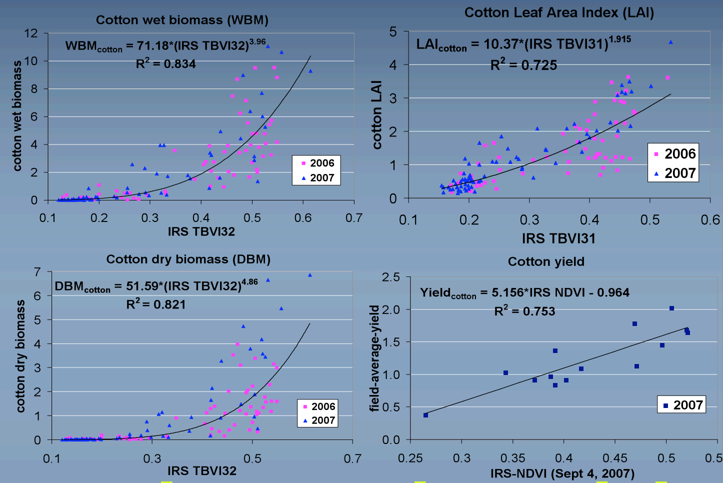
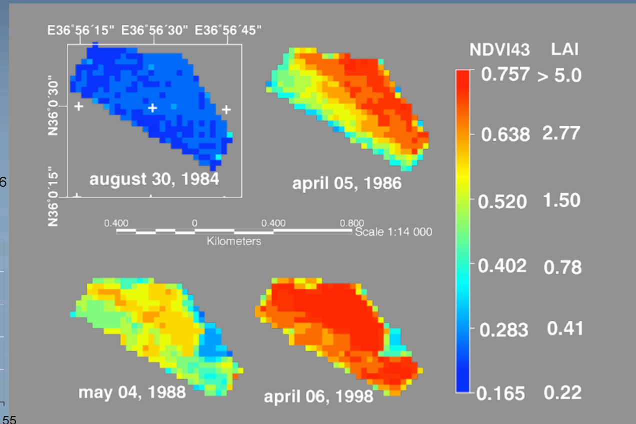
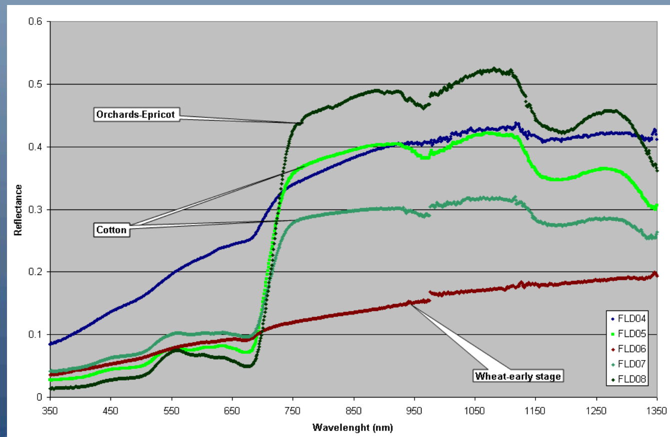
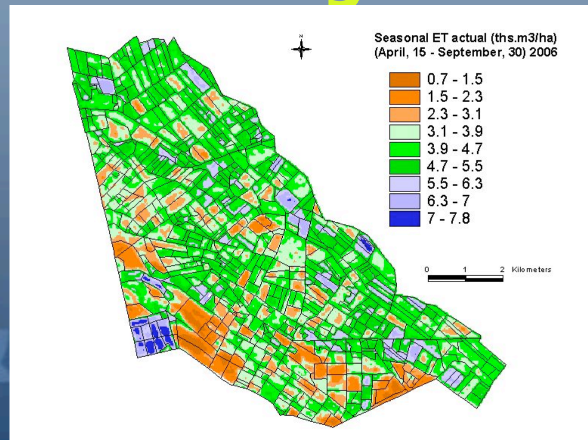
Water Productivity Mapping using Remote Sensing to solve Global Food Crisis





Strategies to Understand, Model, and Map Water Productivity and determine Factors Affecting Them





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Presented @ the 3rd Global Earth Observing System of Systems (GEOSS) Asian Pacific Symposium.
Kyoto, Japan. February 5, 2009.

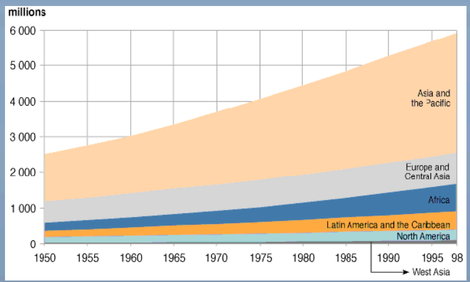
How Can WPMs Help:

Answering the Questions related to Food Security?

Water Productivity Mapping using Remote Sensing (WPM)

Need, Scope, Context

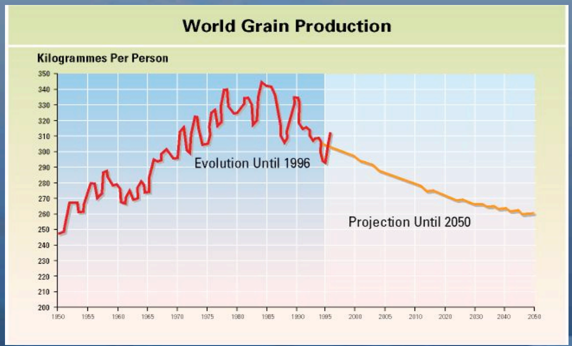
- **Water use Assessments and Food Security:** World population is increasing by about 90 million per year, calorie intake has increased to 2,800 calories per person per day (from 2255 in 1961). Global croplands are increasing at much slower phase. Irrigated areas have nearly stagnated, environmental issues related to irrigated areas have come to sharp focus, salinization and siltation of reservoirs a major concern……so where is the extra food going to come from?.



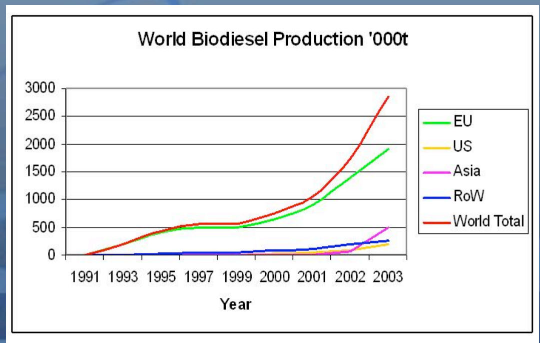
Can we feed 10+ billion by 2050?

Account for increasing consumption + waste

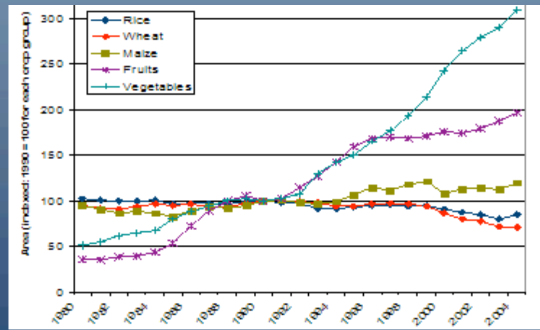
- **Change in Trends in Global Croplands:** Croplands are turned to areas for bio-fuels, consumption trends are changing (e.g., more fruits and vegetables), grain areas decreasing……



China alone grain production went down equivalent to entire Canada's harvest over last decade



Corn for bio-fuels?



More vegetables and fruits

- **Climate change impact on Croplands:** (e.g., droughts in Australia);
- **Alternative demands for water use:** increasing urbanization, industries, recreation, environmental flows;
- **Global scenario studies:** Irrigated areas-water use-food production-population growth-virtual water trade.

Water Productivity Mapping (WPM) using Remote Sensing

Questions Related to WP that WPMs can answer

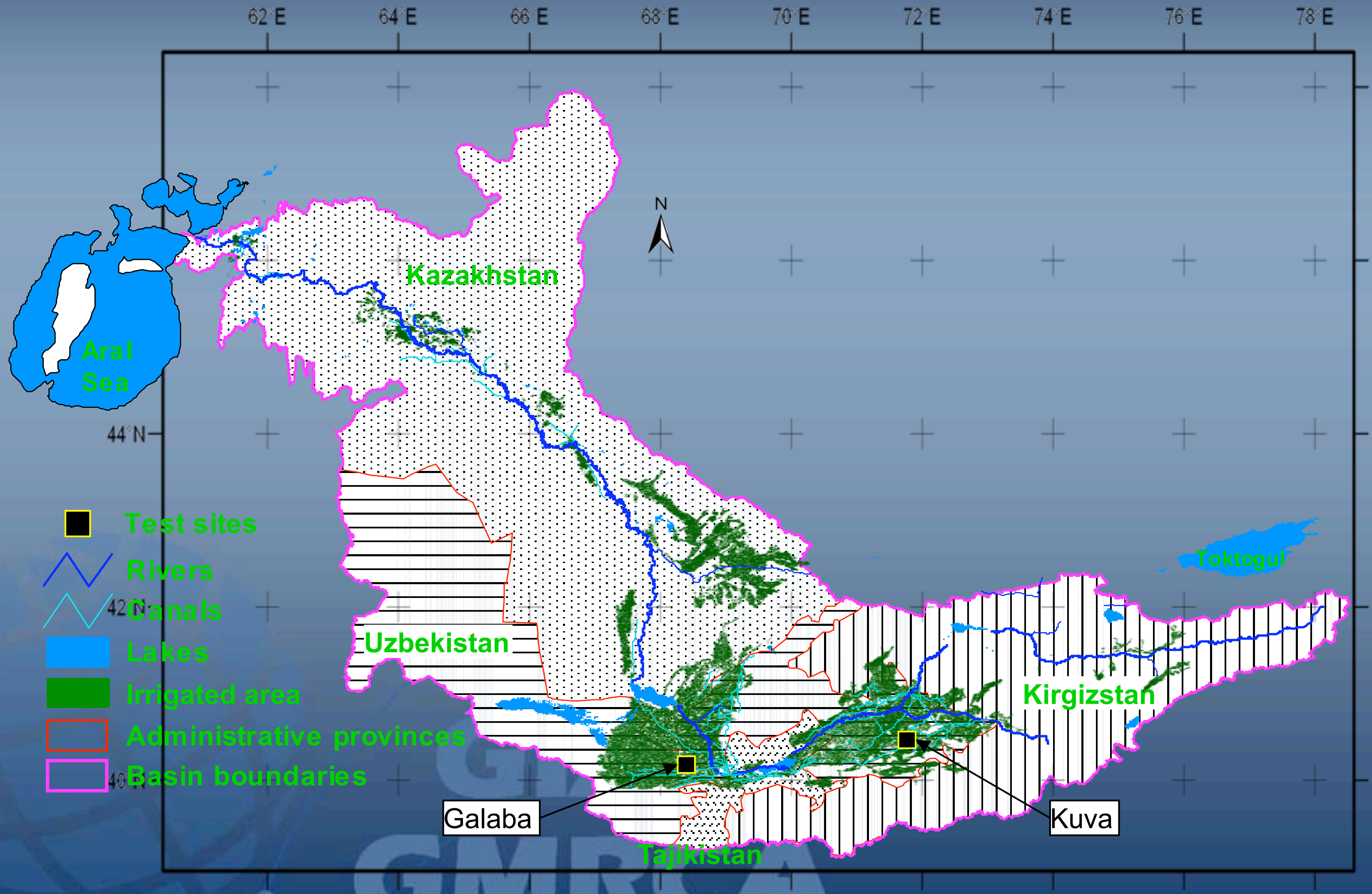
- ➔Can we grow more crop with less water?;
- ➔Can we grow more crop with less land?
- ➔Can we continue to feed the world with same amount of land and water as of now and if so how long?, If not what alternatives do we have?

