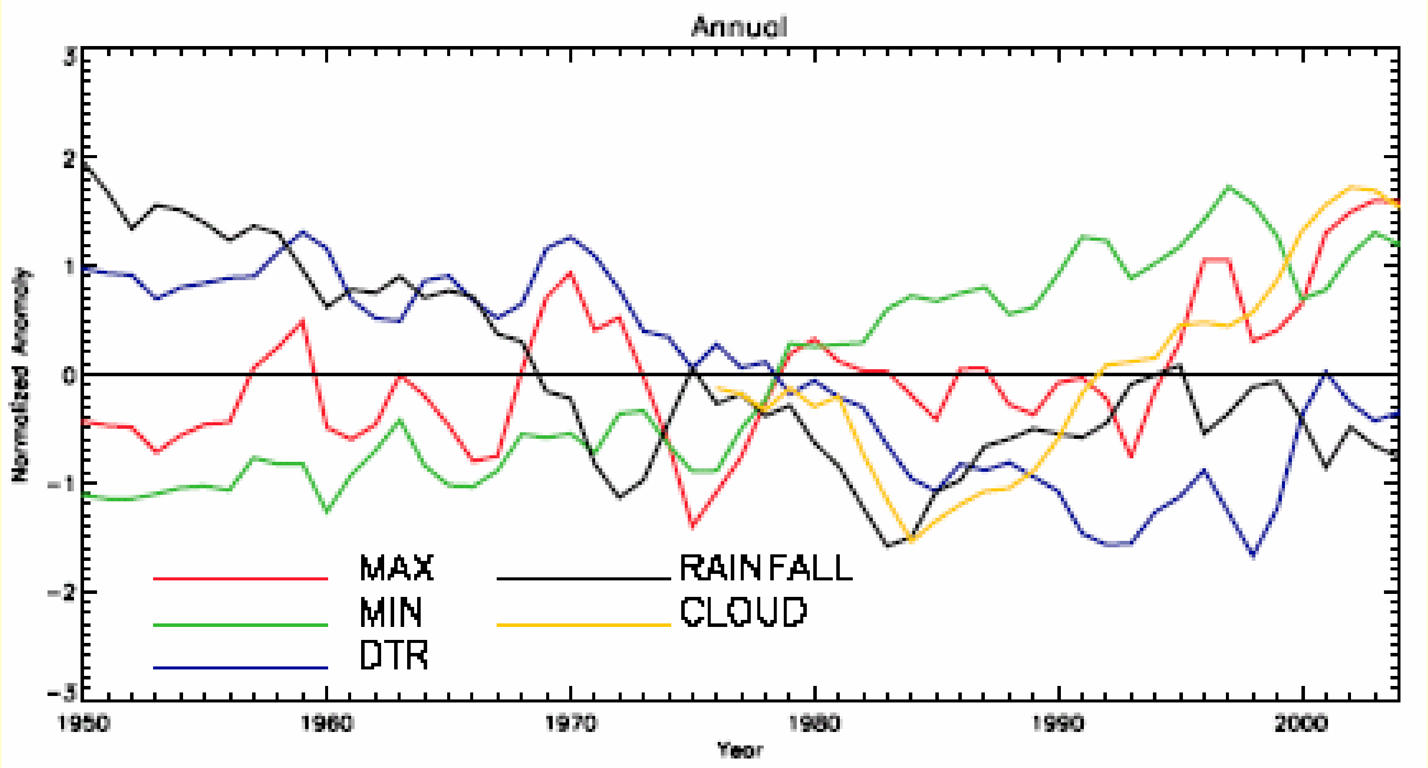
Observed DTR Trends: Global Statistics

- The drier the climate, the stronger the warming in T_{max} and T_{min}, and the larger the DTR reduction - the warming of T_{min} and the reduction of DTR are strongest over the driest regions.



Observed DTR Trends: The Sahel

- T_{min} has a strong/significant warming trend while T_{max} shows a small/insignificant trend, and thus the DTR declines.



Normalized time series anomalies of annual T_{max},T_{min}, DTR, cloud cover, and rainfall for 1950-2004.

Clouds/Rainfall Decreased the DTR?

- Increased clouds, precipitation, and soil moisture have been used to explain the worldwide reduction of DTR

clouds/soil moisture/precipitation ↑ → DTR ↓

clouds/soil moisture/precipitation ↓ → DTR ↑

cannot explain the DTR trends over the Sahel

Relationship between DTR and Rainfall/Clouds

		$Y = \beta_0 + \beta_1 X + \beta_2\,\text{time}$			$\Delta Y = \beta_0 + \beta_1 \Delta X$	
Y	X	R^2	β_1	β_2	R^2	β_1
DTR	rainfall	0.60	**-0.57**	**-0.030**	0.42	**-1.21**
DTR	clouds	0.15	0.06	**-0.025**	0.15	**-0.11**

New Hypothesis for Reducing the DTR?

Drought and land use change -induced reduction in vegetation cover and soil emissivity

- Soil aridation and vegetation removal due to drought and land use change (e.g., deforestation, overgrazing, overfarming) increase albedo and decrease emissivity.

- Higher albedo reduces the absorption of solar radiation but such effect is compensated by more incoming radiation due to less cloud cover.

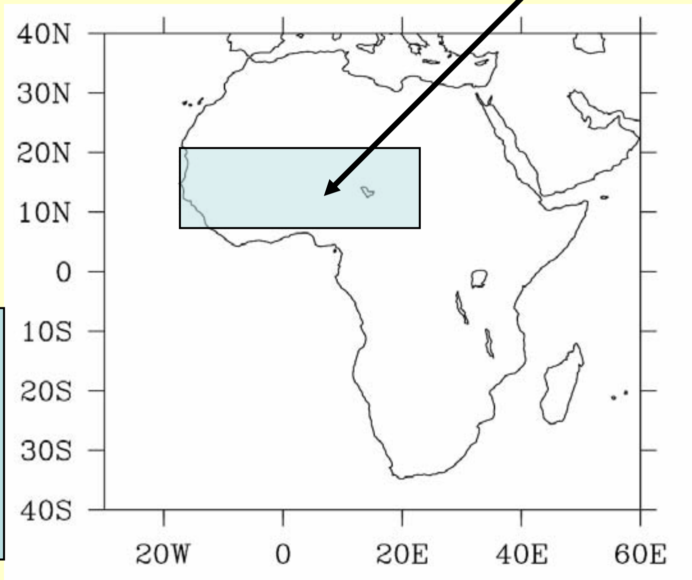
- Lower emissivity reduces thermal emission and less vegetation increases soil heat storage, both warming the surface during nighttime over semiarid regions when and where evapotransporation is very limited.

Climate Model Sensitivity Tests

- Three 20yrs simulations using NCAR CAM3/CLM3:
  - Control run (CTL): no changes in vegetation and ε_g =0.96
  - Exp A: remove all vegetation and ε_g =0.89
  - Exp B: remove all vegetation and ε_g =0.96

Typical soil emissivity:
$\varepsilon_g = 0.96$
Desert soil emissivity:
$\varepsilon_g = 0.89$

