Comparing spatial interpolation with non-spatial predictions to model spatial WTP

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Model Specification

$$
\begin{gathered}
V = \\
\beta_0 ASCsq \\
+[\beta_1 ShFor + \beta_2 ShFor^2] \\
+[\beta_3 ShMai + \beta_4 ShMai^2] + [\beta_5 ShGra + \beta_6 ShGra^2] \\
+\beta_7 FiSizHalf + \beta_8 FiSizDouble + \beta_9 Biodiv \\
+\beta_{\mathrm{price}} Price
\end{gathered}
$$

Marginal WTP Function

- MWTP is defined as
  - $MWTP(x_n) = -\frac{f'(x_n)}{f'(Price)}$

- For forest share (inverse u-shaped):

$$MWTP_{ShFor}\ (SQ_{ShFor}) = -(\beta_1 + 2\beta_2\ SQ_{ShFor})/\beta_{Price}$$

Estimation Results

	Mixed Logit	
	Mean	SD
ASCsq	-.204	3.428***
ShFor	.125***	.104***
ShFor^2	-.00127***	.000411
FiSiz: Half	-.665***	1.01***
FiSiz: Double	-.409***	.907***
BioDiv	.222***	.746***
ShMai	.006	.0047
ShMai^2	-.00029***	.0003***
ShGra	.0113	.0003
ShGra^2	-.00027*	.00044***
Price	-.0127***	-

$^{*}p < 0.1$ $^{**}p < 0.05$ $^{***}p < 0.01$

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Empirical Strategy

Non-Spatial Prediction	In-Sample WTP prediction and Kriging	Individual WTP and Kriging
simple model sufficient	Simple model sufficient	Requires model with unobserved heterogeneity
Neglects unobserved preference heterogeneity and spatial patterns	Neglects unobserved heterogeneity but includes spatial patterns	Includes unobserved heterogeneity and spatial patterns
Uncertainty comes from one source	Uncertainty comes from 2 sources	Uncertainty comes from 3 sources

Individual WTP vs. Predictions: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Forest_Share	1,233	15.92	13.35	0	80.04
WTP_Ind	1,233	6.71	5.48	-10.56	23.465
WTP_pred	1,233	6.70	2.66	-6.11	9.88
WTP_diff	1,233	.0078	4.93	-16.00	17.23

Correlation between WTP_Ind and WTP_pred (and forestshare): 0.44

Individual WTP vs. Predictions: Summary

- **Obviously:**
  - Variation in individual WTP much higher than in predictions
  - Predicted values correspond 1:1 to forest share
- **Not so obviously:**
  - Correlation between individual WTP and predicted WTP rather small (0.44)
  - But: Mean differences nearly zero
- **Which ones to use for spatial analysis?**

Kriging vs. Prediction

- **So far, we only looked at in-sample predictions**
- **How to use the estimated values to map spatially different WTP**
  - Option A: Use WTP function to predict for each spatial unit
    - 250x250m raster
    - County level
  - Option B: Krige predicted (in-sample) WTP values
  - Option C: Krige individual WTP values