…….first, we need to understand where we more WP………and where we have less WP………then we need to measure WP, map WP………then we will be ready to understand it and start looking for solutions……

Study Area

Water Productivity Mapping using Remote Sensing (WPM)

The Syr Darya River Basin, Central Asia



iwmigiam.org

Classic Large Scale Soviet Era Irrigation

Methods of WPM
using Remote Sensing

GIAM &
GMRCA

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Water Productivity Mapping using Remote Sensing (WPM)

Methods

The study involved 3 major steps leading to water productivity maps (WPMs):

I. Crop productivity (kg\m^2) maps (CPMs)

- **Crop type mapping;**
- **Spectra-biophysical\yield modeling;**
- **Extrapolation to larger areas;**

II. Water use (m^3\m^2) maps (WUMs) or ET$_{actual}$

- **simplified surface energy balance (SSEB) model;**

III. Water productivity (kg\m^3) maps (WPMs).

****

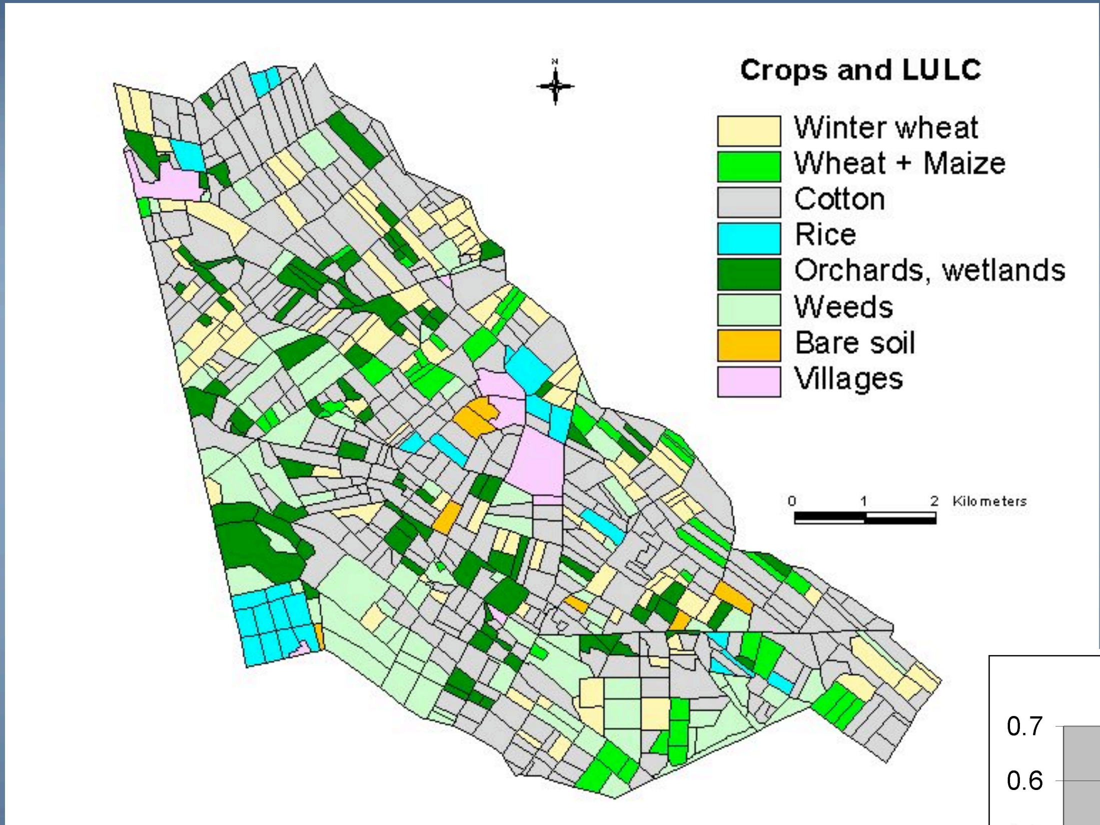
A. Factors affecting water productivity.

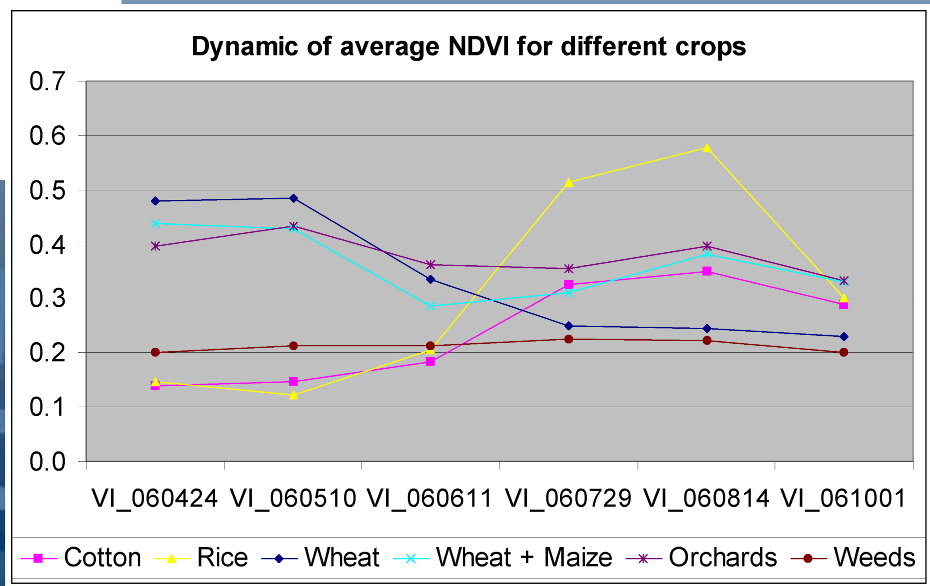
WPM Methods

1.0 Crop Croductivity Mapping

Methods of WPM: 1.0 Crop Type Mapping

Crop Types Mapped using Multi-Date Landsat ETM+ 30m Data





2.0 WPM RS: Spectro-Biophysical Modeling Process

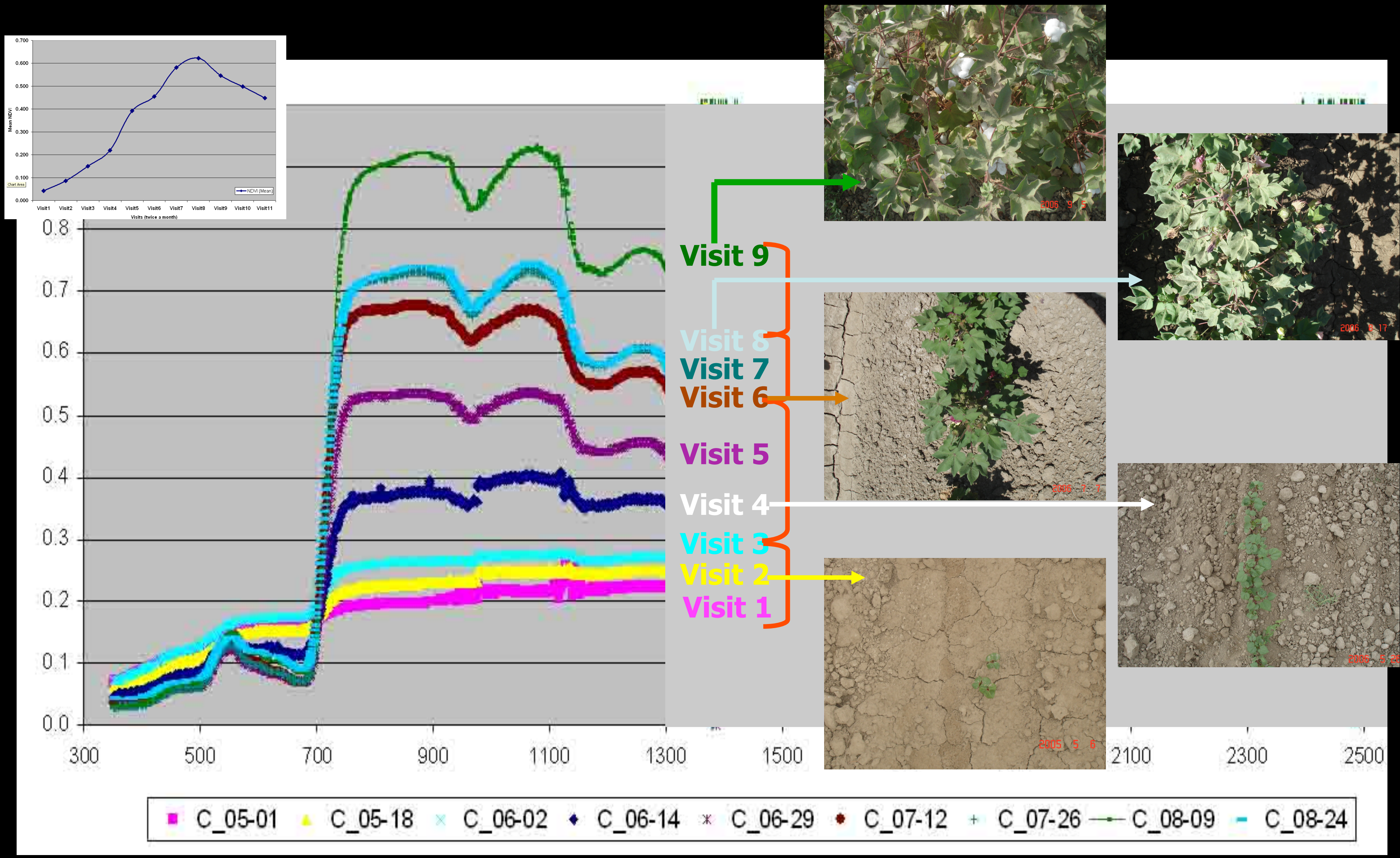
Field-plot Data: Variables, Sample size, and Mean Values of the Variables

Variable	Unit	Collecting method	Sample size	Mean value	Sample size	Mean value	Sample size	Mean value	Sample size	Mean value
A. General			**Cotton**	**Cotton**	**Wheat**	**Wheat**	**Maize**	**Maize**	**Rice**	**Rice**
Coordinate	degree	Hand-held GPS	585	-	191	-	116	-	43	-
Soil type	-	Eye observation	15	-	15	-	6	-	2	-
B. Crop variables for spectro-biophysical\Yield modeling										
NDVI	-	NDVI camera	566	0.487	166	0.622	105	0.571	43	0.602
PAR	μmol $m^{-2}s^{-1}$	LAI meter	580	1060	174	1029	105	960.429	38	957.868
Leaf area index	-	LAI meter	580	1.338	173	2.057	105	1.204	38	2.84
Wet biomass	kg/m^2	Cut and counting	577	1.801	172	1.499	108	2.186	37	2.166
Dry biomass	kg/m^2	Cut and counting	575	0.772	172	0.563	106	0.994	37	0.884
Crop height	mm	Ruler	576	453	172	569.535	108	920.88	41	610.244
Soil cover	%	Eye estimation	585	61.753	175	30.144	113	49.301	42	8.2
Canopy cover	%	Eye estimation	585	34.087	173	58.035	113	36.451	42	69.78
Yield	ton/ha	Laboratory	45	2.109	45	3.495	18	2.983	6	4.523
C. Variables to study the factors affecting Water Productivity										
EC	dS/m	EM-38[a]	315	106.567	48	91.077	62	110.279	26	79.933
Soil moisture	%	Laboratory (weight)	36	12.55	9	16.9	15	11.95	6	18
Crop density	plant/m^2	Cut and counting	577	21.133	172	253.837	97	18.213	39	343.077
Weed cover	%	Eye estimation	585	5.025	173	12.922	108	14.426	42	10.595
Water cover	%	Eye estimation	585	3.51	173	0.556	108	0.01	42	13.738
Crop health	grading	Eye estimation	572	3.164	172	3.291	108	3.231	41	3.78
Crop vigor	grading	Eye estimation	573	3.004	172	3.087	108	3.028	41	3.61
D. Meteorological variables for plant water use estimations or ET calculations										
Air temperature	Selsius degree	Automated weather	5798	22.1						
Relative humidity	%	station[b]	5798	50						
Wind direction	degree	(February-October)	5798	169.8						
Wind Speed	KM/h		5798	1.38						
Rainfall	mm		5798	151.8						
E. Water applied measurements										
Irrigation application	mm	Weirs	5	293	2	80.57	4	158.9	4	355.2

Note: a = Average value of vertical and horizontal EC.
b = the "watchdog" automated weather station was set up in Galaba site and the weather data was used for all crops.