Test region: Sahel



A-CTL: effects of vegetation + emissivity
B-CTL: effects of vegetation only

Observed vs Simulated Temp: Spatial Pattern

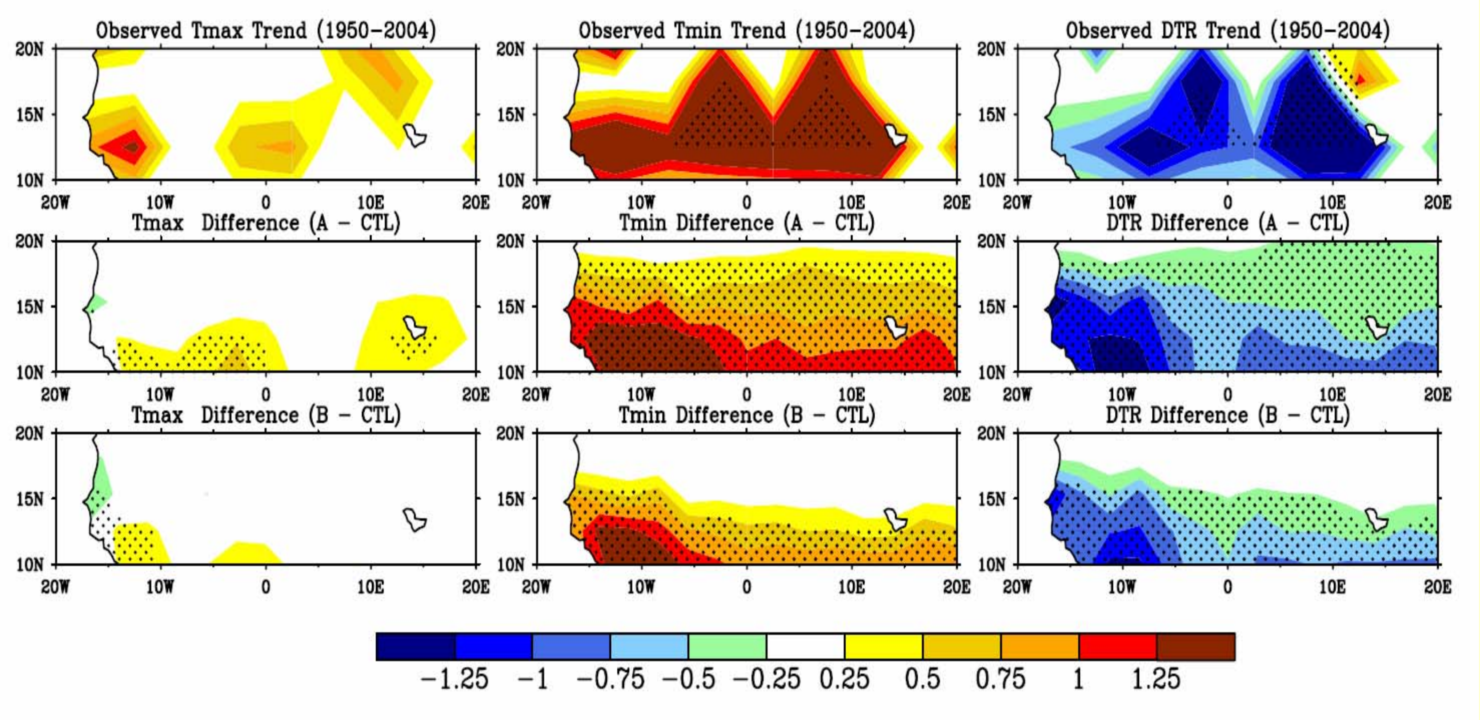
- Stronger warming for T_{min} than T_{max} over the Sahel

T_{max} T_{min} DTR

OBS

A-CTL

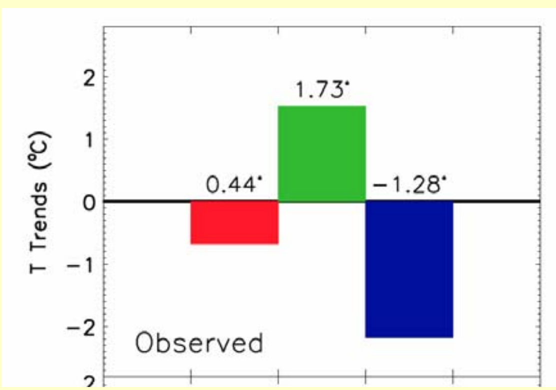
B-CTL



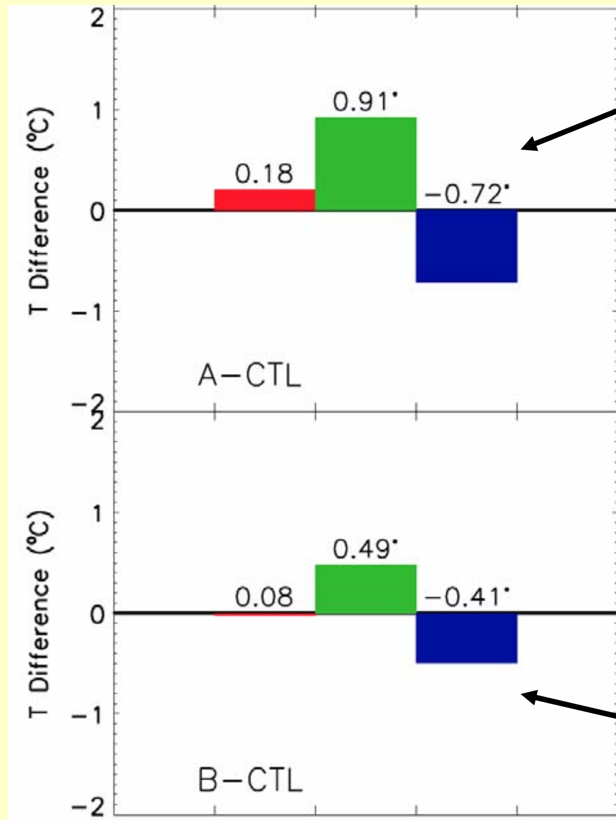
Observed and simulated annual T_{max},T_{min}, and DTR

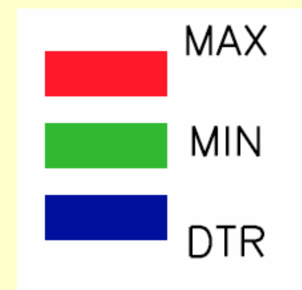
Observed vs Simulated Temp: Regional Mean

