Dr. Paul Wagner
Remote Sensing and Geoinformatics
Institute of Geographical Sciences

Freie Universität Berlin

Reflecting the interdependence of land use and hydrology in SWAT modeling studies

Paul Wagner & Björn Waske

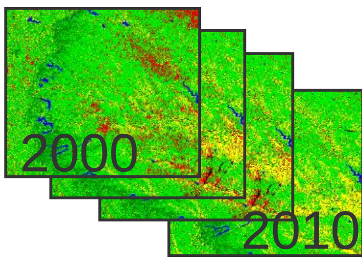
International SWAT Conference
24 June 2015

1. Land use change in SWAT

Freie Universität Berlin

Past land use changes

Land use change



SWAT
simulation

Land use update

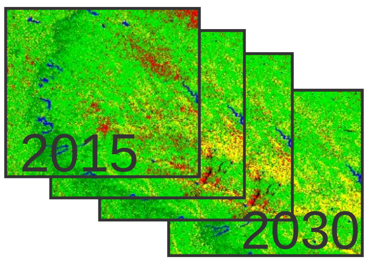
implemented since Version SWAT 2009

SWAT studies by: Chiang et al., 2010; Pai and Saraswat, 2011; Koch et al., 2012

1. Land use change in SWAT

Future land use changes

Land use model



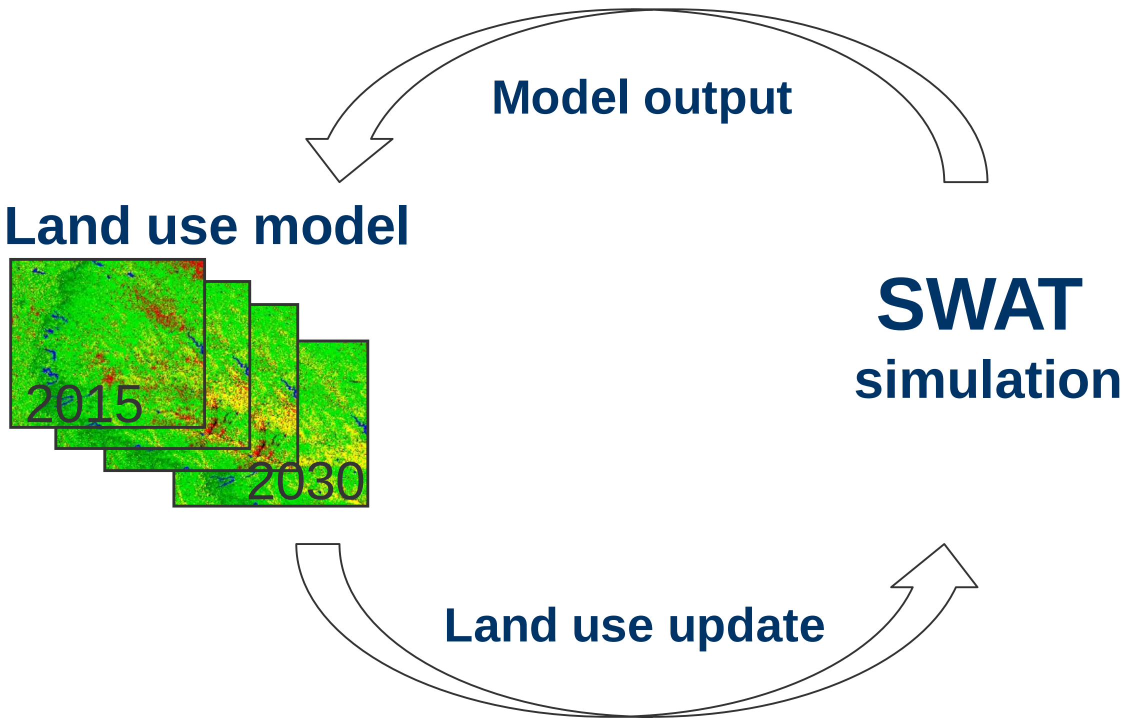
SWAT
simulation

Land use update

SWAT study by: Wagner et al., 2015 (in rev.)