2.0 Spectro-Biophysical\Yield Models

Continuous Spectra of Irrigated Cotton Crop @ different Growth Stage



2.0 Spectro-Biophysical\Yield Models using IRS LISS 23.5m and Quickbird 2.44m Data

Best Model R^2 values and Waveband combinations

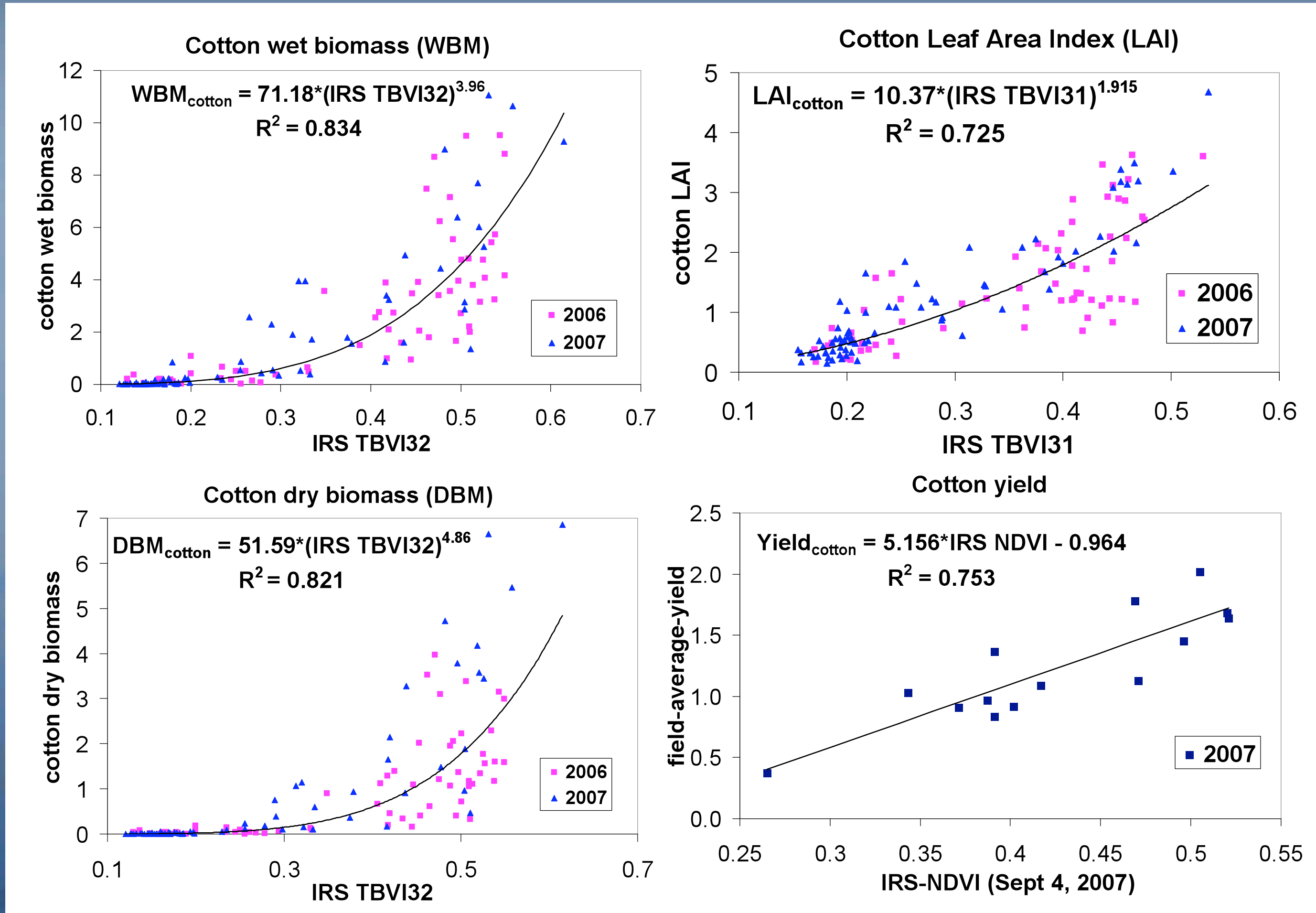
Spectro-biophysical and yield models. The best models for determining biomass, LAI and yield of 5 crops using IRS LISS and Quickbird data (5-10% points sieved)

				Best bands			Best indices		
Crop	**Parameter**	**Sensor**	**sample size**	**Best model**	**band**	**R-square**	**Best model**	**band combination**	**R-square**
Cotton	Wet Biomass	IRS	140	Exp	2	0.697	Power	2, 3	**0.834**
		QB	41	Multi-linear	1, 4	**0.813**	Multi-linear	1,4; 3,4	0.506
	Dry Biomass	IRS	136	Power	2	0.620	Power	2, 3	**0.821**
		QB	41	Exp	2	0.521	Exp	1, 2	**0.661**
	LAI	IRS	135	Multi-linear	3, 4	0.634	Power	1, 3	**0.725**
		QB	41	Multi-linear	2, 4	0.511	Quadratic	2, 4	**0.574**
	Yield	IRS[A]	14				Linear	2, 3	**0.753**
		QB[B]	7				Linear	3, 4	**0.610**
Wheat	Wet Biomass	IRS	9	Quadratic	2	0.425	Quadratic	1, 3	**0.678**
	Dry Biomass	IRS	14	Quadratic	1	0.205	Quadratic	3, 4	**0.309**
	LAI	IRS	18	Quadratic	4	**0.8**	Multi-linear	1,3; 2,3	0.465
	Yield	IRS	12				Linear	2, 3	**0.67**
Maize[D]	Wet Biomass	IRS	19	Power	2	0.815	Power	2, 3	**0.871**
	Dry Biomass	IRS	17	Exp	2	**0.928**	Power	2, 3	0.903
	LAI	IRS	19	Multi-linear	1, 3	0.777	Multi-linear	1,2; 2,3	**0.839**
Rice[E]	Wet Biomass	QB	10	Multi-linear	1, 2	0.535	Multi-linear	1,2; 2,4	**0.600**
	Dry Biomass	QB	10	Multi-linear	1, 2	0.395	Multi-linear	1,3; 2,3	**0.414**
	LAI	QB	10	Multi-linear	2, 4	**0.879**	Quadratic	2, 3	0.234
Alfalfa	Wet Biomass	IRS	21	Power	2	0.838	Quadratic	1, 2	**0.853**
		QB	8	Multi-linear	2, 4	0.772	Multi-linear	1,2; 2,3; 3,4	**0.887**
	Dry Biomass	IRS	21	Power	2	**0.817**	Exp	1, 2	0.812
		QB	8	Multi-linear	2, 4	0.732	Multi-linear	1,2; 2,3; 3,4	**0.867**
	LAI	IRS	21	Power	3	0.499	Exp	3, 4	**0.639**
		QB	8	Multi-linear	1, 3, 4	**0.927**	Multi-linear	1,3; 3,4	0.858

Note: A, Yield model using 2007 data
B, Yield model using 2006 data
C, ∑NDVI camera is the accumulated NDVI derived using the hand hold NDVI camera for field data during 2006
D, Sample points of data from Quickbird for maize was inadequate
E, Sample points of data from IRS for rice was inadequate

2.0 Spectro-Biophysical\Yield Models

Illustrative Examples for Cotton Crop Variables versus IRS LISS 23.5 m Data



Note: * the cotton yield model uses September 4, 2007 IRS LISS image.

3.0 Extrapolation of Spectro-Biophysical\Yield Model understanding

to Larger Areas using Landsat ETM+ 30m Data

The yield - NDVI correlation was applied to all pixels, classified as cotton, inside the study area, to model cotton productivity (Figure 5).

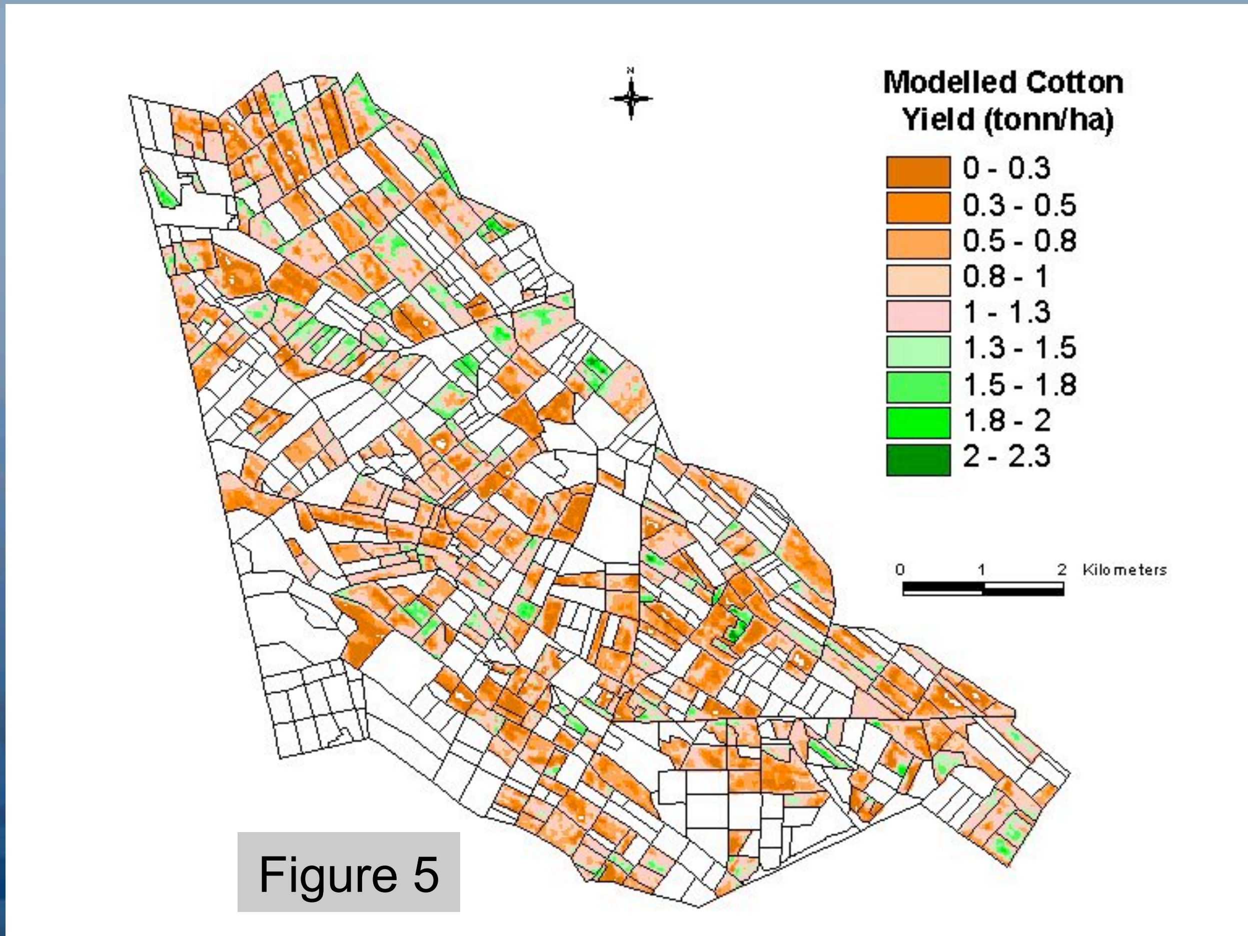
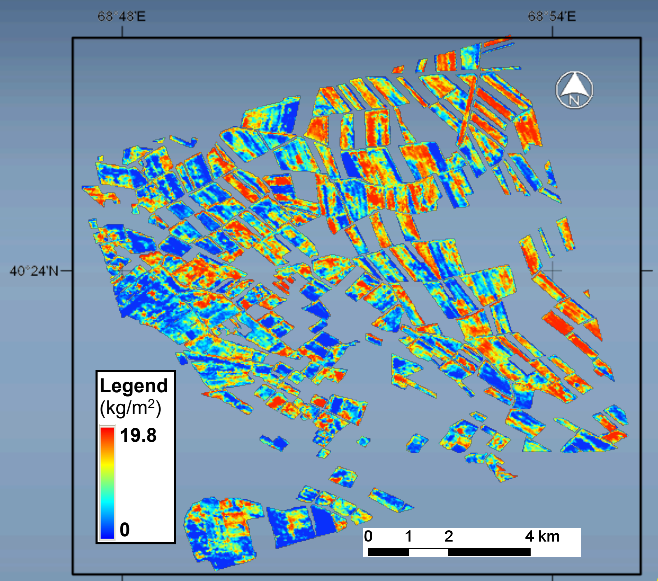
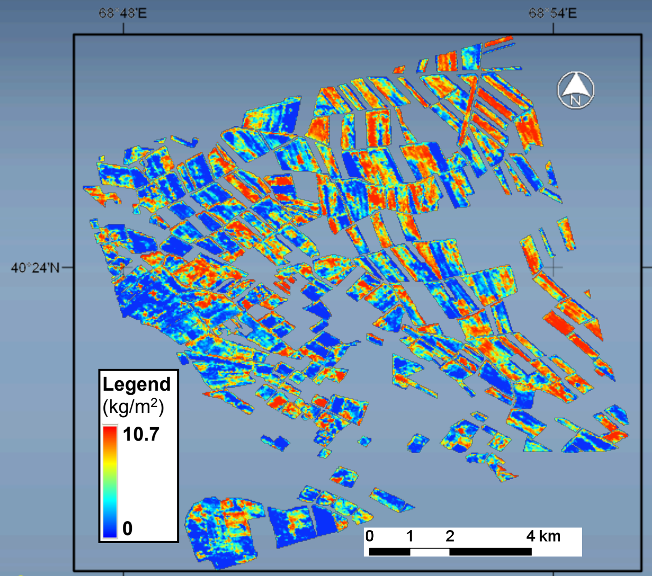