- Reduced soil emissivity and vegetation both decrease DTR



Observed

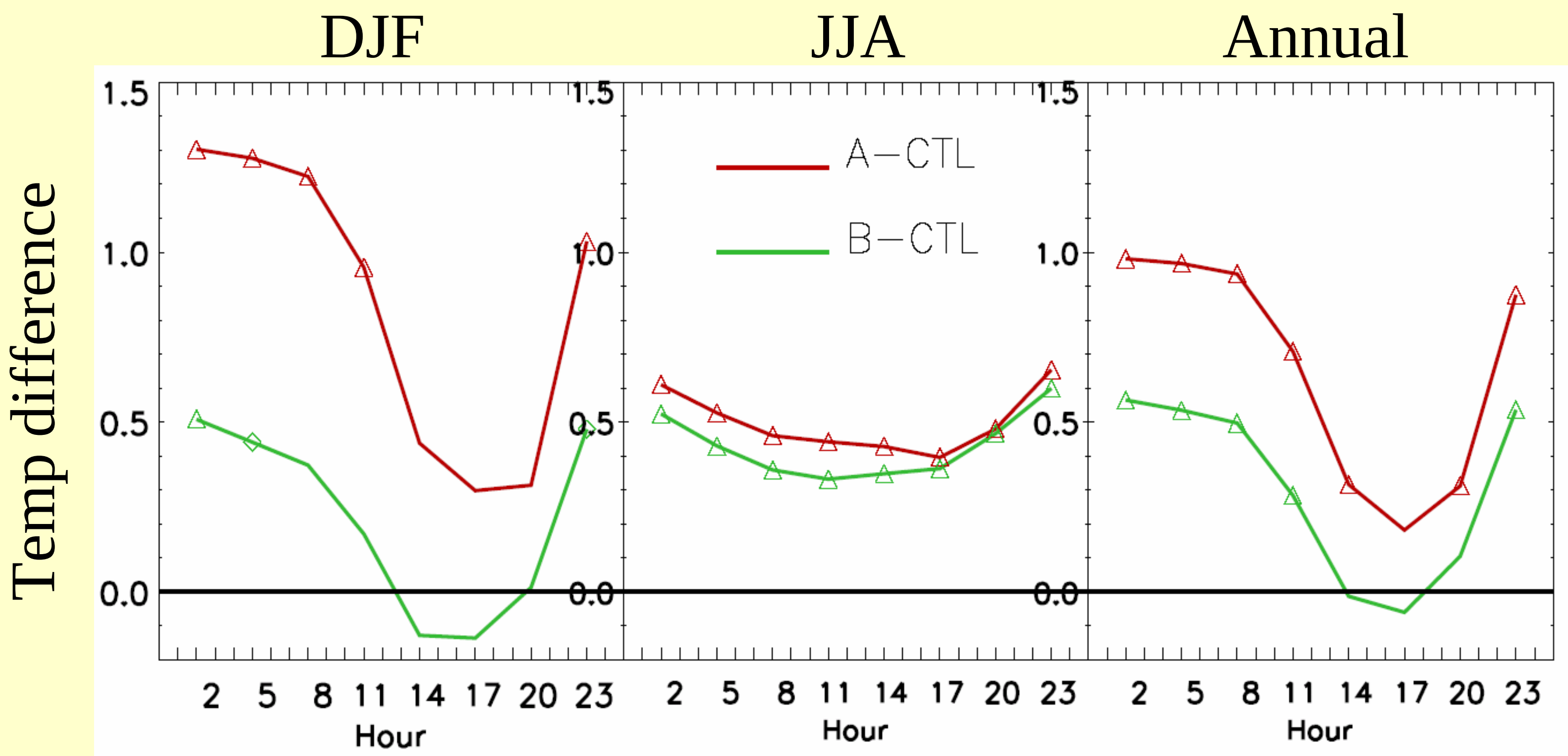




Observed and simulated annual T_{max},T_{min}, and DTR

Simulated Temp Diurnal and Seasonal Cycle

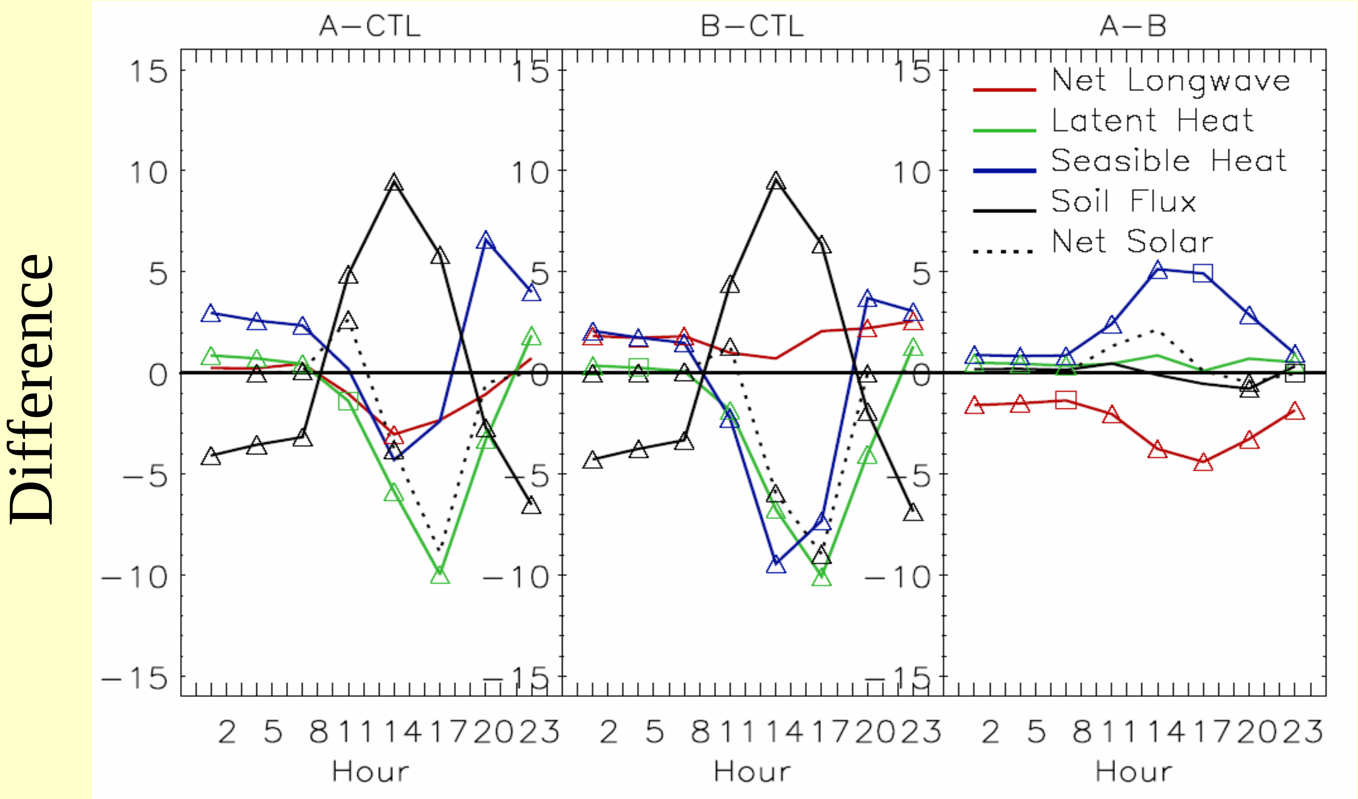
- Largest warming during nighttime and dry seasons
- Smallest warming during daytime and wet seasons
- Larger warming in A-CTL than B-CTL



Differences in the diurnal cycle of temperature

Explanations: Radiation and Energy Budget?

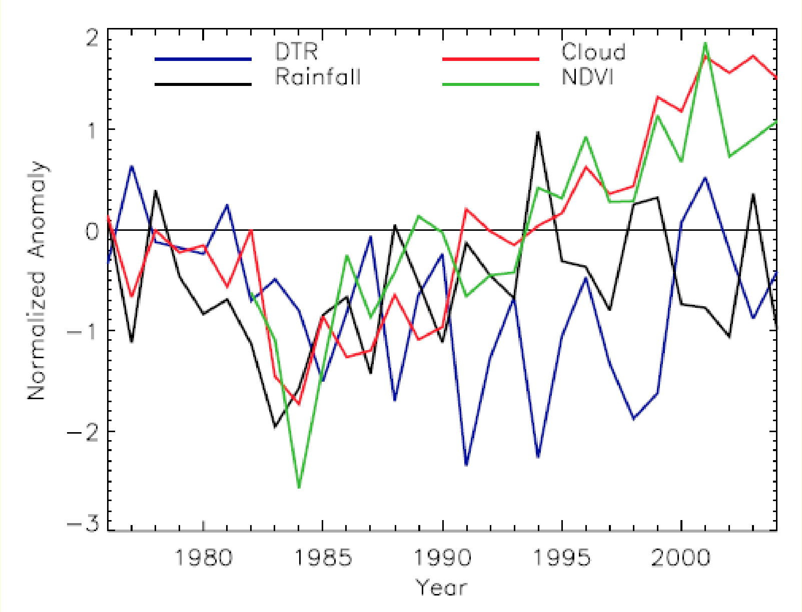
- emissivity ↓ ⇨ thermal emission ↓ ⇨ sensible heat ↑ ⇨ T_{min} ↑
- vegetation ↓ ⇨ soil heat storage ↑



Differences in the diurnal cycle of radiation and energy budget

Consistent with Observations

- The observed long-term decreasing DTR trend reversed after rainfall and vegetation recovered.
- Satellite observed a greening trend over the Sahel
- T_{min} negatively correlated with NDVI significantly



Time series of annual DTR, cloud cover, rainfall, and NDVI for 1976-2004

Relationship between Temperature and NDVI

		$Y = \beta_0 + \beta_1 X + \beta_2\,\text{time}$			$\Delta Y = \beta_0 + \beta_1 \Delta X$	
Y	X	R^2	β_1	β_2	R^2	β_1
Tmax	NDVI	0.26	-6.93	0.39	0.04	-15.29
Tmin		0.33	**-21.96**	**0.47**	0.21	**-22.86**
DTR		0.07	14.87	-0.10	0.01	6.01

Conclusions

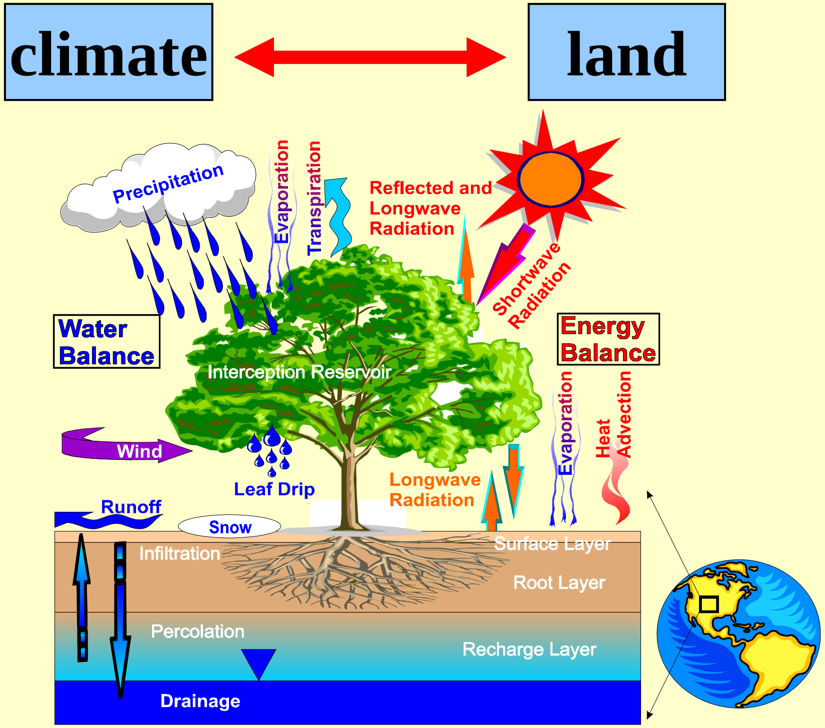
- Climate model simulations show that the **reduction in vegetation and soil emissivity warms T_{min} much faster than T_{max}** and thus **substantially declines** the **DTR**.