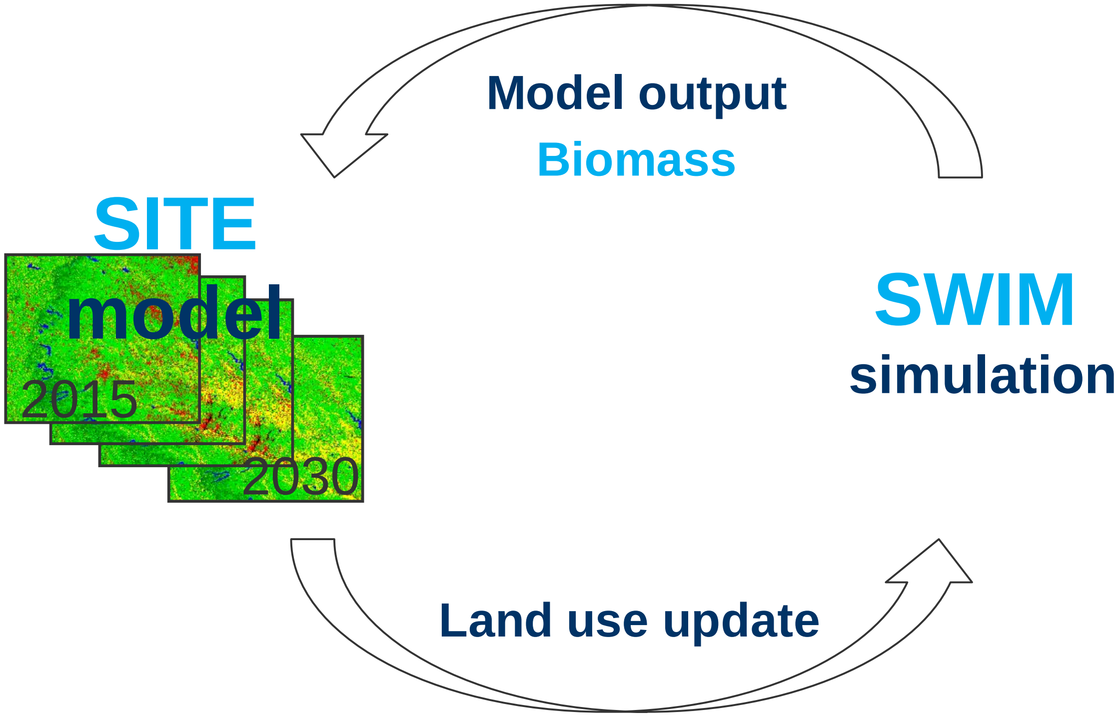
1. Land use change in SWAT

Future land use changes



1. Land use change in SWAT

Future land use changes



Yalew et al. 2014 (IEMSS proceedings)

1. Land use change in SWAT

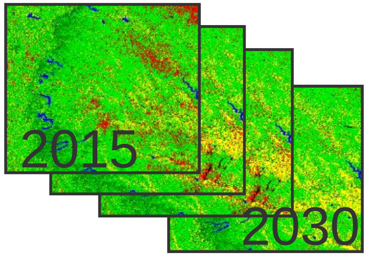
Freie Universität Berlin

Future land use changes

Model output

Water availability

Land use model



SWAT

simulation

Land use update

=> Better and consistent land use and hydrologic predictions

1. Objective

Future land use changes

Model output
Water availability

Land use model

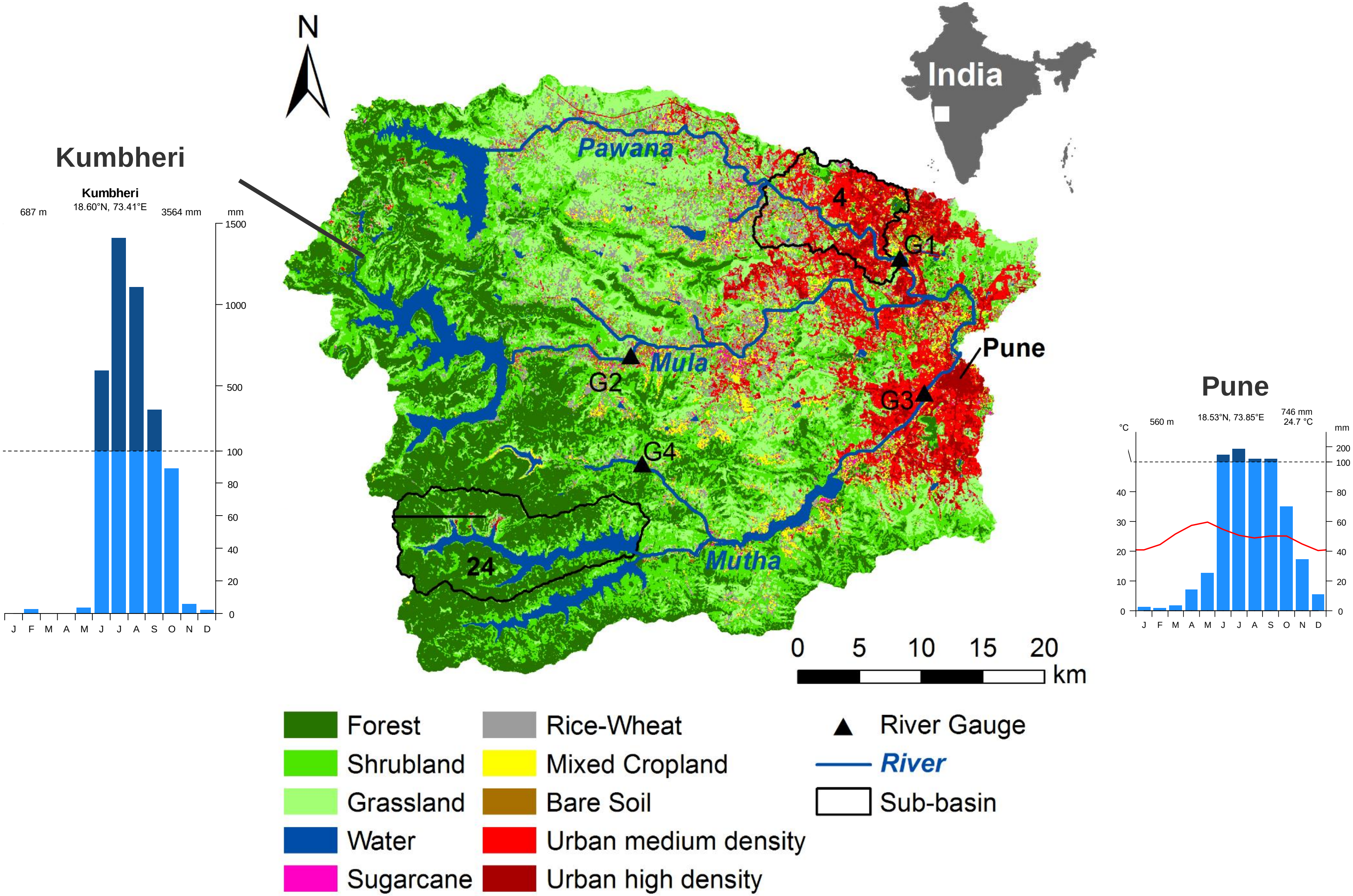
SWAT
simulation

Land use update

Are hydrologic output variables from SWAT suitable to predict land use change?