Figure 5

3.0 Extrapolation of Spectro-Biophysical\Yield Model understanding to Larger Areas using IRS 23.5m Data

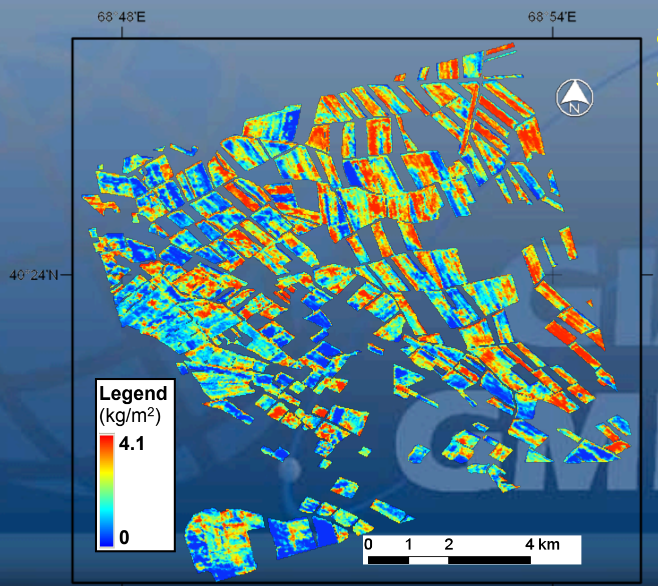


Wet biomass map (18-Jul-2006)

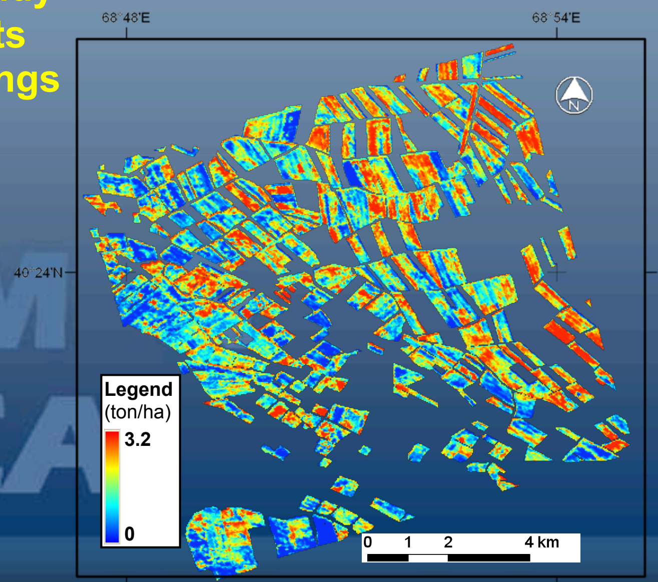


Dry biomass map (18-Jul-2006)

Cotton crop, Galaba study area and its surroundings



LAI map (18-Jul-2006)



Yield map

2.0 Water Use or ET_{actual} (m^3)

Methods of WPM: 4.0 Water use or ET_{actual}

ET_{actual} Theory (Surface Energy balance Models)

Actual evapotranspiration (ET) is calculated as the residual of the difference between the net radiation to the surface and losses due to the sensible heat flux (energy used to heat the air) and ground heat flux (energy stored in the soil and vegetation).

$$LE = Rn - G - H$$

LE = Latent heat flux (energy consumed by ET) (W/m^2)
Rn = Net radiation at the surface (W/m^2)
G = Ground heat flux (W/m^2)
H = Sensible heat flux (W/m^2)

Different Methods of Determining ET_{actual}

1. Surface energy balance models (SEBAL);
2. Mapping Evapotranspiration with high resolution and internalized calibration (METRIX):
3. Simplified Surface Energy balance Model (SEBAL);
4. Water applied (direct inflow and outflow measurement);
5. Water balance equations.

Methods of WPM: 4.0 Water use or ET_{actual}
Simplified Surface Energy Balance Model (SSEBM) Approach

Water use is determined by multiplying Evaporative fraction by reference ET

$$ET_{frac} = \frac{T_H - T_x}{T_H - T_C}$$

$$ET_{act} = ET_0 * ET_{frac}$$

ET_{act} – the actual Evapotranspiration, mm.

ET_{frac} – the evaporative fraction, 0-1, unitless.

ET_0 – reference ET, mm.

T_x – the Land Surface Temperature (LST) of pixel x from thermal data.

T_H/T_C – the LST of hottest/coldest pixels.

SSEBM for ET_{actual} or water use of Crops

4.1 Step 3 : ET_{actual}

Step 3: Determining ET_{actual}

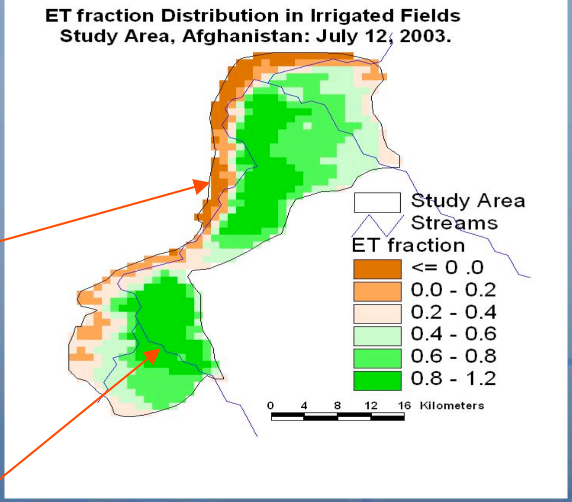
ET act = ET frac * ET ref

$$ET\ frac = \frac{T_{hot} - T_x}{T_{hot} - T_{cold}}$$

ET ref (penman-monteith)

ET fraction Map (based on ETM+ thermal data)

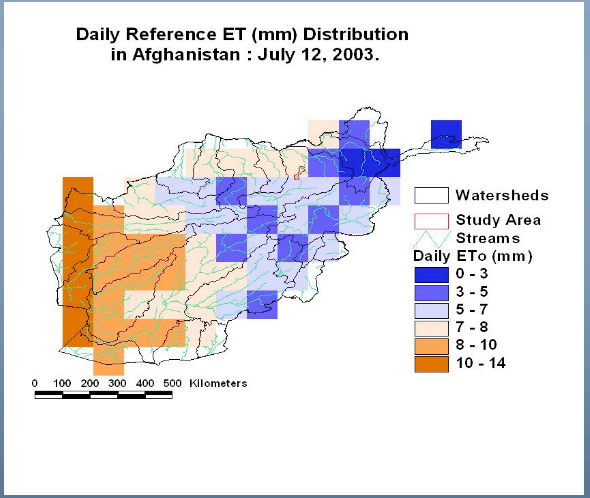
Hot Pixel (T_{hot})



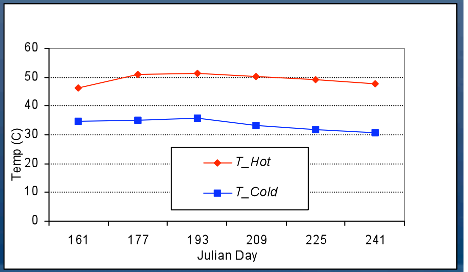
Cold Pixel (T_{cold})

X

Reference ET map (based on long-term met data)



= ET act



(Senay et al., 2005)

SSEBM for ET_{actual} or water use of Crops

4.1 Step 1 : $ET_{fraction}$ using Landsat ETM+ Thermal Data

The raster layers of surface temperature, calculated from each Landsat ETM+ image were used for ET fraction modeling (Figure 6) by applying Simplified Surface Energy Balance (SSEB) model (see section 6.1).