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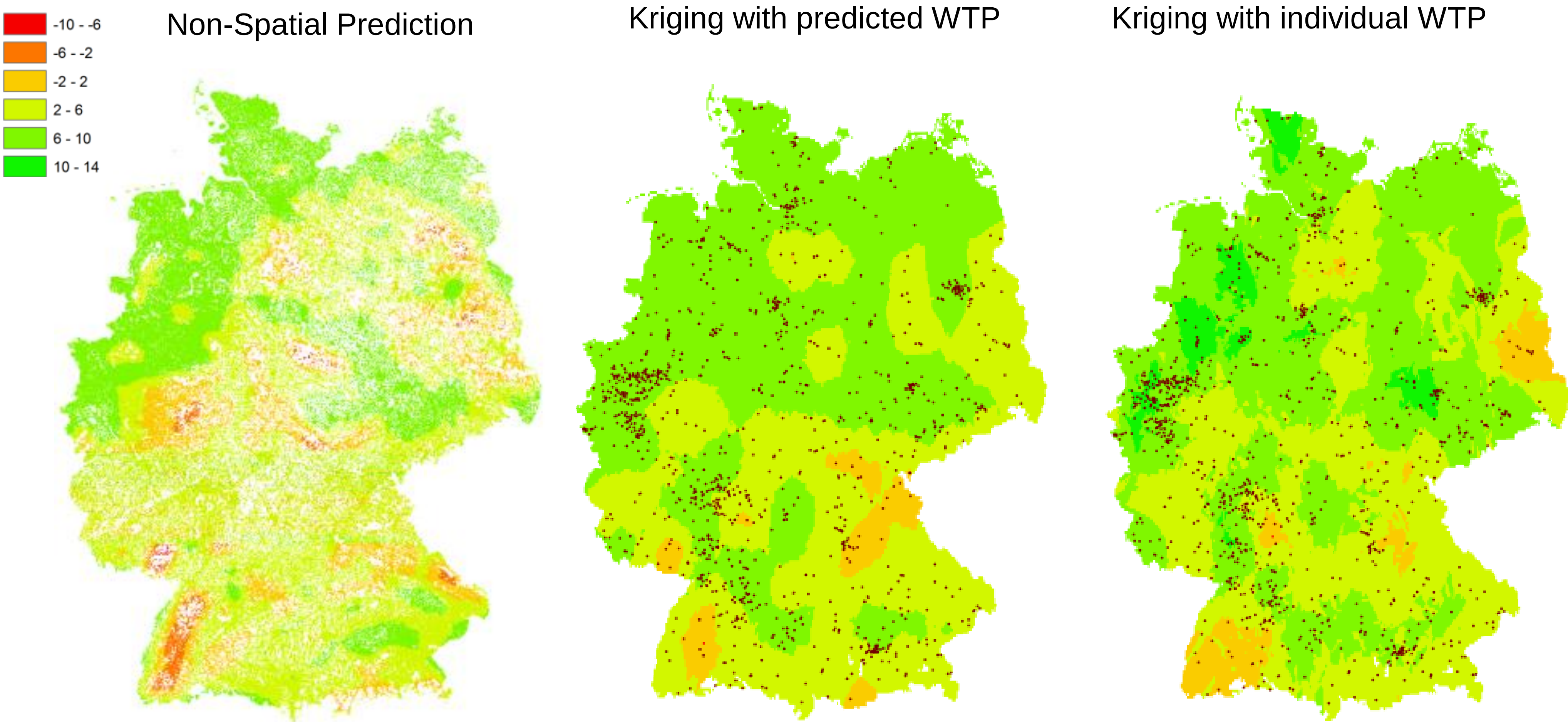
Kriging vs. Prediction: Maps



Kriging vs. Prediction: Results

- **Overall, similarities are observable**
  - E.g., WTP in North West Germany are similar in all three maps
  - But in some regions large differences

- **Non-spatial prediction gives more extreme values**
- **Prediction can better locate hot and cold spots**
- **Differences also between the two kriging maps**

How to compare and validate

- **Problem: We have no idea on true spatial patterns**
  - No reference (true values) to compare it with
- **Possible strategies:**
  - Estimate model only for (geographically stratified) subsample and predict for out-of-sample observations. Then compare methods
  - Monte-Carlo simulations: Simulate WTP on a 10x10km raster, sample 1000 observations, estimate a model, then try the different approaches and compare results with true values
    - Results will depend on assumptions of simulation.

References

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Thank you for your time and attention