=> Better and consistent land use and hydrologic predictions

2. Study area



Kumbheri
Kumbheri
687 m
18.60°N, 73.41°E
3564 mm
mm
1500
1000
500
100
80
60
40
20
0
J F M A M J J A S O N D
N
India
Pawana
4
G1
Mula
G2
Pune
G3
G4
24
Mutha
0 5 10 15 20
km
Pune
560 m
18.53°N, 73.85°E
746 mm
24.7 °C
°C
mm
200
100
40
30
20
10
0
80
60
40
20
0
J F M A M J J A S O N D
Forest
Shrubland
Grassland
Water
Sugarcane
Rice-Wheat
Mixed Cropland
Bare Soil
Urban medium density
Urban high density
River Gauge
River
Sub-basin

3. SWAT model

1. **Freely available input data:**
   Data archives, Remote sensing, Measurements, Agencies
2. **Data processing:**
   a) **Digital elevation model[1,2]**
   b) **Landuse classifications (1989, 2000, 2009)[1,3]**
   c) **Meteorological data and river runoff[1,2]**
   d) **Rainfall interpolation[2]: TRMM Regression-Kriging**
3. **Model adaptation:**
   Parameterization and development
   Plant growth[1] & dam management[1,2]
4. **Model application:**
   Land use change[3] and climate change impact[4]

[1] Wagner, P.D., Kumar, S., Fiener, P., Schneider, K., 2011. *Transactions of the ASABE*, Vol. 54, 1783-1790.
[2] Wagner, P.D., Fiener, P., Wilken, F., Kumar, S., Schneider, K., 2012. *Journal of Hydrology*, Vol. 464-465, 388-400.
[3] Wagner, P.D., Kumar, S., Schneider, K., 2013. *Hydrology and Earth System Sciences*, 17, 2233-2246.
[4] Wagner, P.D., Reichenau, T.G., Kumar, S., Schneider, K., 2015. *Regional Environmental Change*, 15, 435-447.

3. Model validation

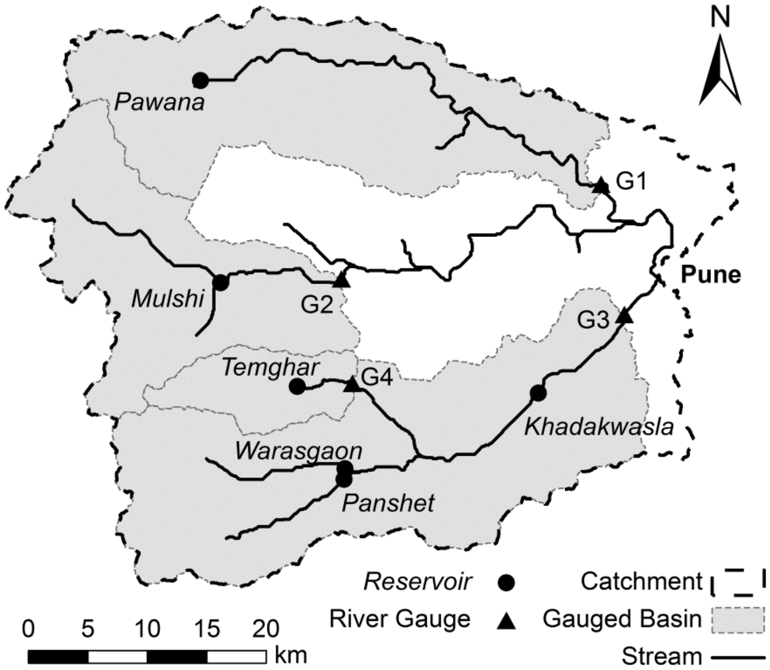
Runoff in rainy seasons 2001-2007

Nash-Sutcliffe Modellefficiency:

0.68 (G1) ++
0.67 (G4) ++

Percentage Bias (PBIAS):

+4% (G1) +++
+24% (G4) +



Model performance[1]

+++ very good
++ good
+ satisfactory

[1] Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. *Transactions of the ASABE* 50, 885-900.