Galaba Study Area in Syr Darya, Uzbekistan using Landsat ETM+ Thermal Data

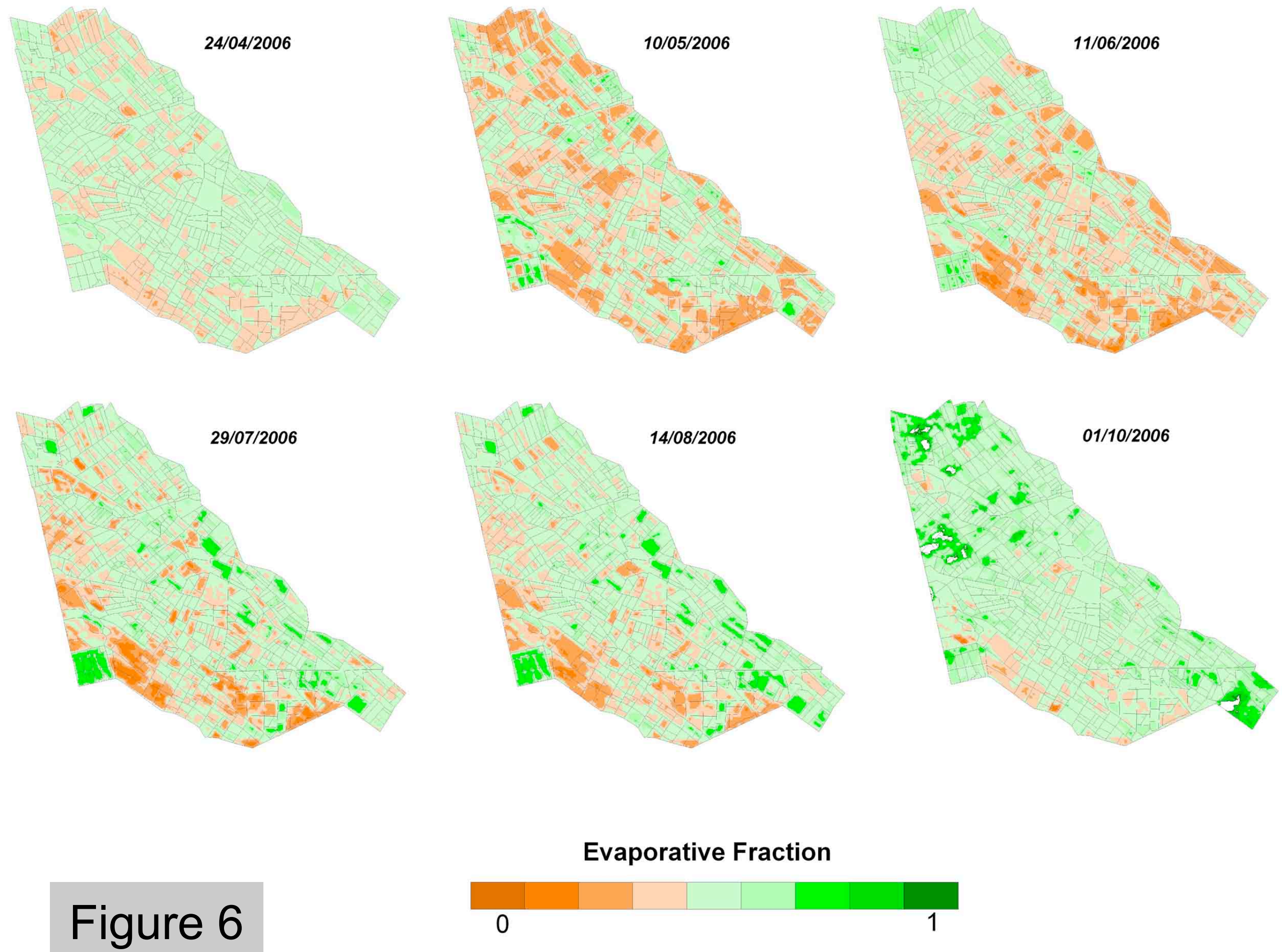


Figure 6

4.0 Water Use or ET_{actual}

Water Use or $ET_{actual} = ET_{fraction} * ET_{reference}$

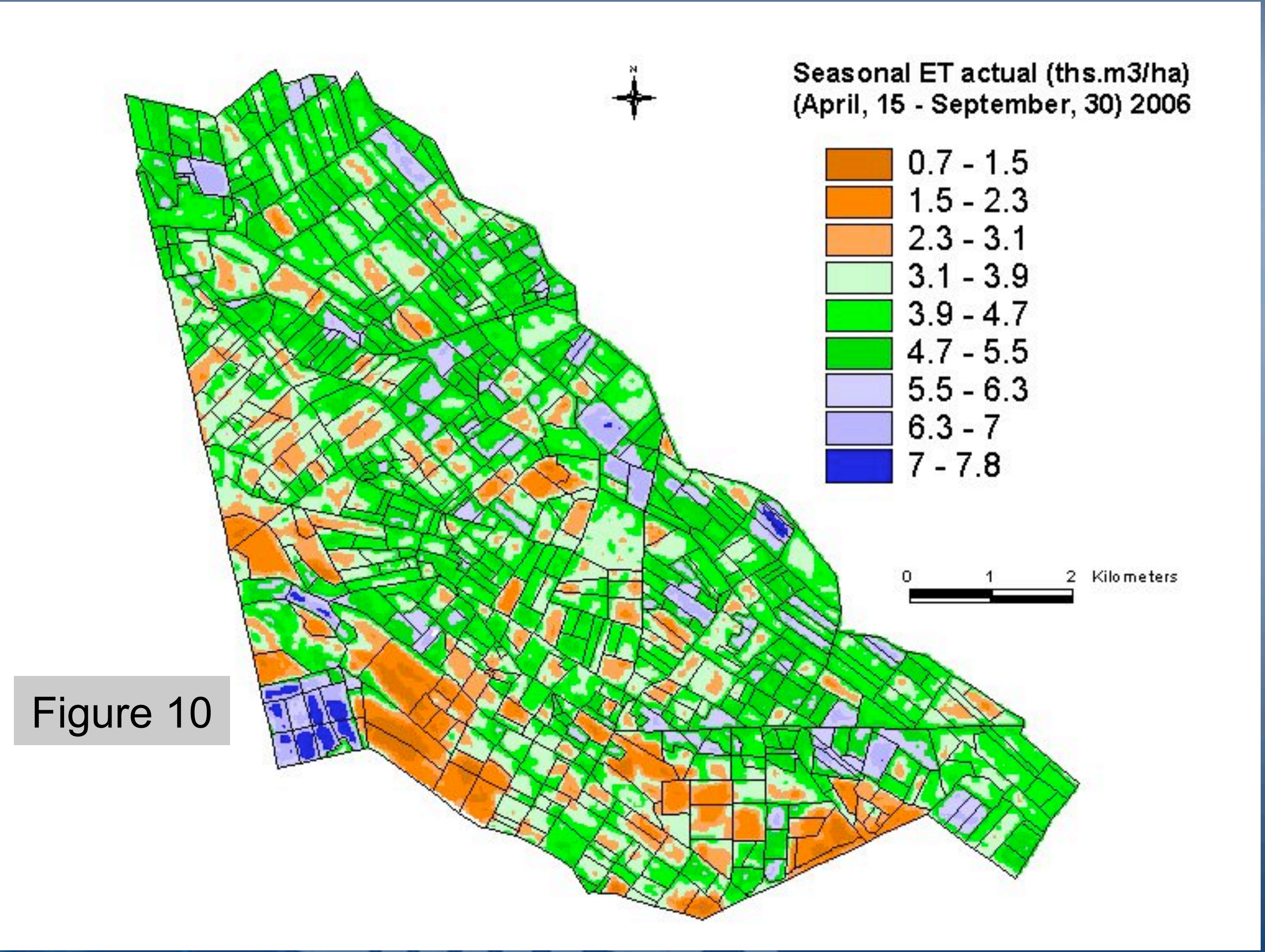


Figure 10

Galaba Study Area in Syr Darya, Uzbekistan using Landsat ETM+ Thermal Data

3.0 Water Productivity Maps (WPM)

Water Productivity Mapping (WPM) using Remote Sensing

Increase Water Productivity of Existing Croplands

$$\textbf{WP} = \frac{\textbf{Crop Productivity}}{\textbf{Water use}}$$

WP is crop water productivity (kg/m3)/($/m3)
Crop Productivity in units of Biomass (kg/m2) or Yield (tonn/ha) or Value ($/ha)
Water use is seasonal actual ET (thousand m3/ha)

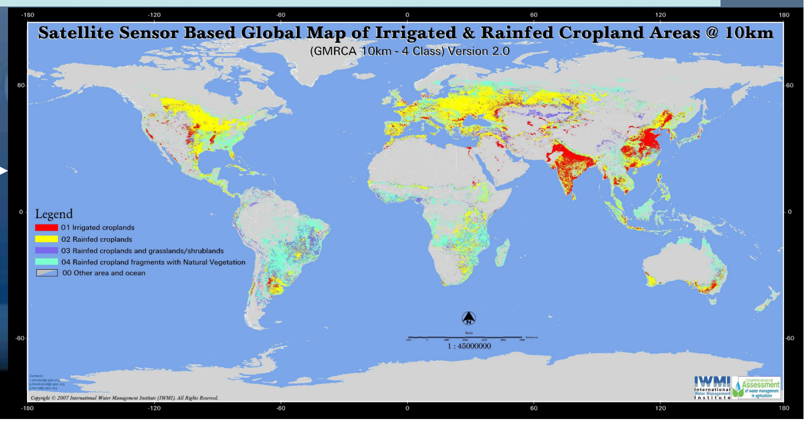
Crop Productivity = f (NDVI)

NDVI – Normalized Difference Vegetation Index (-), from satellite images:

NDVI = (NIR – Red) / (NIR + Red)

NIR and **Red** are reflectance in near-infrared and red bands

The best bet scenario is to continue to produce more (increase water productivity) food from existing croplands and water



Methods of Water Productivity Mapping (WPM) using Remote Sensing

WPM of Agricultural Croplands

Cotton water productivity (kg\m3) map (Figure 11) is determined by dividing crop productivity (tonn\ha) map (Figure 5) by water use (thousands m3\ha) map (Figure 10).