- These results suggest a **new hypothesis** that **drought** and **human** induced vegetation removal and soil aridation may have **enhanced** the **warming of T_{min}** and thus the **decreasing of DTR** over semiarid regions.

- This new hypothesis is **consistent** with **observations**.

(*Zhou et al., PNAS, 2007; Zhou et al., JGR, 2007*)

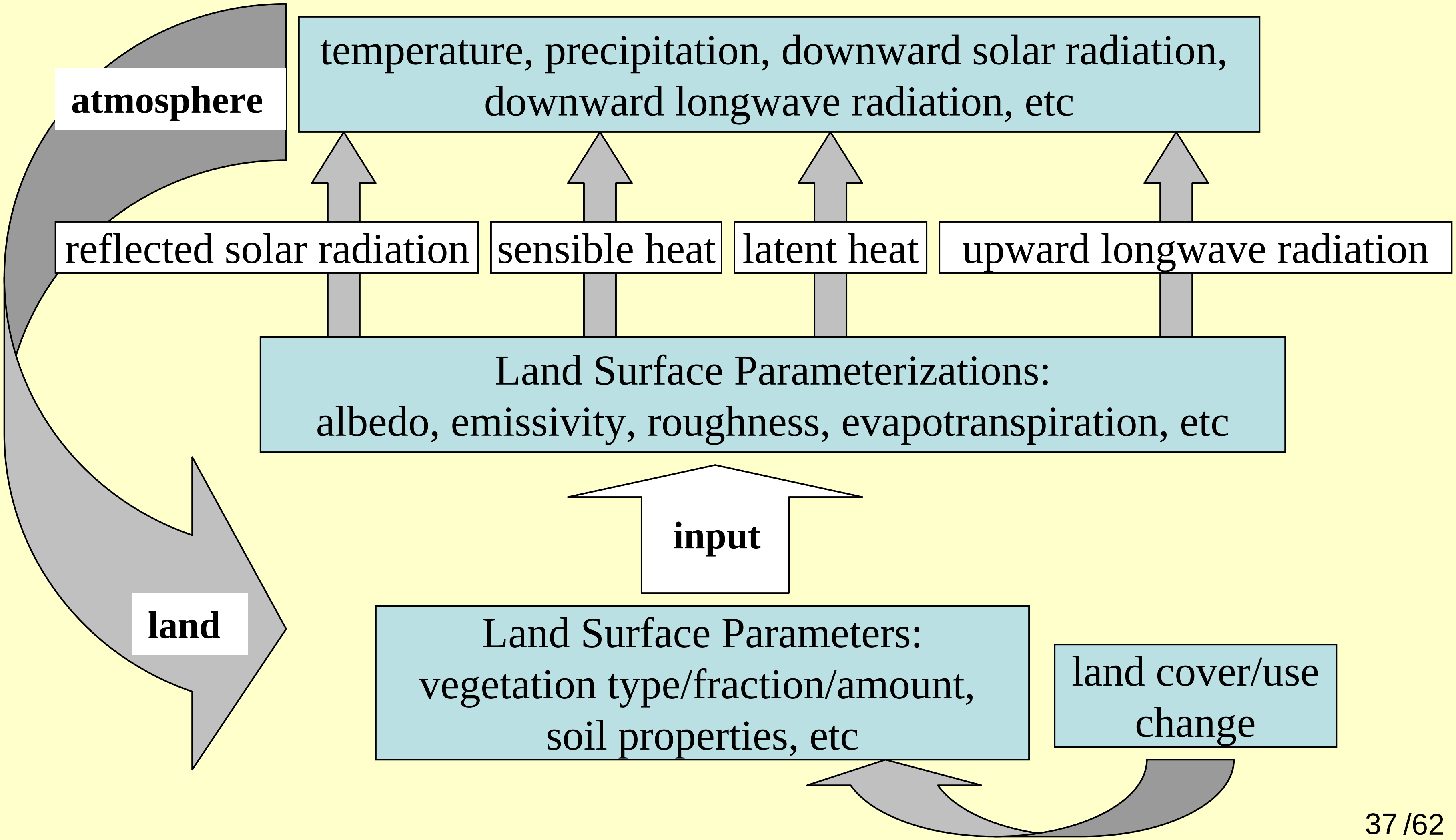
Topic III: Improving Land-Climate Interaction Modeling



Applications of remote sensing data to improve land surface processes modeling

(*Zhou et al., GRL, 2003; 2005; Zhou et al., JGR, 2003b; 2003c*)

Land-Climate Interactions in Climate Models



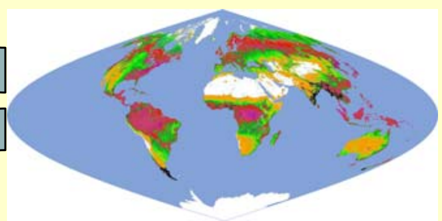
Using RS Data to Improve Climate Models

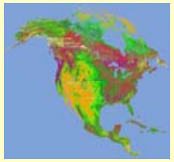
RS Land Products | Better LSPs | Modeled Climate

LAI

%vegetation cover

land cover type





albedo

emissivity

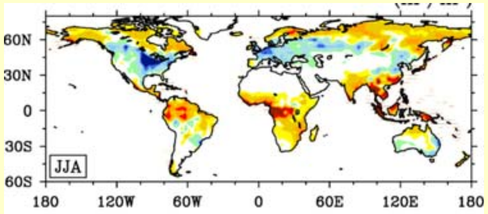
new land surface datasets

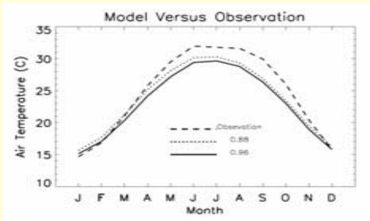
better radiation schemes

temperature

precipitation

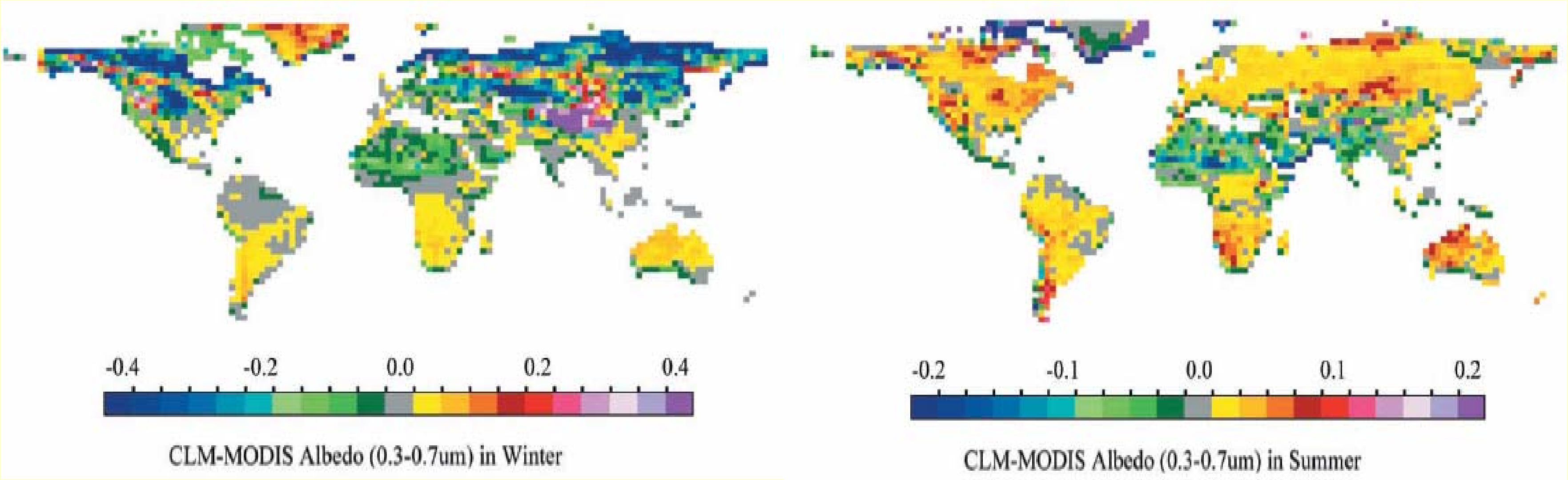
evapotranspiration





Identifying Model Albedo Biases

- **Largest model albedo biases** occur over **snow-covered vegetated surfaces** and over **arid/semiarid regions**.
- Model albedoes are consistent with the MODIS data for dense forests over snow-free regions.