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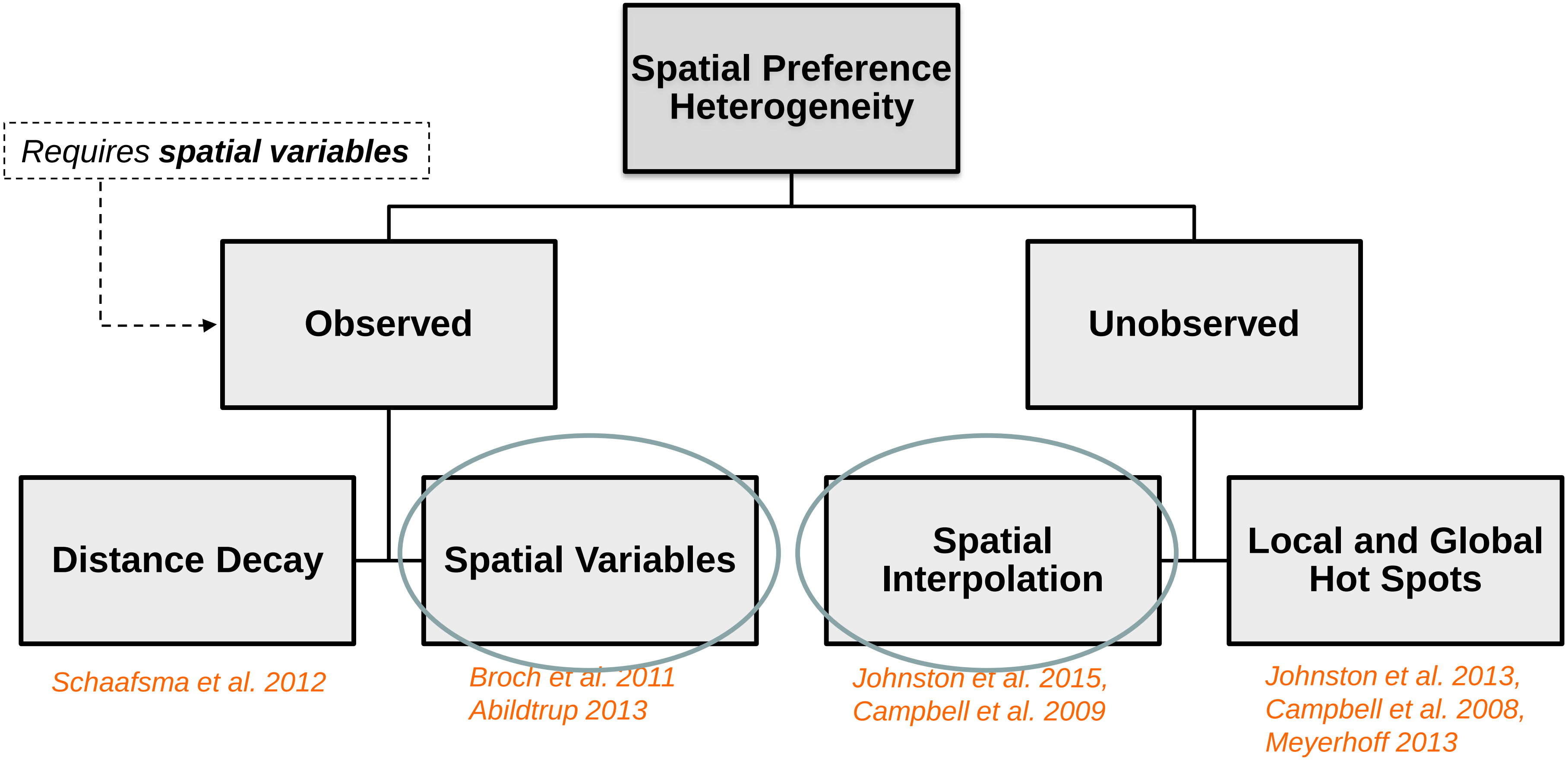
Spatial Preference Heterogeneity



Spatial Variables

- Can be any variable that is differentiated in space
  - Current endowment of attributes
  - Demographics, political setting
  - Landscape features
- Incorporation in DCE as interaction terms
  - Explain variance in MWTP (observed preference heterogeneity)
  - Predict MWTP on different spatial units
- Idea: Make use of spatial variables to predict MWTP for different spatial units (e.g. counties)