Galaba Study Area in Syr Darya, Uzbekistan using Landsat ETM+ Thermal Data

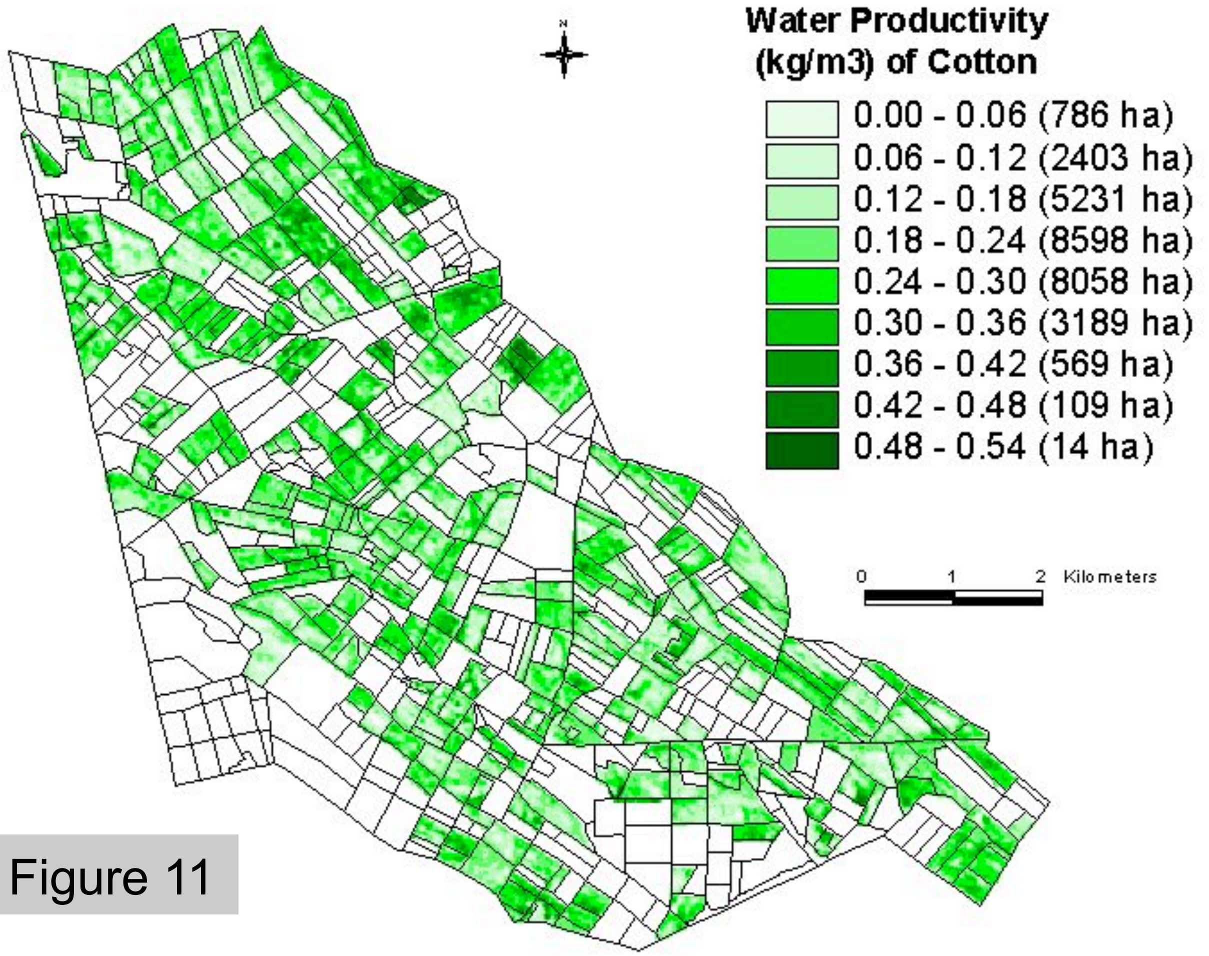


Figure 11

6.0 How Can WPM Pin-Point Areas of Low and High WP

Helping us focus on growing more food from available land and water

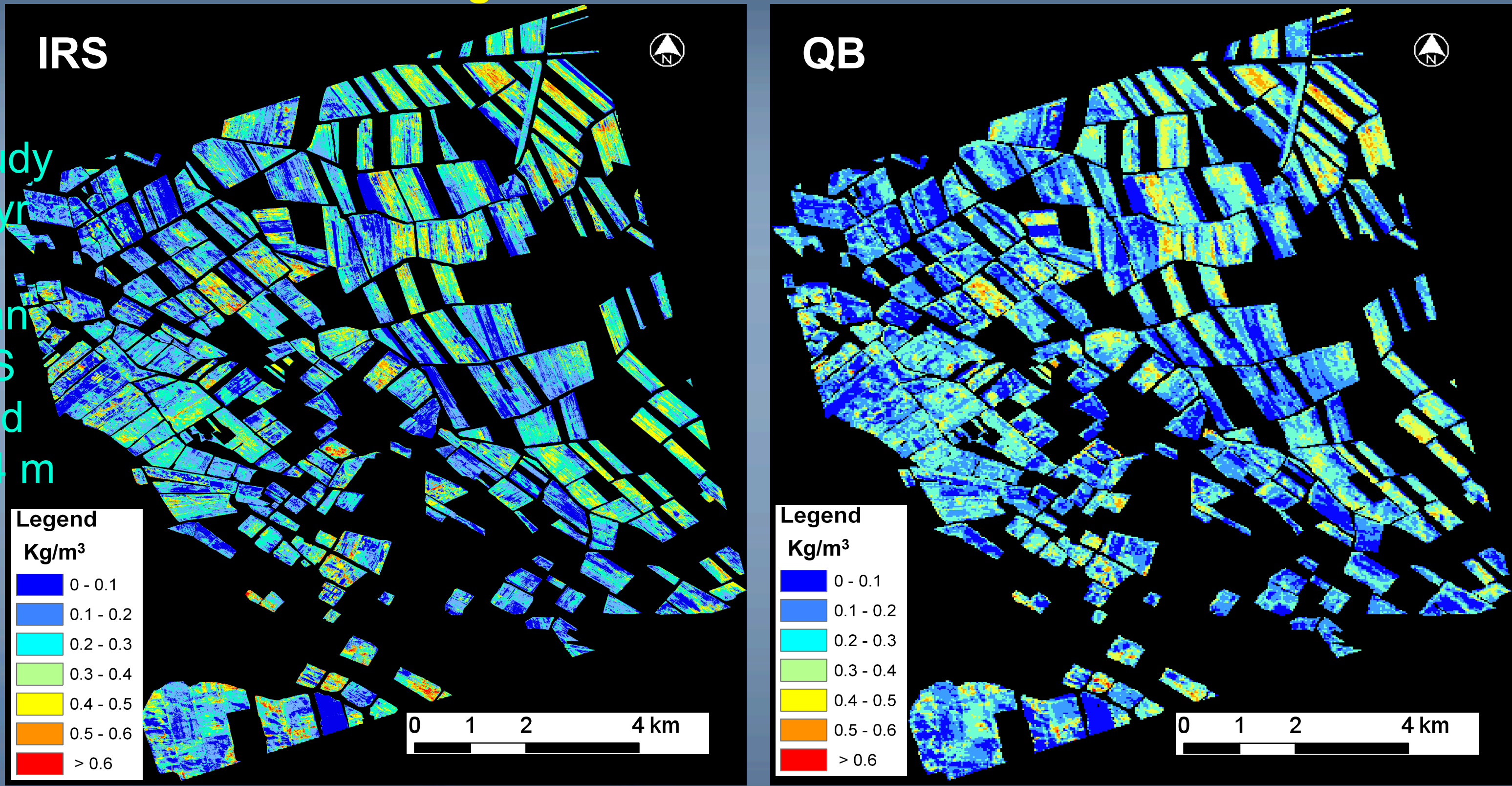
GIAM & GMRCA

Water Productivity Mapping (WPM) using Remote Sensing

WPM of Agricultural Croplands

WPM using IRS LISS 23.5 m and Quickbird 4 m

Galaba Study Area in Syr Darya, Uzbekistan using IRS 23.5m and Quickbird 4 m data



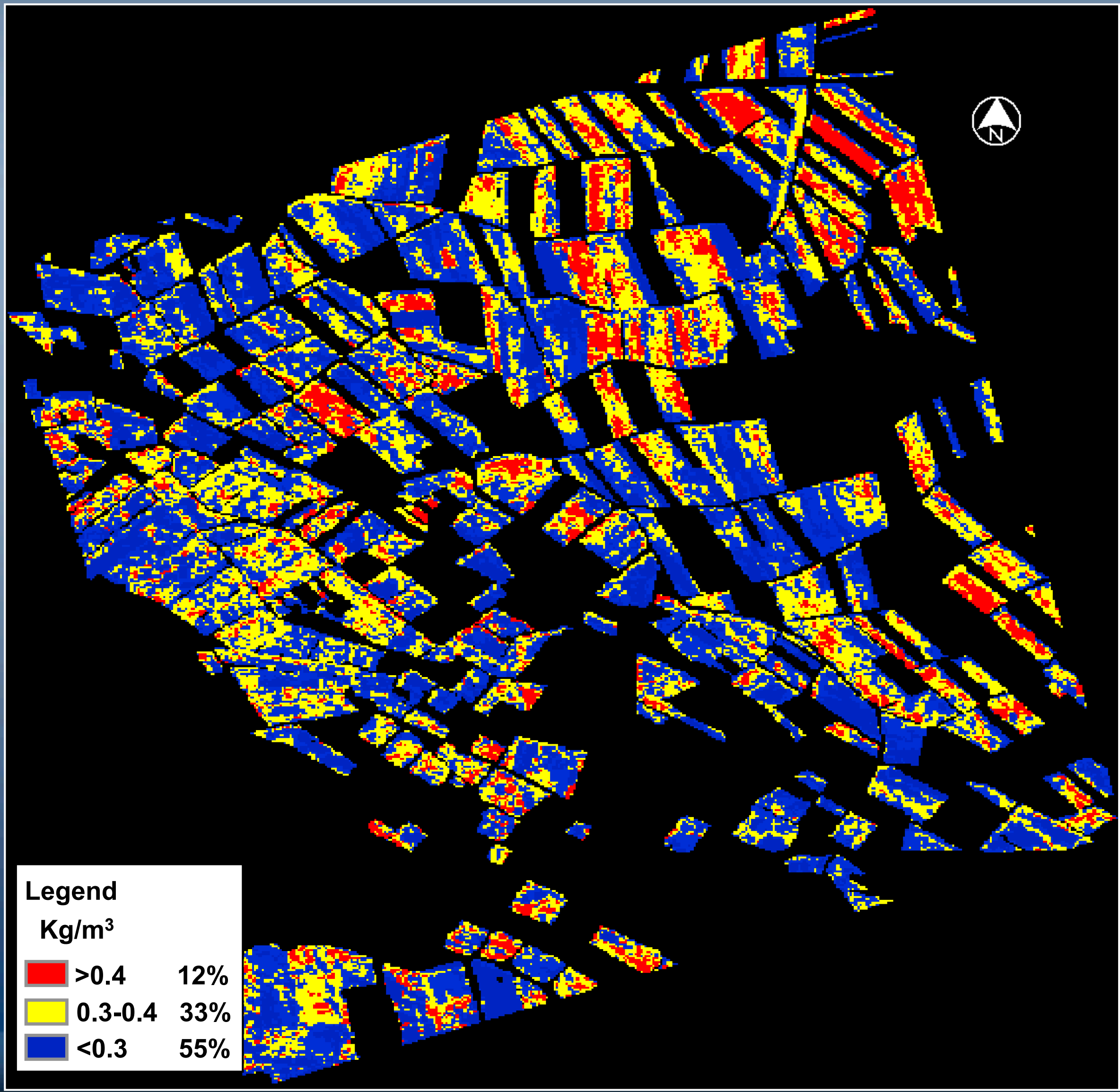
	IRS		Quickbird	
group	area (ha)	share (%)	area (ha)	share (%)
0-0.1	167.9	4.1	85.1	1.8
0.1-0.2	695.5	16.8	970.2	21.0
0.2-0.3	1421.0	34.4	1550.7	33.5
0.3-0.4	1381.7	33.4	1370.0	29.6
0.4-0.5	414.7	10.0	542.7	11.7
0.5-0.6	50.3	1.2	93.0	2.0
>0.6	2.4	0.1	17.9	0.4

	Mean	Min	Max	Range	No. Pixels
IRS	0.285	0	0.70	0.7	74850
QB	0.289	0	1.06	1.06	7776175

Unit: kg/m³

6.0 Water Productivity Maps pin-pointing Areas of Low and High WP

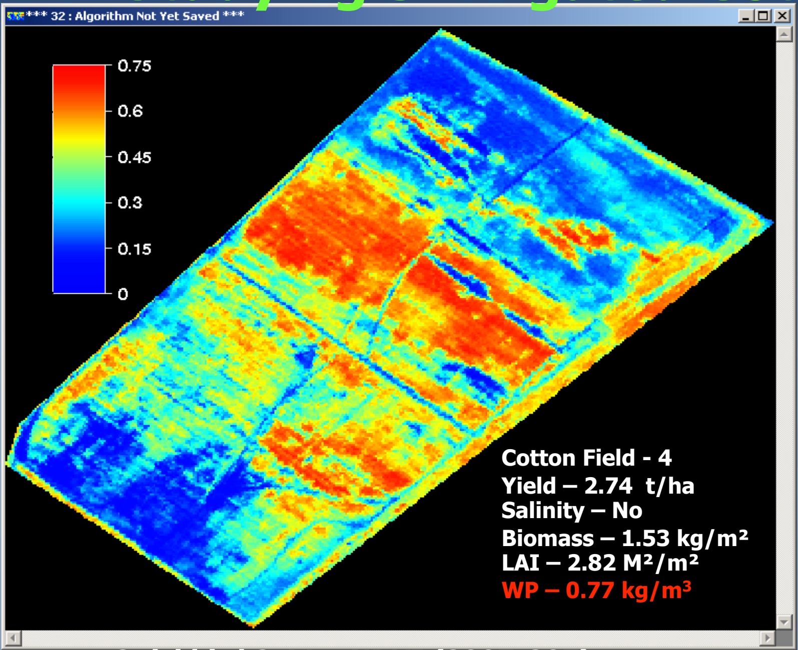
Opportunities to Grow More Food from Existing Lands



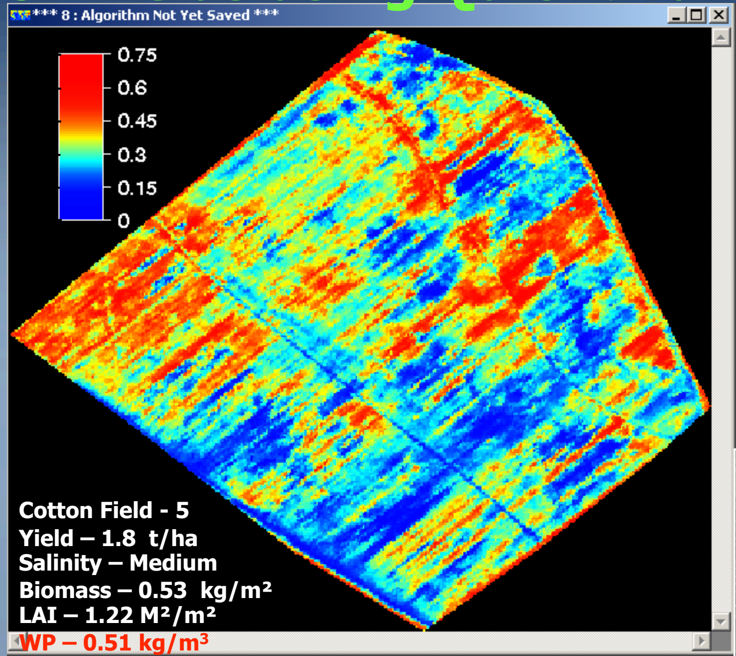
……here is an huge opportunity to grow more food from existing land and water resources……………..