Albedo differences (CLM-MODIS)

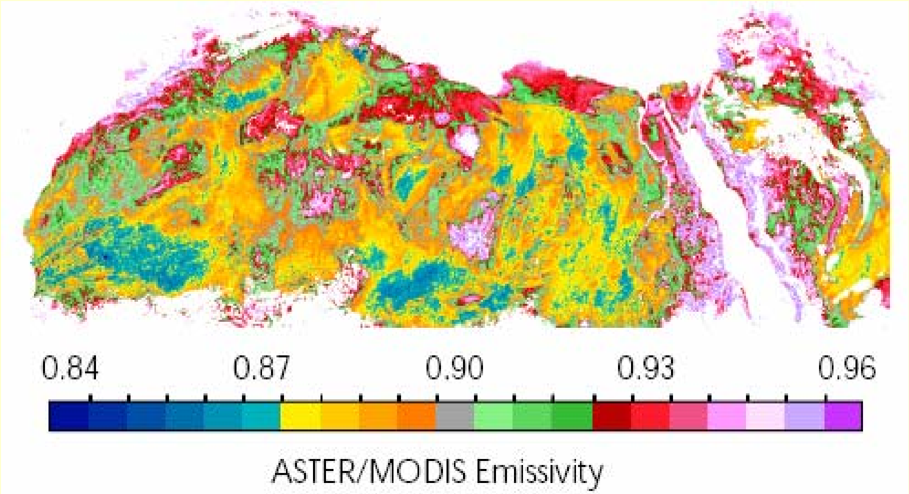
(*Zhou et al., JGR, 2003b)*

Identifying Model Emissivity Biases

- NCAR models use a constant soil emissivity while satellite data show considerable spatial variability over North Africa.
- **Biggest emissivity biases** occur over **arid/semiarid regions.**

Soil emissivity = 0.96

CLM2 emissivity



ASTER/MODIS emissivity

(*Zhou et al., JGR, 2003c)*

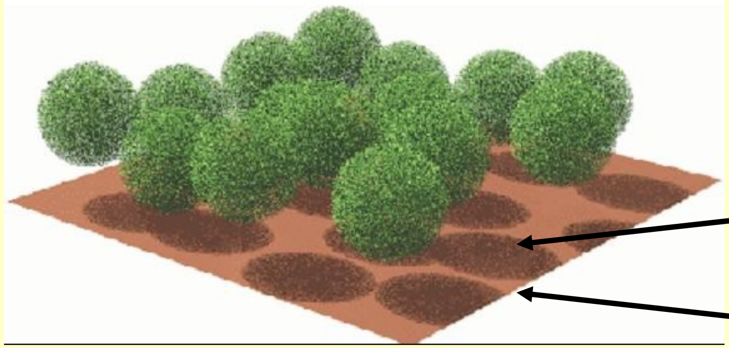
Essential Problem?

- Climate models generally use two-stream radiation schemes to calculate albedos/emissivities for vegetated surfaces.

climate model view of vegetation

Problem: accuracy for horizontally homogeneous canopies but largest errors for semiarid and snow-covered vegetated surfaces

Solution: a more realistic 3D radiation model plus a more accurate boundary condition



shading effects

soil albedo/emissivity

what it looks like for semi-arid system

Case Study #1:

Develop more accurate soil albedos

Why Necessary?

- Current climate models represent soil albedos by a limited number of prescribed values. Soil albedos
  - vary only by several soil colors globally
  - have a near-infrared to visible albedo ratio of 2
  - are independent of solar zenith angle
- Such simple representation produces notable albedo biases over arid and semi-arid regions

To develop a more accurate soil albedo dataset from MODIS for use in climate models

MODIS Albedos with 21 Parameters

- MODIS has **7** spectral bands. Each band uses **3** parameters to represent direct and diffuse albedos:

$$\alpha_{dir}(\theta,\lambda) = f_{iso}(\lambda)(1.0 - 0.007574\theta^2 - 1.284909\theta^3) + f_{vol}(\lambda)(-0.070987\theta^2 - 0.166314\theta^3) + f_{geo}(\lambda)(0.307588\theta^2 + 0.041840\theta^3),$$

$$\alpha_{dif}(\lambda) = f_{iso}(\lambda) + 0.189184 f_{vol}(\lambda) - 1.377622 f_{geo}(\lambda)$$

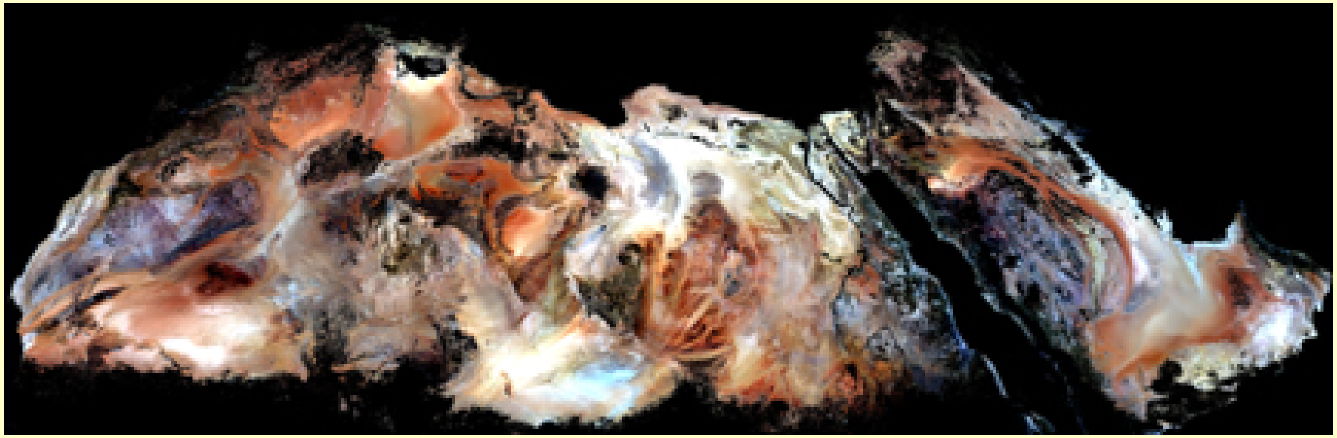
In total, 21 parameters:
7 spectral bands x 3 parameters (f_{iso}, f_{vol}, f_{geo})

- Spectral-to-broadband conversions used to produce albedos for **3** broadbands: visible (0.4~0.7 µm), near-infrared (0.7~5.0 µm), and shortwave (0.4~5.0 µm)

Data and Study Region

- MODIS albedo parameters for 7 spectral bands averaged from high quality pixels in dust-free seasons from 2000 to 2005
  - ➢ 21 parameters
  - ➢ 1 km resolution
  - ➢ vegetated pixels excluded