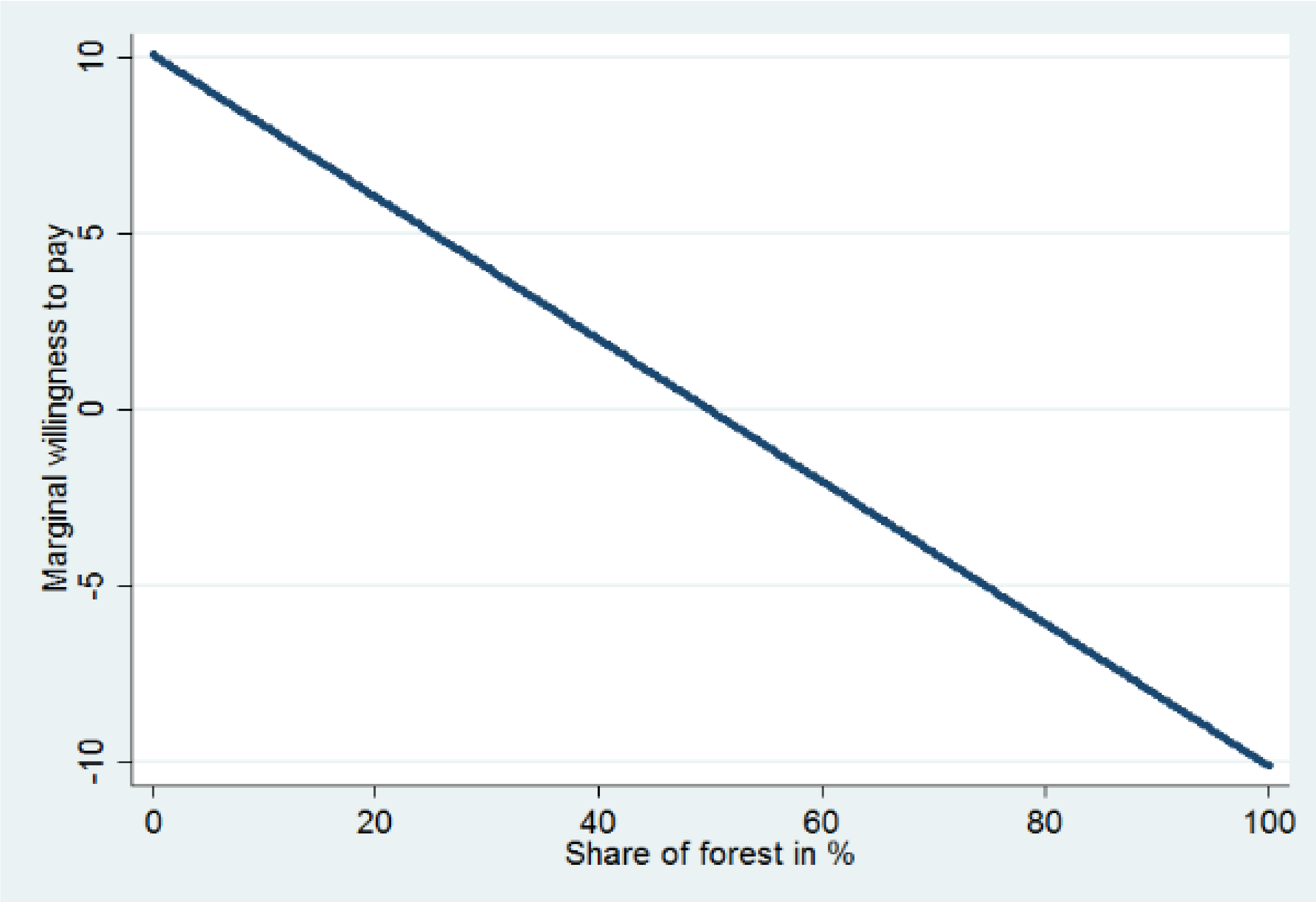
Spatial Interpolation

– Main Idea: Closer things are more related than distant things

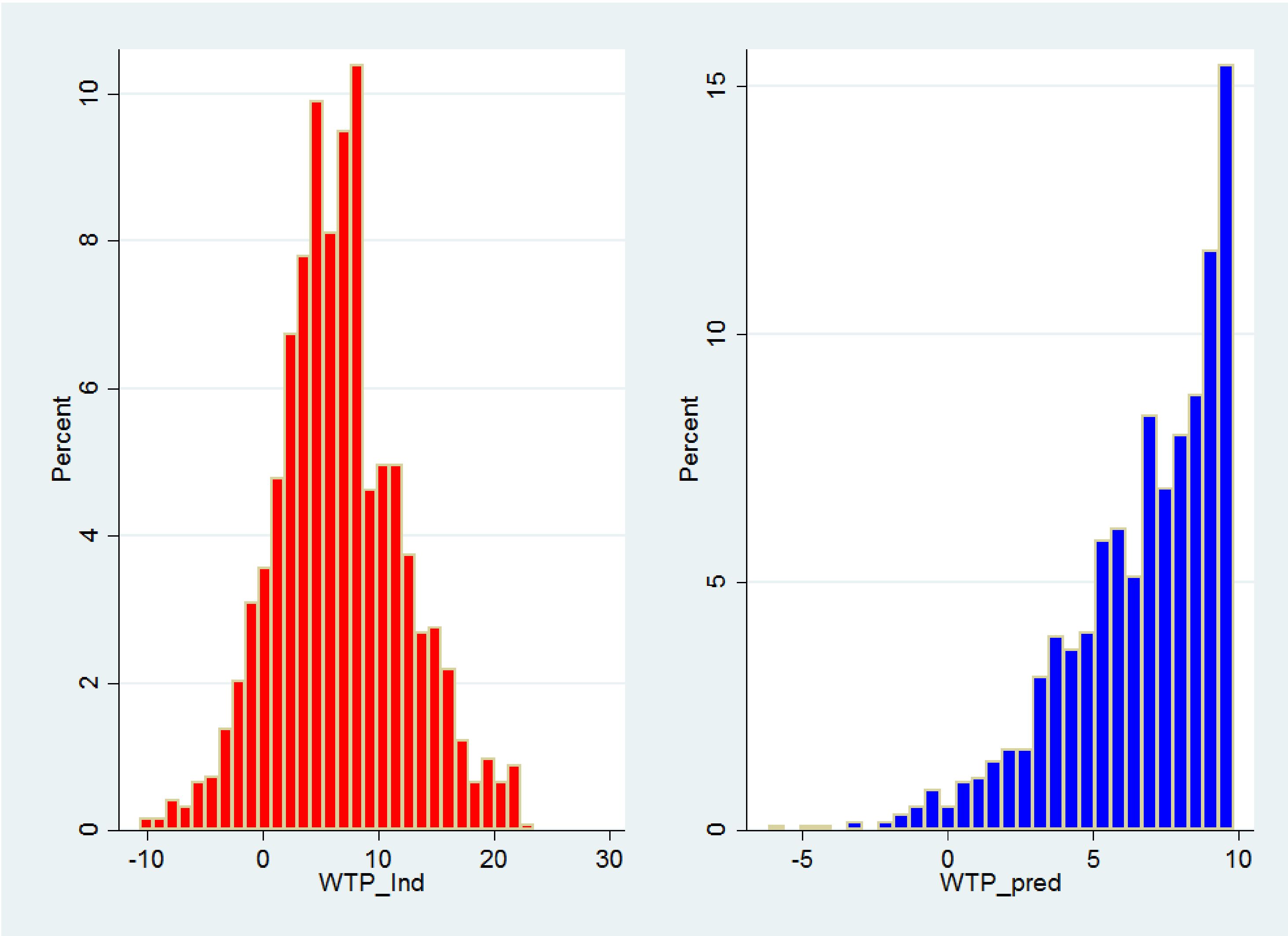
– Various methods such as Kriging, inverse distance weighting, Spline

– Kriging: predict the value of a function at a given point by computing a weighted average of the known values of the function in the neighborhood of the point (Wikipedia).