Water Productivity Mapping (WPM) using Remote Sensing

Studying 3 Irrigated Cotton Fields using Quickbird 2.44 m Data

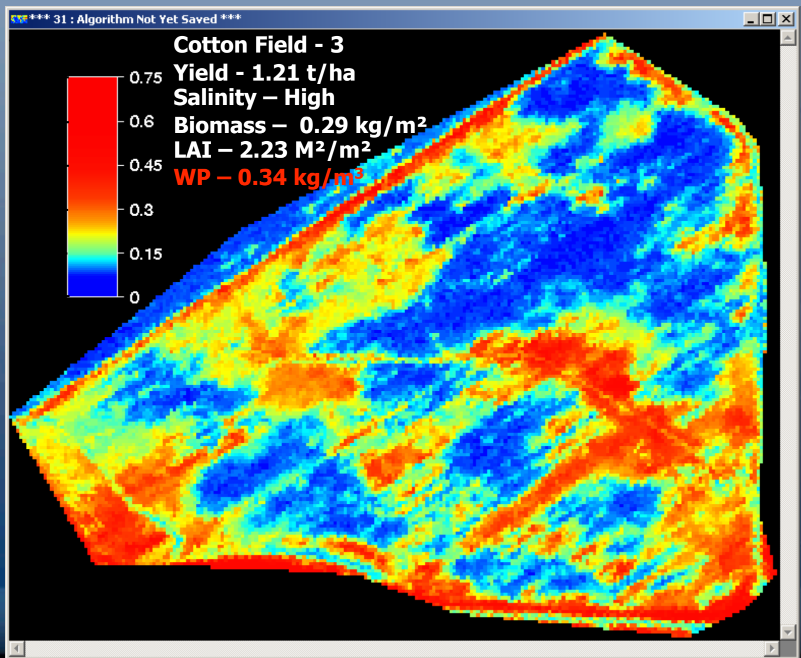


Quickbird 2.44m NDVI (2007-207)



Quickbird 2.44m NDVI (2007-207)

The trends in spatial variability in Quickbird 2.44m (this slide) and IRS LISS 23.5m (next slide) are similar.



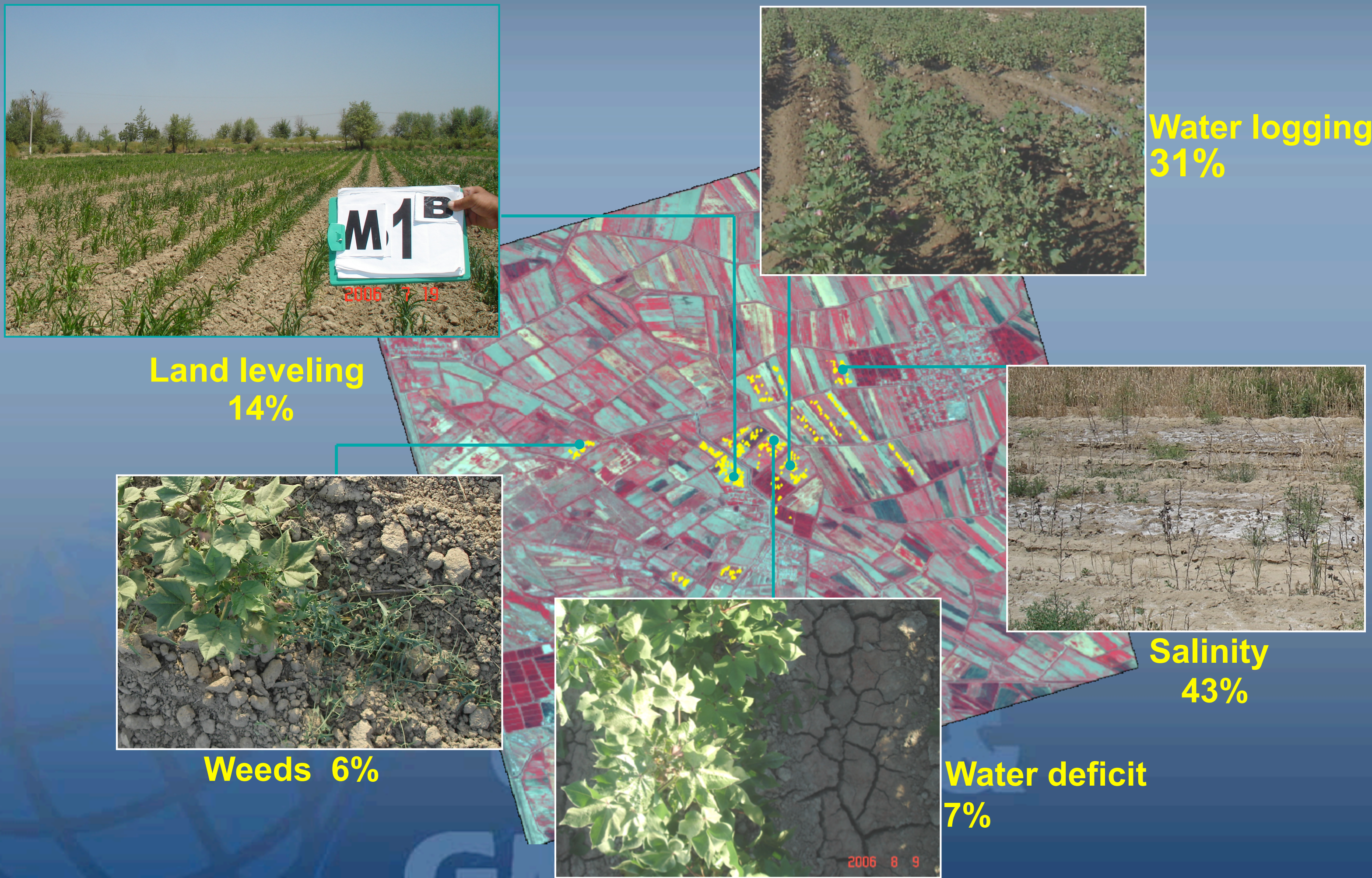
Quickbird 2.44m NDVI (2007-207)

……what is important to note is the spatial variability within field……..indeed, about 50% of the field has low productivity……….if we can increase spatial variability through better land and water management, we can afford to feed increasing populations (that are also more consuming) with available land and water……..

4.0 Factors Affecting Water Productivity

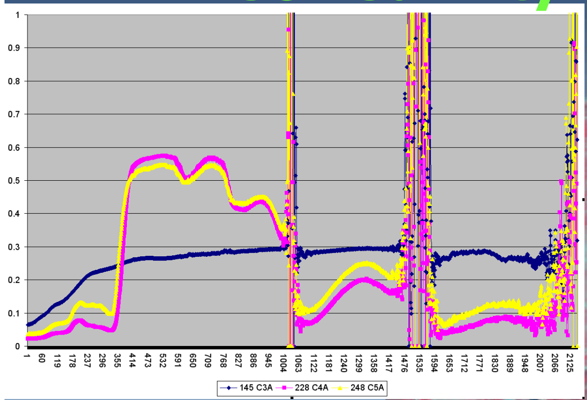
7.0 Factors Affecting WP

Degree of influence of Various factors on WP variations within and between field as measured during field work

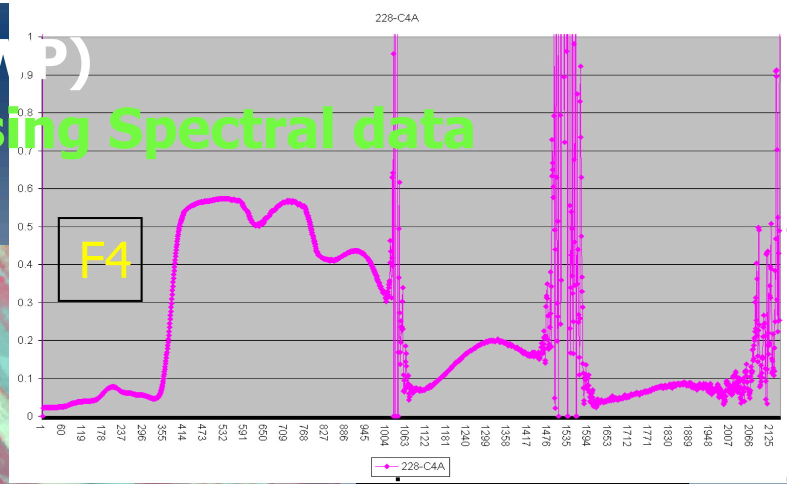


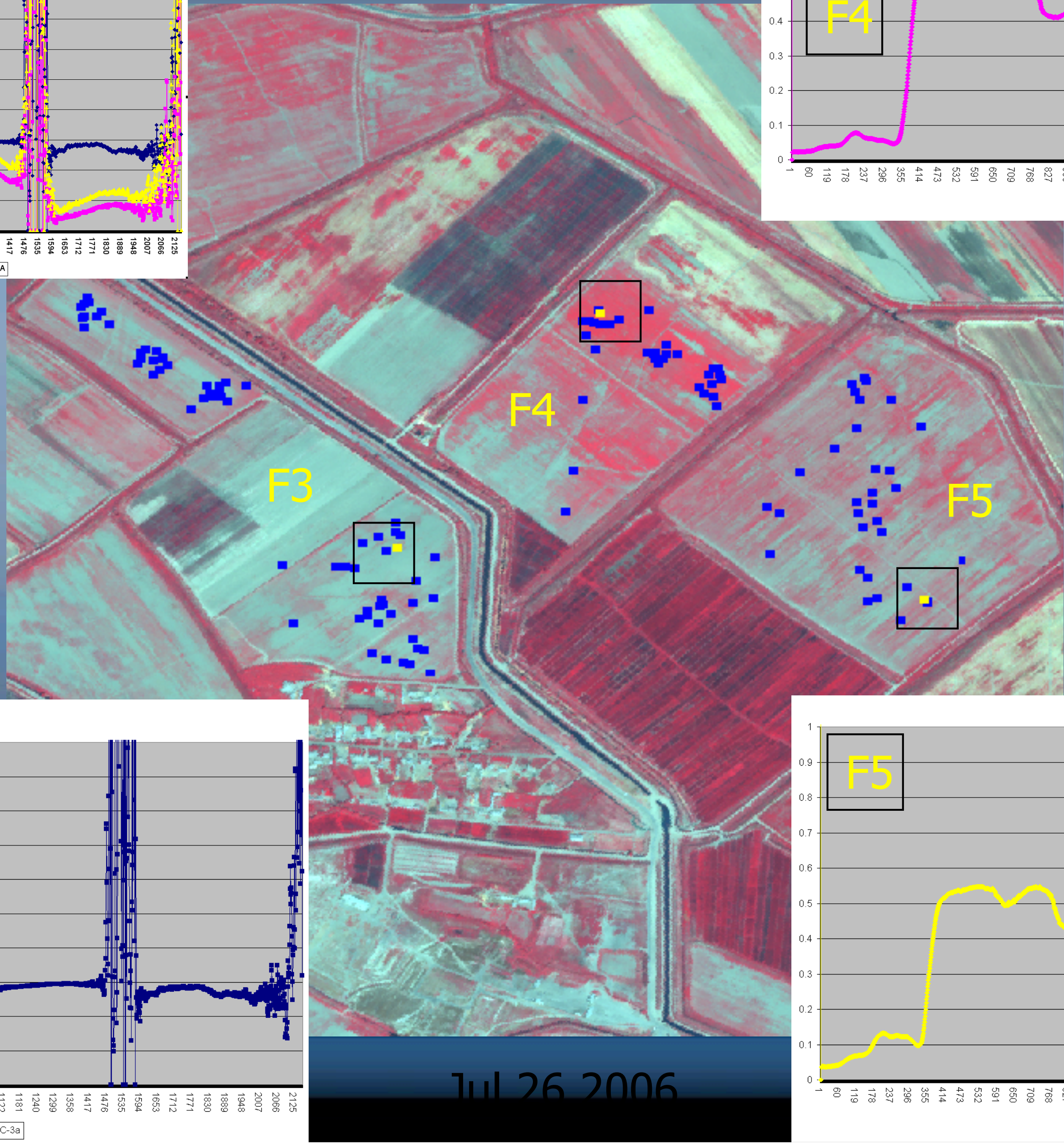
5.2 Factors Affecting Water Productivity (WP)