3. Methodology

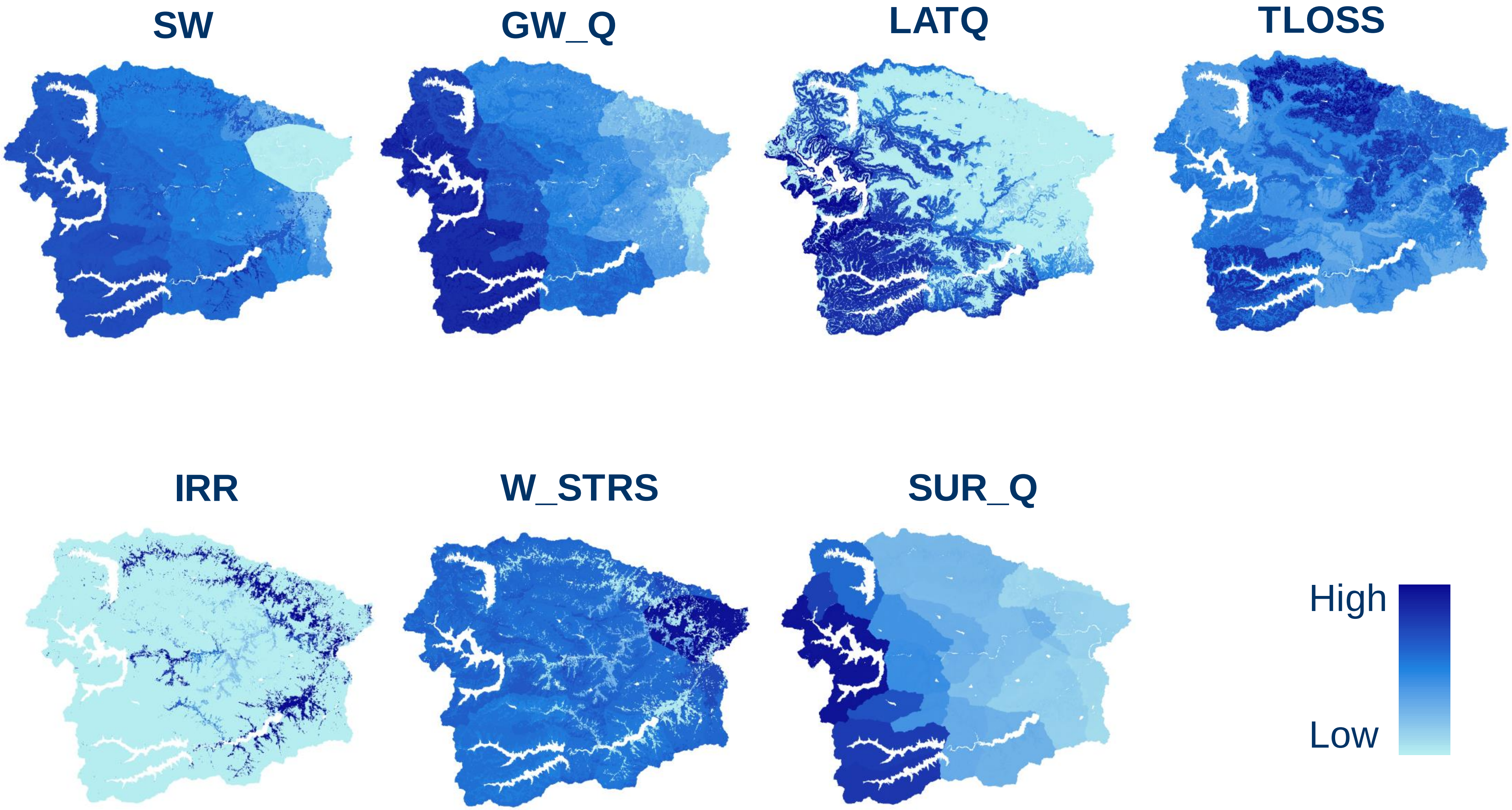
1. SWAT model run with 1989 land use from 1989 to 1999 and extraction of HRU-output
2. Identification of land use change areas between 1989 and 2000, and binary coding for each class: 1 change, 0 no change
3. Logistic regression for each changed class using variables from the HRU-output as predictor variables
4. Validation using ROC statistic and land use change maps between 2000 and 2009
5. Visual evaluation of probability maps

3. Selection of variables

Mean monthly values based on SWAT run (1989–99):

SW_END (mm)	Soil water content
GW_Q (mm)	Groundwater contrib. to streamflow
LATQ (mm)	Lateral flow contrib. to streamflow
TLOSS (mm)	Transmission losses
IRR (mm)	Irrigation amount
W_STRS (d)	Water stress days
SURQ_GEN (mm)	Surface runoff

3. Selection of variables



Mean monthly values based on SWAT run (1989–99)

3. Logistic regression

Freie Universität Berlin

$$Log\left(\frac{P_i}{1-P_i}\right)=\beta_0+\beta_1 X_{1,i}+\beta_2 X_{2,i}+\ldots+\beta_n X_{n,i}$$

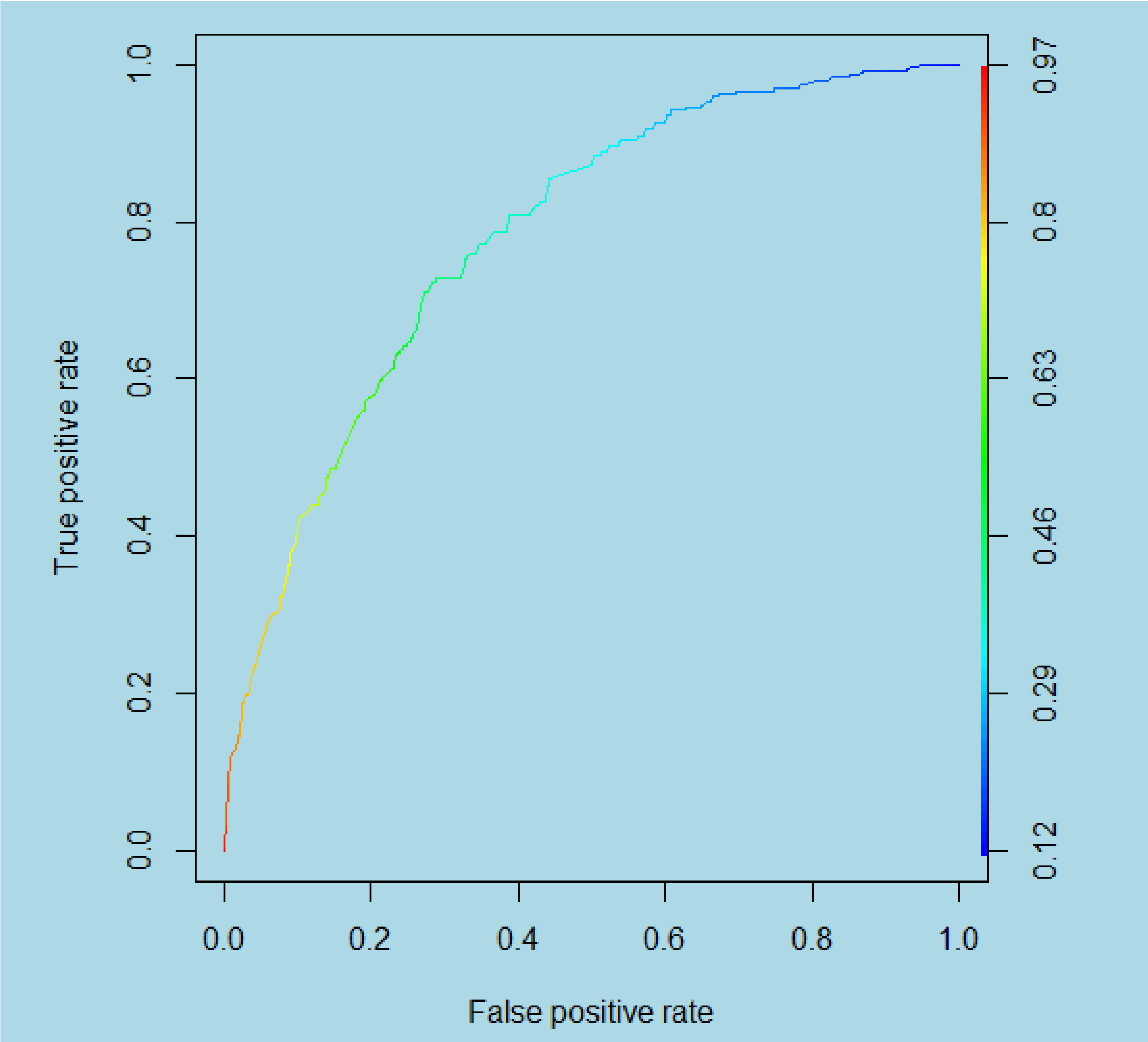
P_i Probability of a grid cell to be changed to land use type *i*