Marginal WTP Function



Individual WTP vs. Predictions: Histograms



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Discussion: Prediction

Advantages

– Straightforward estimation
– Prediction on arbitrary scales
– Inclusion of several exogenous variables possible
– Flexible utility functions possible
– No need for individual estimates

Limitations

– GIS Data requirement
– Unobserved heterogeneity/spatial autocorrelation
– Accuracy?
– Multicollinearity in spatial variables

Discussion: Kriging

Advantages

- Incorporates unobserved heterogeneity
- No further GIS information required
- Can but does not have to rely on individual WTP

Limitations

- Does not account for landscape variables
- Does not account for population density (only ex post)
- At least two estimations
- Assumes individual WTP as observations

Introduction: Spatial Willingness to Pay

- MWTP varies in space
  - People have different (intrinsic) preferences
  - People have different reference points
- Spatial factors to explain preference heterogeneity
- Several attempts to integrate space in MWTP estimates
- Important to design policies

In this presentation…

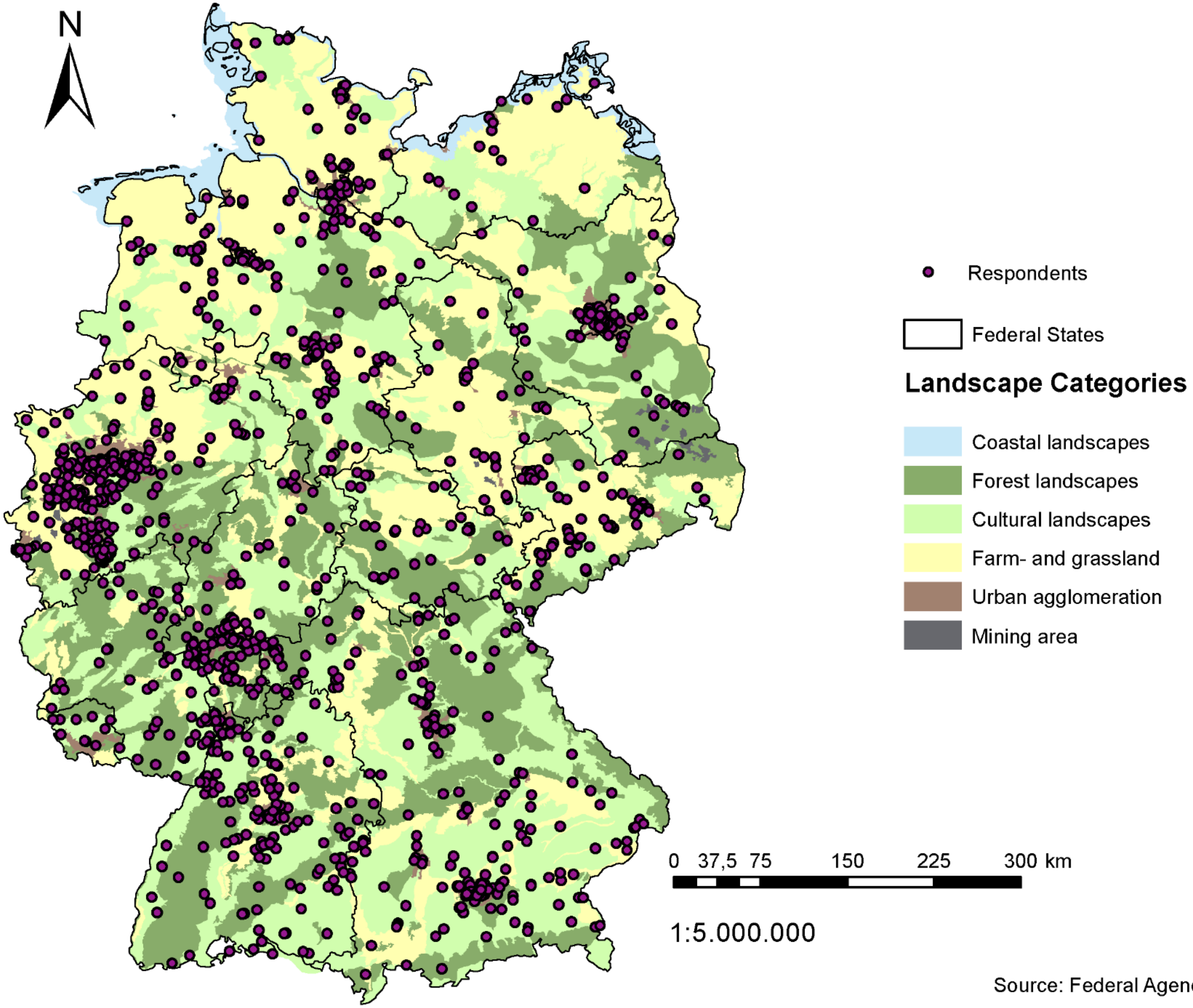
– Present an approach to attain spatially different willingness to pay (MWTP) from discrete choice experiments