Soil Salinity Variations Captured using Spectral data



All spectra

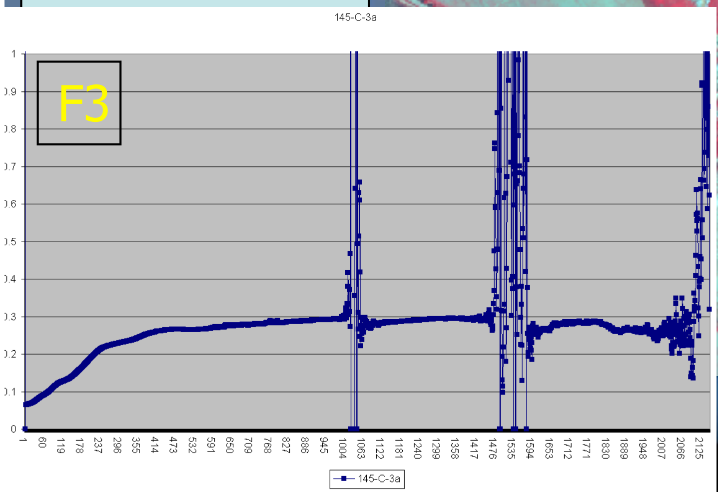


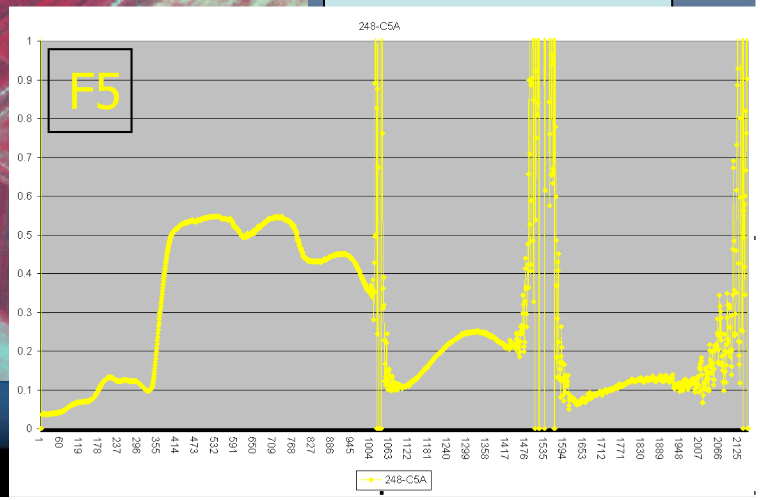


Yield: 2.74 t/ha
Soil salinity: nill
Best field
Biomass: 1.53 kg/m²
LAI : 2.82 M²/m²

Yield: 1.21 t/ha
Soil salinity: 3 (high)
Worst field
Biomass – 0.29 kg/m²
LAI – 1.12 M²/m²

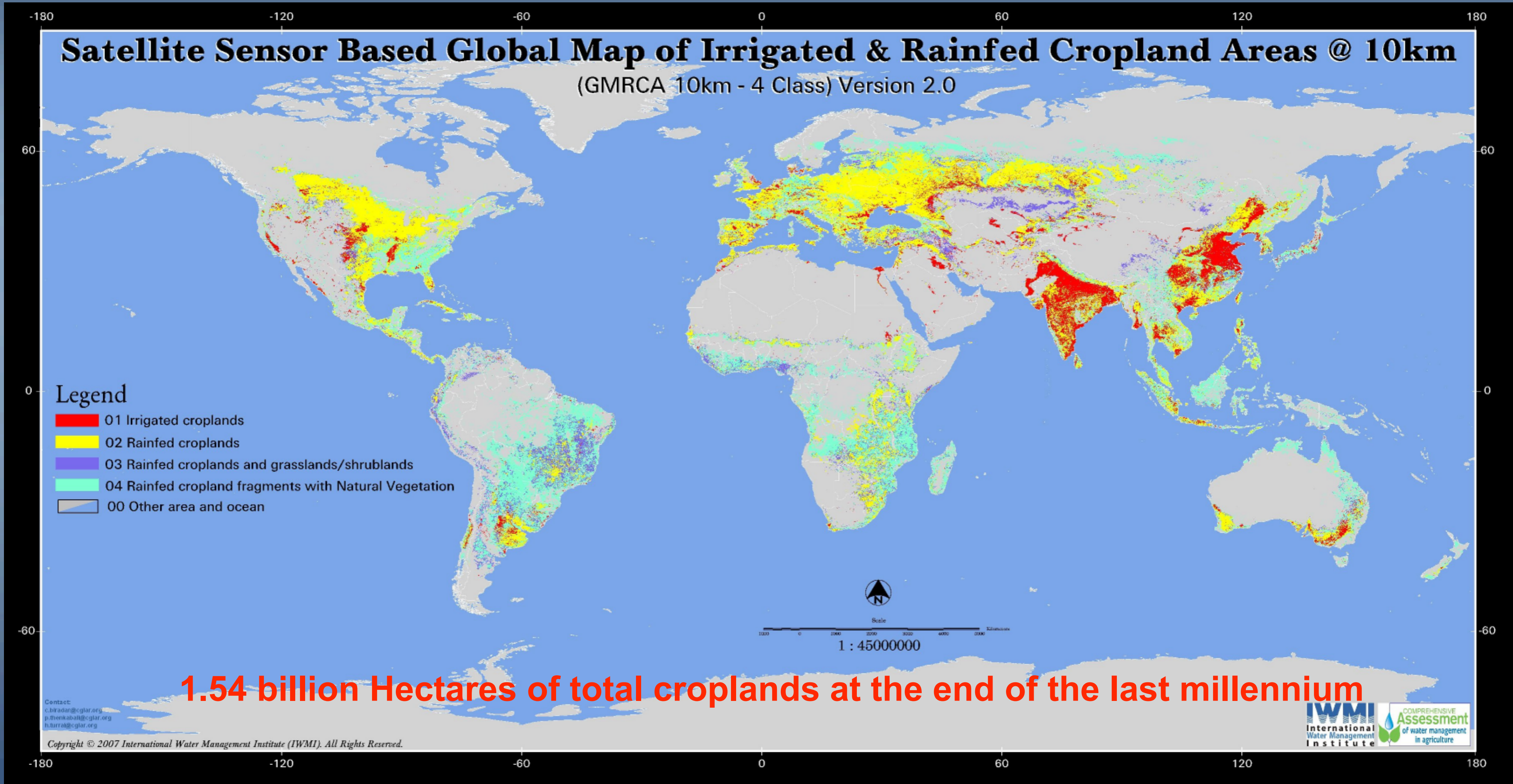
Yield: 1.8 t/ha
Soil Salinity: 2
Moderate field
Biomass : 0.53 kg/m²
LAI : 2.23 M²/m²





Water Productivity Mapping (WPM) using Remote Sensing

WPM of Irrigated and Rainfed Croplands of the World



…………..let us pin-point to areas in the world where there is mediul or low WP in irrigated and\or rainfed croplands……….here is an opportunity for us to push for an world where we use same (and even better less) water and land than we currently use but continue to produce more food…………

Conclusions

Conclusions

1. **WPM methods and protocols established using Multi-resolution RS:** methods to highlight areas of high and low WP is developed using remote sensing. Establishing WP variations can help determine areas of low and high water productivity. This will help us to focus on areas of low WP and establish causes for the same. Once this is achieved strategies can be developed to increase WP of these areas;
3. **Low WP areas dominate:** Results showed that WP of the irrigated cotton crop (the most dominant crop in the Syr Darya river basin) varied between 0-0.6 kg\m3. Of this only 11 percent of the cotton crop area was in 0.4 kg\m3 or higher WP. About 55% of the cotton area had <0.3 kg\m3. The results had similar trends for rice, maize, and wheat.
4. **Scope for increased WP:** The results imply that there is highly significant scope to increase WP (to grow more food from existing land and water resources) through better management practices. The challenge is to increase land and water productivity of the 55% of the areas. If we can achieve that, food security of future generations can be secured without having to increase croplands and\or greater water use.

Water Productivity Mapping (WPM) using Remote Sensing

Research Opportunity to Make a Difference

1. Cropland areas + crop types + geographic precision + irrigated areas + irrigation source (e.g., informal): reduce uncertainty

high spatial resolution + time-series MODIS + field-plot data

2. Water use by croplands: reduce uncertainty

Surface energy balance models

3. Water productivity mapping: pin-point areas of low and high WP

RS + modeling

4. Food security, water security, environmental security: based on above

From step 1 to 3

Global perspective

Further Reading

Water Productivity Mapping (WPM) using Remote Sensing

Further Readings

3 peer-reviewed journal papers (2 published + 1 in review) + 1 poster + this presentation

1. Platonov, A., Thenkabail, P.S., Biradar, C., Cai, X., Gumma, M., Dheeravath, V., Cohen, Y., Alchanatis, V., Goldshlager, N., Ben-Dor, E., Vithanage, J., Manthrithilake, H., Kendjabaev, Sh., and Isaev. S. 2008. Water Productivity Mapping (WPM) using Landsat ETM+ Data for the Irrigated Croplands of the Syrdarya River Basin in Central Asia. Sensors Journal, 8(12), 8156-8180; DOI: 10.3390/s8128156. http://www.mdpi.com/1424-8220/8/12/8156/pdf.

2. Biradar, C.M., Thenkabail, P.S., Platonov, A., Xiangming, X., Geerken, R., Vithanage, J., Turral, H., and Noojipady, P. 2008. Water Productivity Mapping Methods using Remote Sensing. Journal of Applied Remote Sensing, Vol. 2, 023544 (6 November 2008).

3. Cai, X.L., Thenkabail, P.S., Biradar, C., Platonov, A., Gumma, M., Dheeravath, V., Cohen, Y., Goldshlager, N., Eyal Ben-Dor, Victor Alchanatis, and Vithanage, J.V. 2008. Water Productivity Mapping Methods and Protocols using Remote Sensing Data of Various Resolutions to Support “more crop per drop”. Photogrammetric Engineering and Remote Sensing (in review).