$X_{n,i}$ Predictor variable *n* for a change to land use *i*

β_n Coefficient for the n-th predictor variable

3. Relative Operating Characteristic

Freie Universität Berlin



ROC-Value: Area under curve: >50% better than random

100% perfect discrimination

4. Results

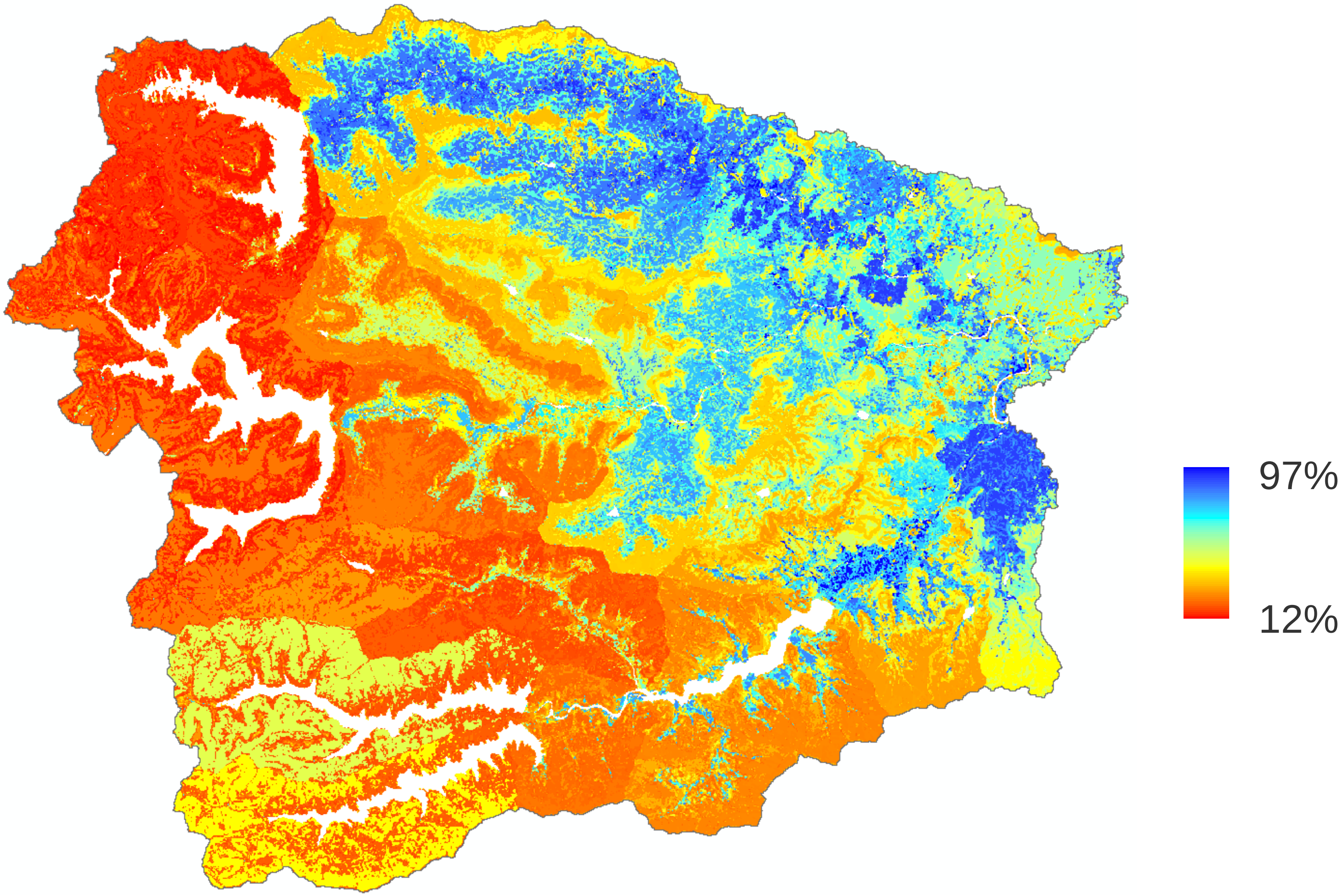
Influence of water variables on LUC probability