an image with 21 bands over 14 million pixels



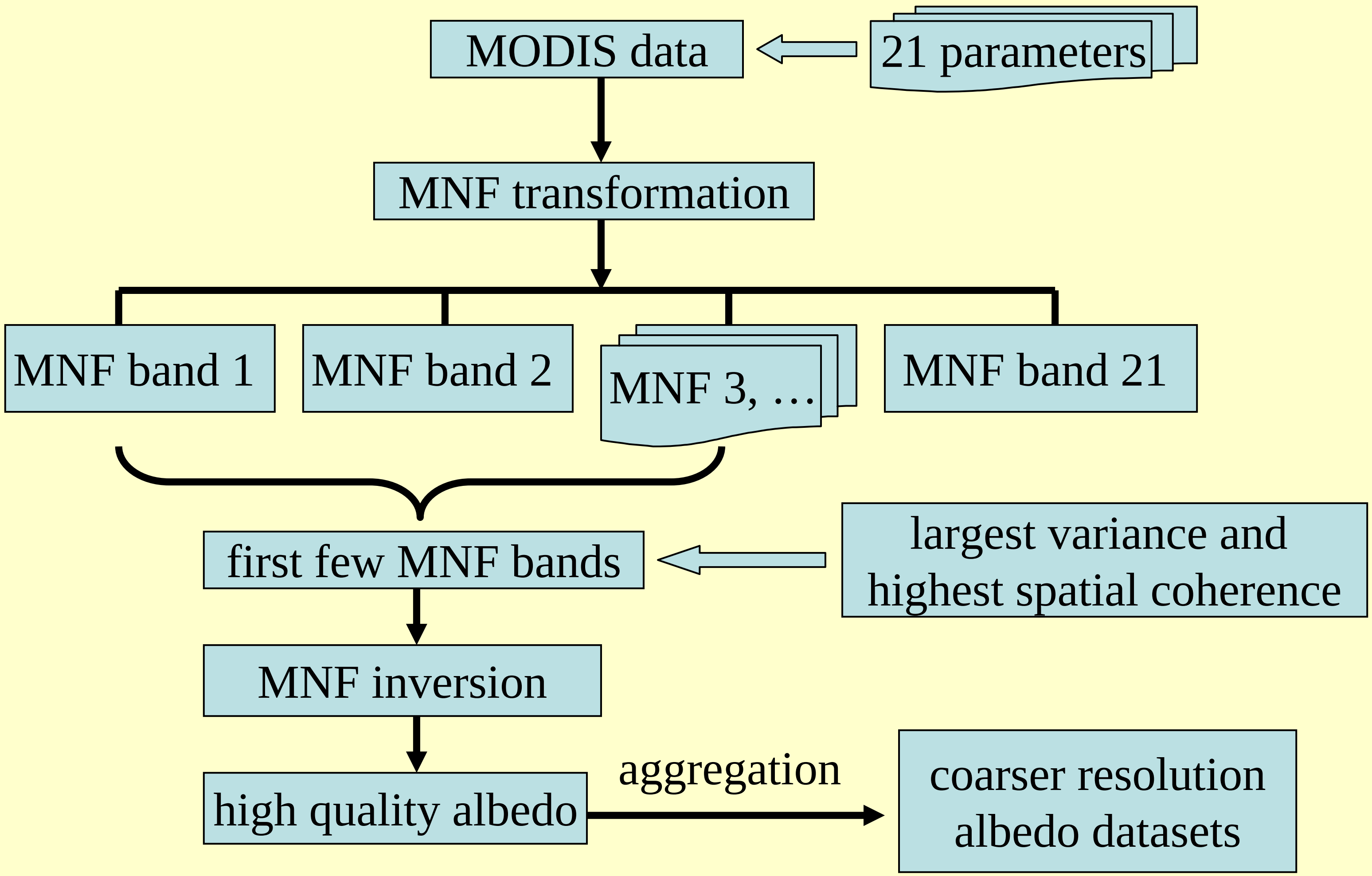
Example: True-color RGB image for parameter f_{iso}

Need a Simple Statistical Model

- Further statistical analyses are more useful for MODIS data
  - to reduce the data redundancy
  - to segregate the data noise
  - to separate albedos into spatial patterns of large-scale, local-scale and noise

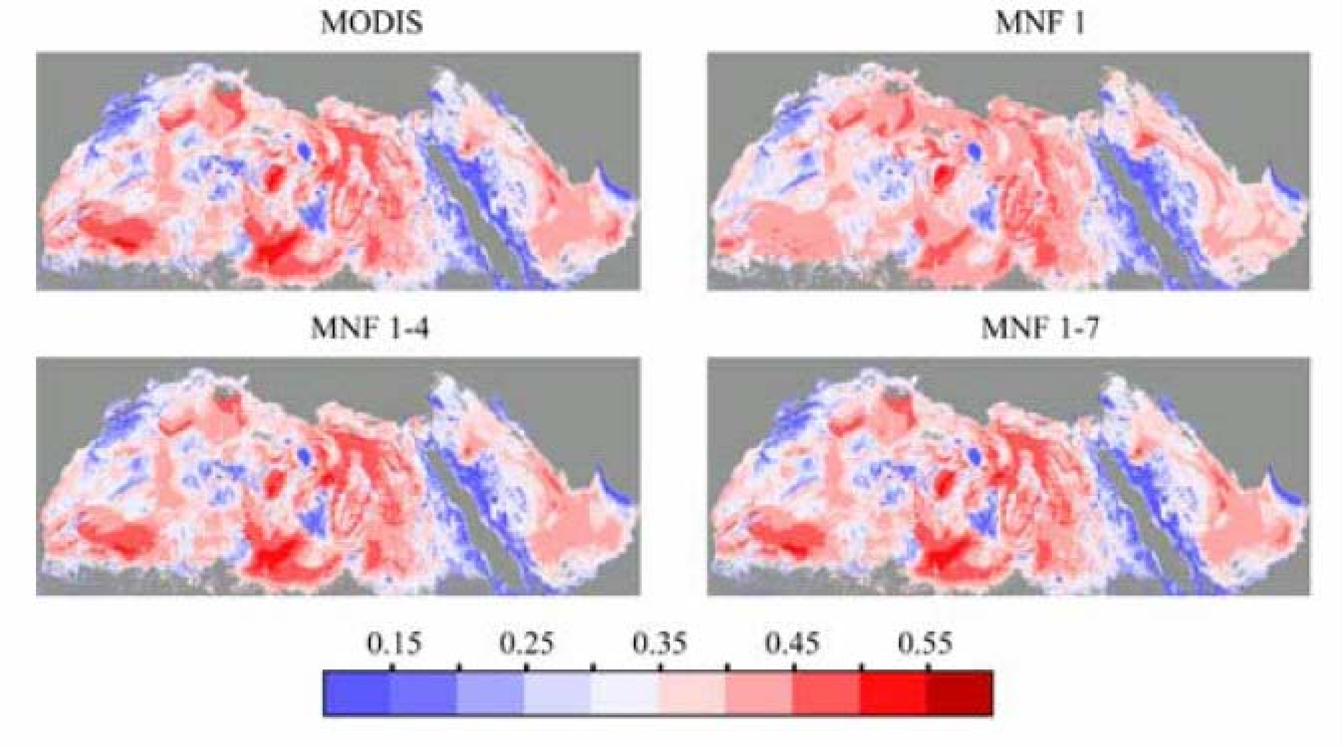
Methods

- Minimum noise fraction (MNF) transformations



MODIS vs MNF-based Albedos: Spatial Pattern

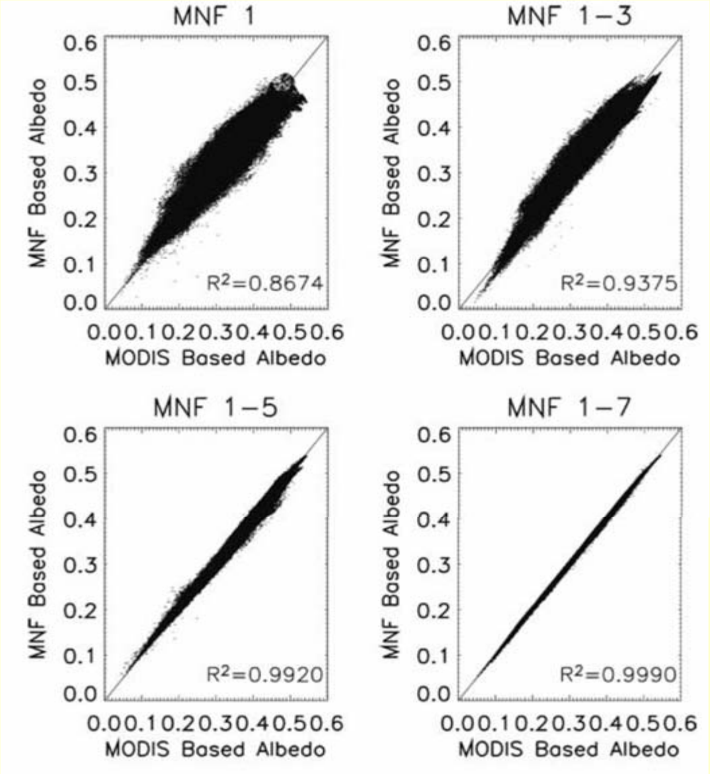
- More local-scale variations described with more MNF bands



Shortwave diffuse albedos at 10 km resolution

MODIS vs MNF-based Albedos: Scatter Plots

- The first **7** MNF explains **99.9%** of the total variance in MODIS data at 10 km resolution



Total grids: 151,520

Shortwave diffuse albedos at 10 km resolution

Conclusions

- **First few MNF bands** are sufficient to create a more **accurate soil albedo** dataset with high quality for use in **climate models** through MNF transformations of MODIS data.

- **The statistical method** is able to **capture** most of the MODIS **albedo variance** and **extract** large-scale **albedo patterns** from the original MODIS data while **improving** the data **quality** and **reducing** the number of **parameters** needed to represent the data.

(*Zhou et al., GRL, 2005)*

Case Study #2:

Characterize soil albedo-moisture relationship

Why Necessary?

- Soil albedo varies with soil moisture used in NCAR climate models

$$\Delta\alpha_s=0.01(11-40\theta)$$

where α is soil albedo and θ is the ratio of surface soil water volumetric content over its saturated value

- Dickinson used this formulation in his BATS model and it has been widely used thereafter

- This formulation was based on limited observations from few points and thus needs further improvement using large-scale satellite measurements

Data

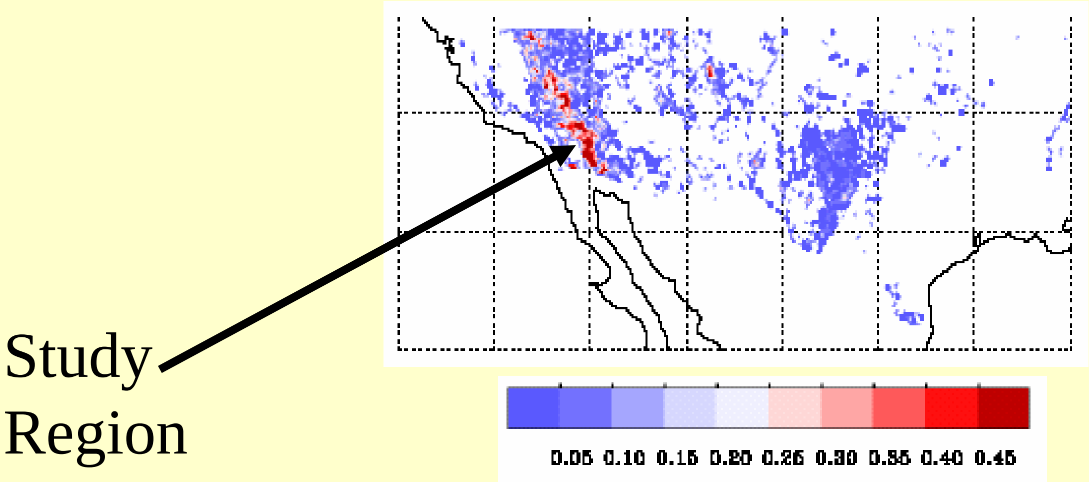
- Surface daily soil moisture retrieved from TRMM/TMI at 1/8° over southern US (2000-2002) (Gao et al., 2006)
    - unaffected by clouds and atmospheric water vapor
    - best quality over sparsely vegetated regions
    - active precipitation, snow and frozen soils excluded

- MODIS diffuse albedos over southern US (2000-2002)

Data Processing

- Soil moisture was temporally aggregated into 16-day averages and MODIS albedos were spatially aggregated into 1/8° from high quality pixels.

- Focusing on a region in southwestern USA where barren fraction > 50% to ensure the best quality in soil data and to minimize the contribution from vegetation to soil albedos.

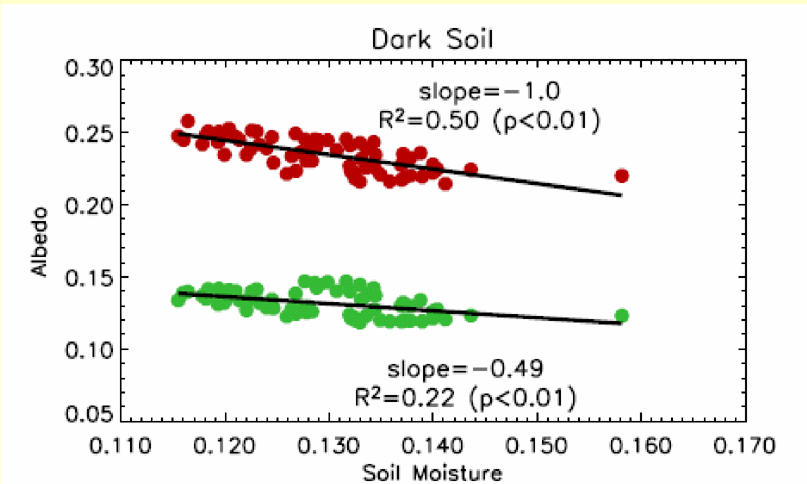


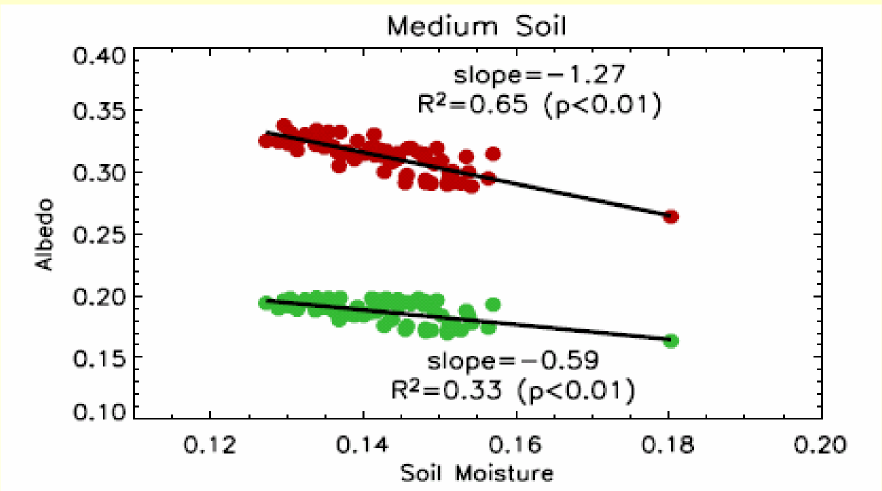
Barren fraction at 1/8°

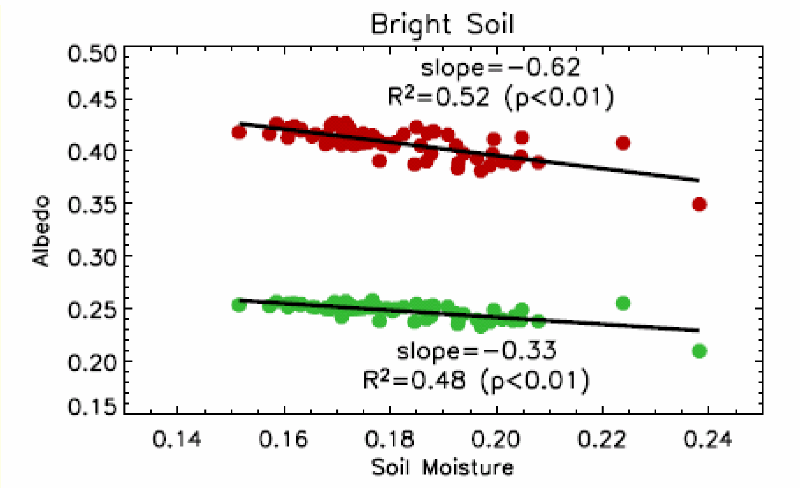
Soil types:
dark
medium
bright

Results

- Observed slopes differ largely between VIS and NIR, and among soil types while NCAR models use a constant slope







slope = -0.4
for both VIS and NIR
in NCAR models:

$$\Delta\alpha_s = 0.01(11-40\theta)$$

Conclusions

- **Soil albedo decreases linearly** with **soil moisture** and such **decrease depends on soil color** and **spectral bands**.

- On average, an **increase** of **soil moisture** by **10%** will **decrease soil albedo** by **3~6%** for the **visible band** and **6~12%** for the **NIR band**, while **4%** is used for both visible and NIR bands in **NCAR models**.