	SW	TLOSS	IRR	W_STRS	SURQ	GW_Q	LATQ
Change to Rice	+	+	+	-		-	
Change to Cropland		+	+	-	-		
Change to Sugarcane	-	+		-		-	
Change to Forest	+	-	-				+
Change to Shrubland	+	-	+	+	+		-
Change to Grassland	+	-	+	+	-		+
Change to Urban	+	+	+	+		-	-

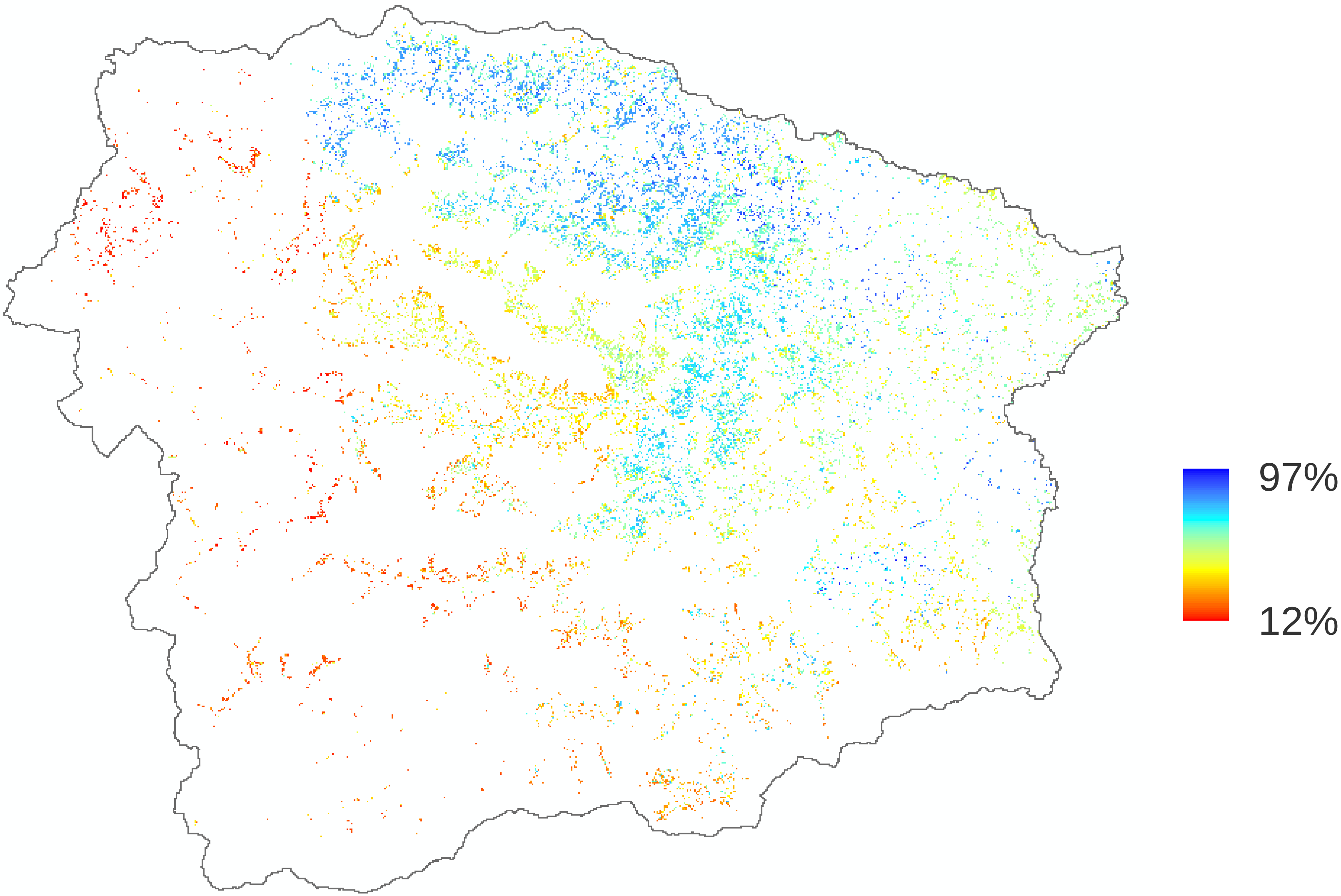
Some predictors not included due to collinearity

4. Probability for change to rice

Freie Universität Berlin



4. Validation change to rice in 2009



4. Results

Freie Universität Berlin

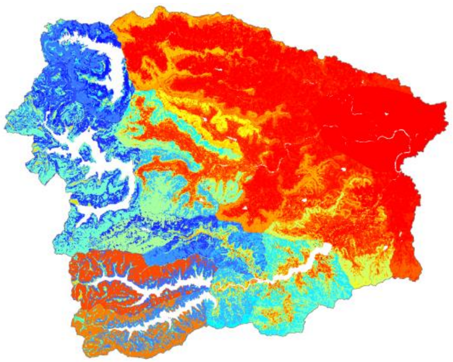
Validation

	ROC	Mean of Validation areas	Difference compared to other areas
Change to Rice	0.78	55%	+16%
Change to Cropland	0.75	61%	+19%
Change to Sugarcane	0.84	59%	+28%
Change to Forest	0.88	47%	+19%
Change to Shrubland	0.63	50%	+3%
Change to Grassland	0.68	49%	+3%
Change to Urban	0.84	68%	+37%