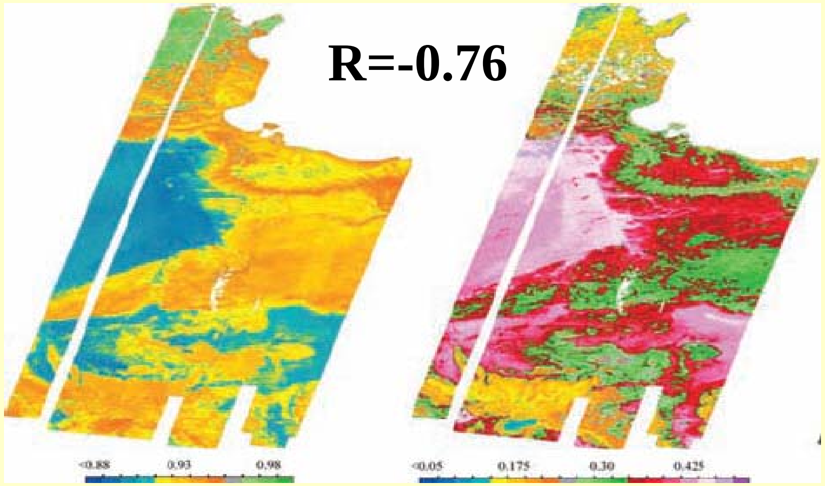
Case Study #3:

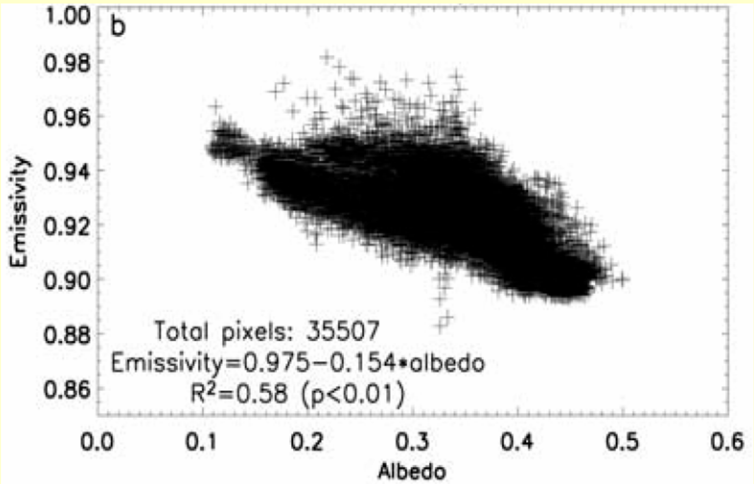
Develop thermal infrared emissivity schemes

Negative Emissivity-Albedo Correlation

- A significant negative linear albedo-emissivity relationship

ASTER emissivity   MODIS albedo



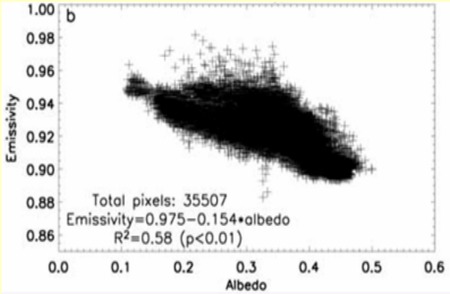


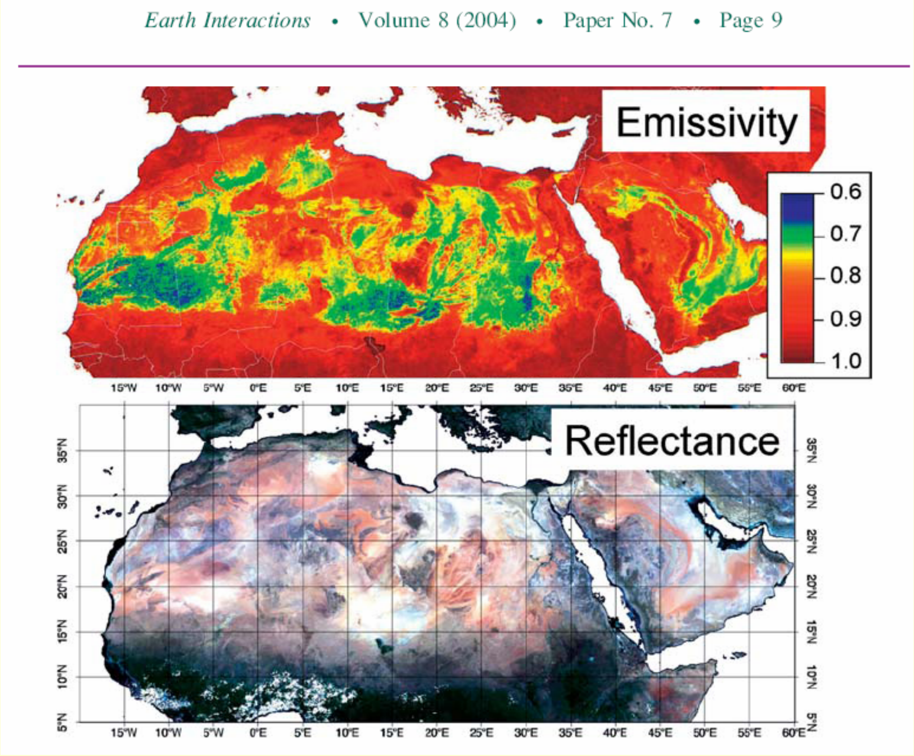
MODIS bands	1	2	3	4	5	6	7
Correlation (R)	-.76	-.74	-.16	-.52	-.77	-.77	-.85

(*Zhou et al., GRL, 2003*)

New Emissivity Schemes: Combining Albedo to Derive Emissivity

- Complementing ASTER data with MODIS to derive thermal infrared emissivity products by USDA/ARS



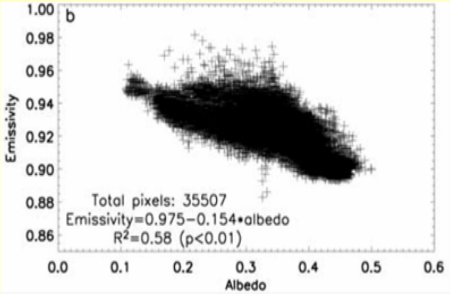


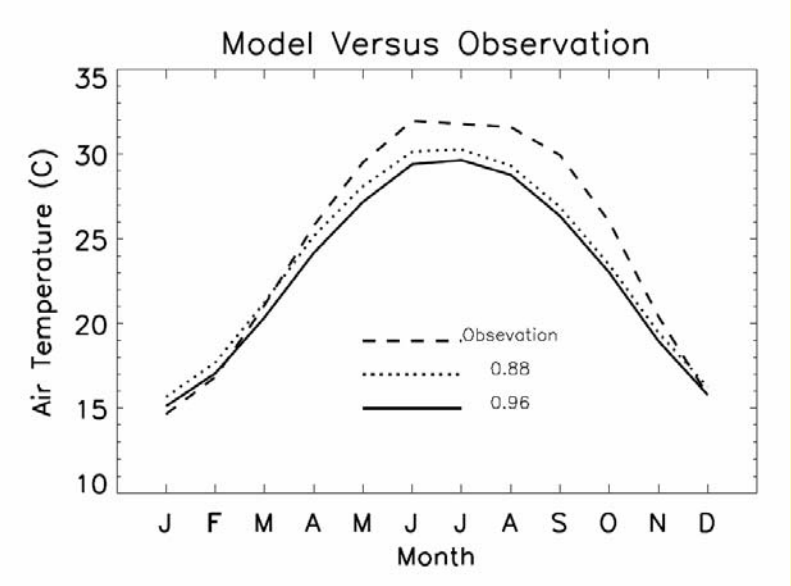
(*Ogawa et al., EI, 2004)*

ASTER/MODIS emissivity

New Emissivity Schemes: Relating Emissivity to Albedo in GCM

- Better temperature simulations due to improved soil emissivity





Improved temperature simulation over Sahara

(*Zhou et al., JGR, 2003c)*

Conclusions

- NCAR models have the **biggest emissivity bias** over **arid and semiarid regions**.

- There is a strong **negative correlation** between soil **albedo** and **emissivity** over arid and semiarid regions.

- **This relationship** can help **develop new schemes** to derive thermal infrared **emissivity products** and to better characterize land surface **emissivity** in climate models.

(Zhou et al., GRL, 2003; Zhou et al., JGR, 2003c)

Future Work

To develop and apply remote sensing data for land surface modeling in NWP and environmental monitoring

- Improve and develop remote sensing algorithms/products for environmental monitoring and climate modeling.
- Identify major model deficiencies in land surface processes (e.g., LAI, FVC, albedo, emissivity) using remote sensing and observational data.
- Design sensitivity experiments to test and attribute these deficiencies.
- Develop, test, and improve model parameters/schemes by examining hydroclimate variables (e.g., T, P, soil moisture, ET, runoff) with observations.