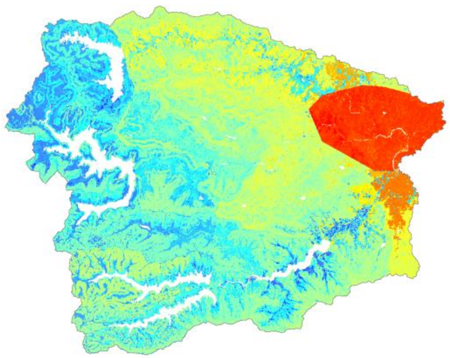
4. Probability maps

Freie Universität Berlin

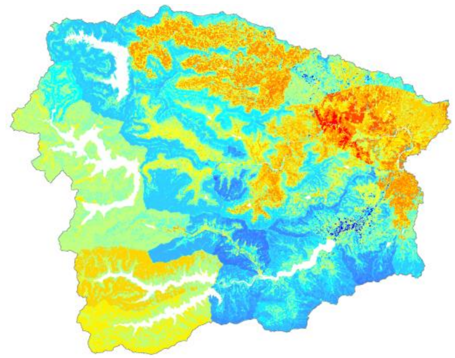
Forest



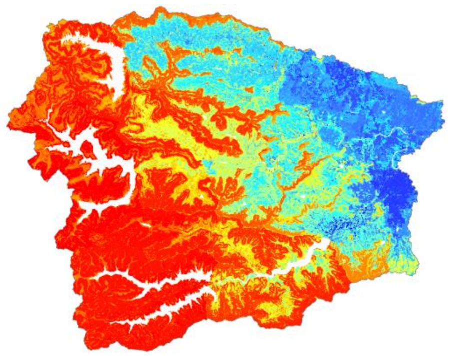
Shrubland



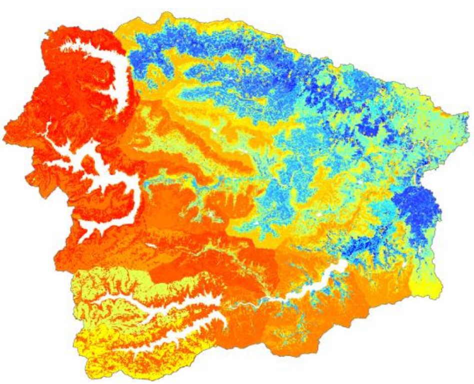
Grassland



Urban

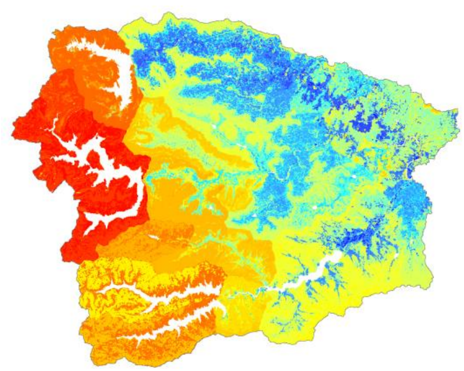


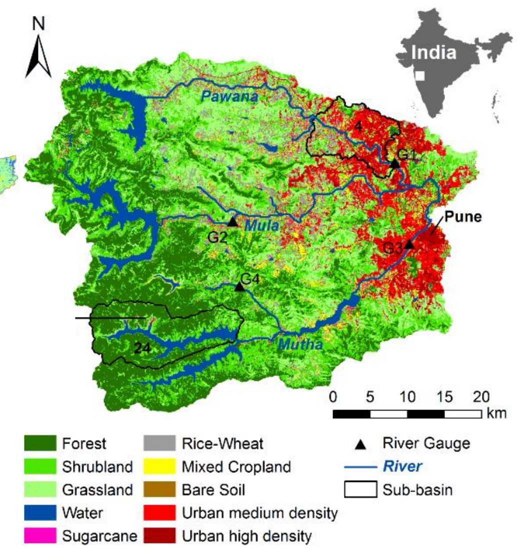
Rice



Sugarcane

Other Cropland

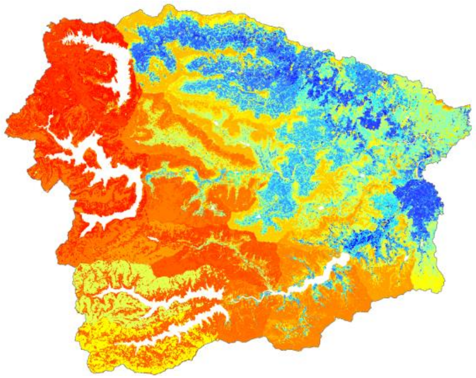




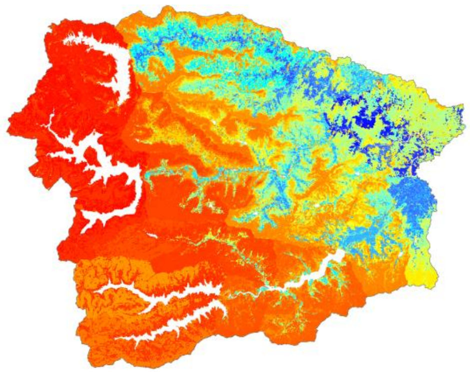
Low  High

4. Probability maps

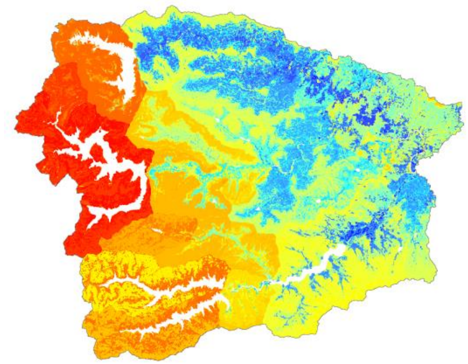
Rice

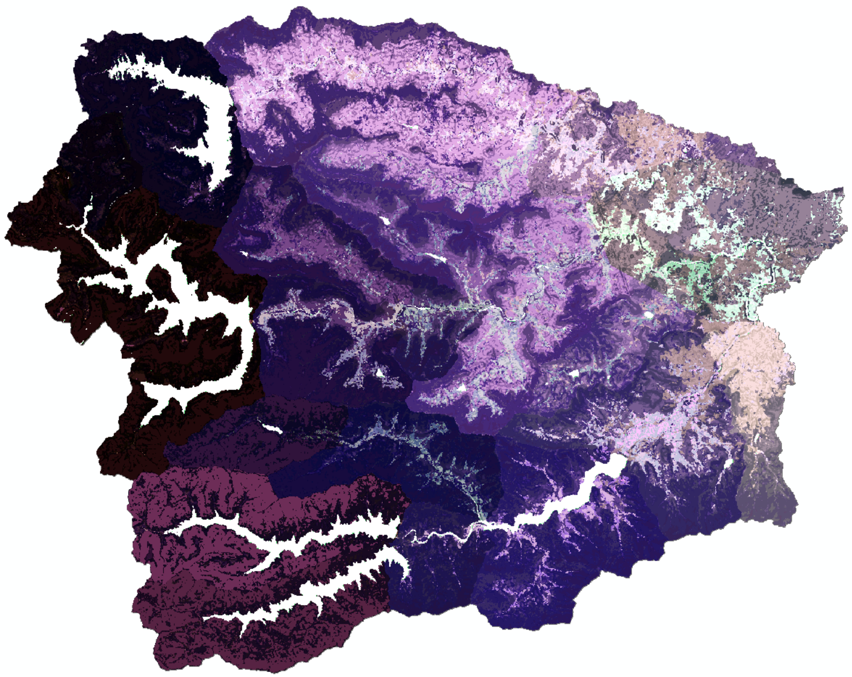


Sugarcane

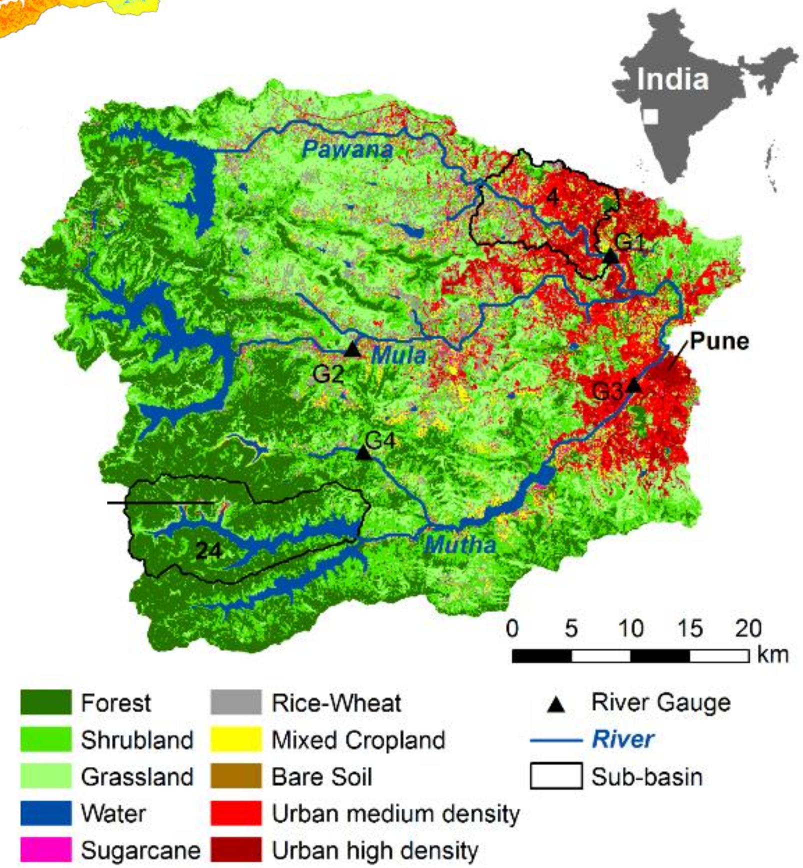


Other Cropland





R-G-B: Rice - Sugarcane - Other Cropland



4. Model use

Input: Demand (non-spatial)

Weighting of probability maps until demand is met

Output: Land use prediction (spatially distributed)

6. Conclusions

Freie Universität Berlin

Water availability variables from SWAT can be used to reasonably predict probabilities for land use change

- *Agriculture was better predicted than semi-natural vegetation*

Driving factor influence:

- *Higher probability for semi-natural vegetation when*
  water stress is high and soil water content is high
- *Higher probability for agriculture when*
  water stress is low

Very promising outcome, steps ahead:

- *Test seasonal output variables*
- *Combine water availability with other driving factors (e.g., distance to roads, distance to rivers, population density)*
- *Drive a land use model with these factors and couple it to SWAT*


Thank you very much for your attention!

4. Results: Logistic regression

		SW_	GW_Q	LATQ	TLOSS	IRR	WSTRS	SURQ
Rice	-0.723	0.002	-0.147	-	16.846	0.035	-0.039	-
Crop-land	-0.497	-	-	-	12.427	0.020	-0.066	-0.010
Sugar-cane	2.317	-0.015	-0.140	-	15.236	-	-0.213	-
Forest	-9.399	0.115	-	0.344	-53.377	-0.152	-	-
Shrub-land	-2.441	0.024	-	-0.260	-5.177	0.015	0.045	0.000
Grass-land	-1.843	0.019	-	0.087	-12.240	0.040	0.147	-0.004
Urban	-1.149	0.009	-0.256	-1.505	7.997	0.074	0.177	-