– Exemplify it with data from a discrete choice experiment (DCE) on local land use changes

The survey

- March/April 2013
- 1,322 randomly sampled respondents all over Germany
- Online questionnaire of about 30 minutes
  - Socio-demographics
  - Land use and climate change: attitudes, perceptions, knowledge
  - Recreational activities
- Each respondent revealed his place of residence on a map (WGS84)

Spatial Distribution of Sample and Landscape Categories



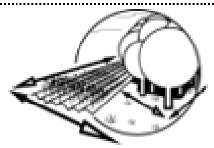
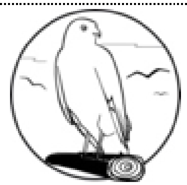
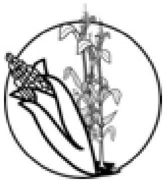
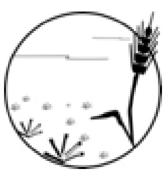
Source: Federal Agency for Nature Conservation

The discrete choice experiment

- <u>Local</u> land use changes
  - Within 15 kilometer radius of place of residence
  - Each respondent has a unique status quo situation
- 27 choice sets in three blocks
  - D-efficient design for multinomial logit model
  - Minimize MWTP standard error
- Three alternatives of which one is status quo (“as today”)
- Six land-use related attributes

Attribute	Levels
Share of forest (ShFor)	As today, decrease by 10%, increase by 10%
Field size (FiSiz)	As today, half the size, twice the size
Biodiversity in agrarian landscapes (Biodiv)	As today, slight increase (85 points), considerable increase (105 points)
Share of maize on arable land (ShMai)	As today, max. 30% of fields, max. 70% of fields
Share of grassland on agricultural fields (ShGra)	As today, 25%, 50%
Annual contribution to fund (Price)	0, 10, 25, 50, 80, 110, 160 €

If only the following options were available for the future development of the landscape within a radius of up to 15 kilometers around your place of residence, which one would you choose? If you live in a large city, please consider the surrounding area of the city.

		Landscape A	Landscape B	Landscape C
	**Share of forest**	As today	Increase by 10%	As today
	**Field size**	As today	Twice the size	As today
	**Biodiversity on agricultural fields**	Strong increase	As today	As today
	**Share of maize on arable land**	max. 70% of fields	max. 30% of fields	As today
	**Share of grassland on agricultural fields**	25%	25%	As today
	**Financial contribution to fund per year**	110 €	80 €	0 €
I CHOOSE ☑		☐	☐	☐

A

Data preparation

a) Status quo of share of attributes

b) Incorporate status quo in attributes

B

Model estimation

a) Specify utility function

b) Estimate the utility parameters

c) Derive MWTP function

C

Prediction and mapping

a) Predict MWTP depending on spatial variables

b) Multiply the MWTP with the population

c) Map the MWTP values

d) Aggregate on administrative units

Step A: Data Preparation
a) Calculate status quo

- Calculate within the 15 km radius the status quo of all relevant attributes
  - Any GIS software (ArcGIS, QGIS)
  - Requires land use data

- Elicit the required shares
  - Share of forest
  - Share of maize
  - Share of grassland

Step A: Data Preparation
b) Incorporate status quo in attributes

– Incorporate status quo of respondent e.g. by substituting attribute level "as today" with the status quo situation

Attribute level	Original Coding		SQ Modification	
Status quo is	25%	85%	25%	85%
As today	0	0	25	85
10% less	1	1	15	75
10% more	2	2	35	95

A Data preparation

a) Status quo of share of attributes

b) Incorporate status quo in attributes

B Model estimation

a) Specify utility function

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C Prediction and mapping

a) Predict MWTP depending on spatial variables

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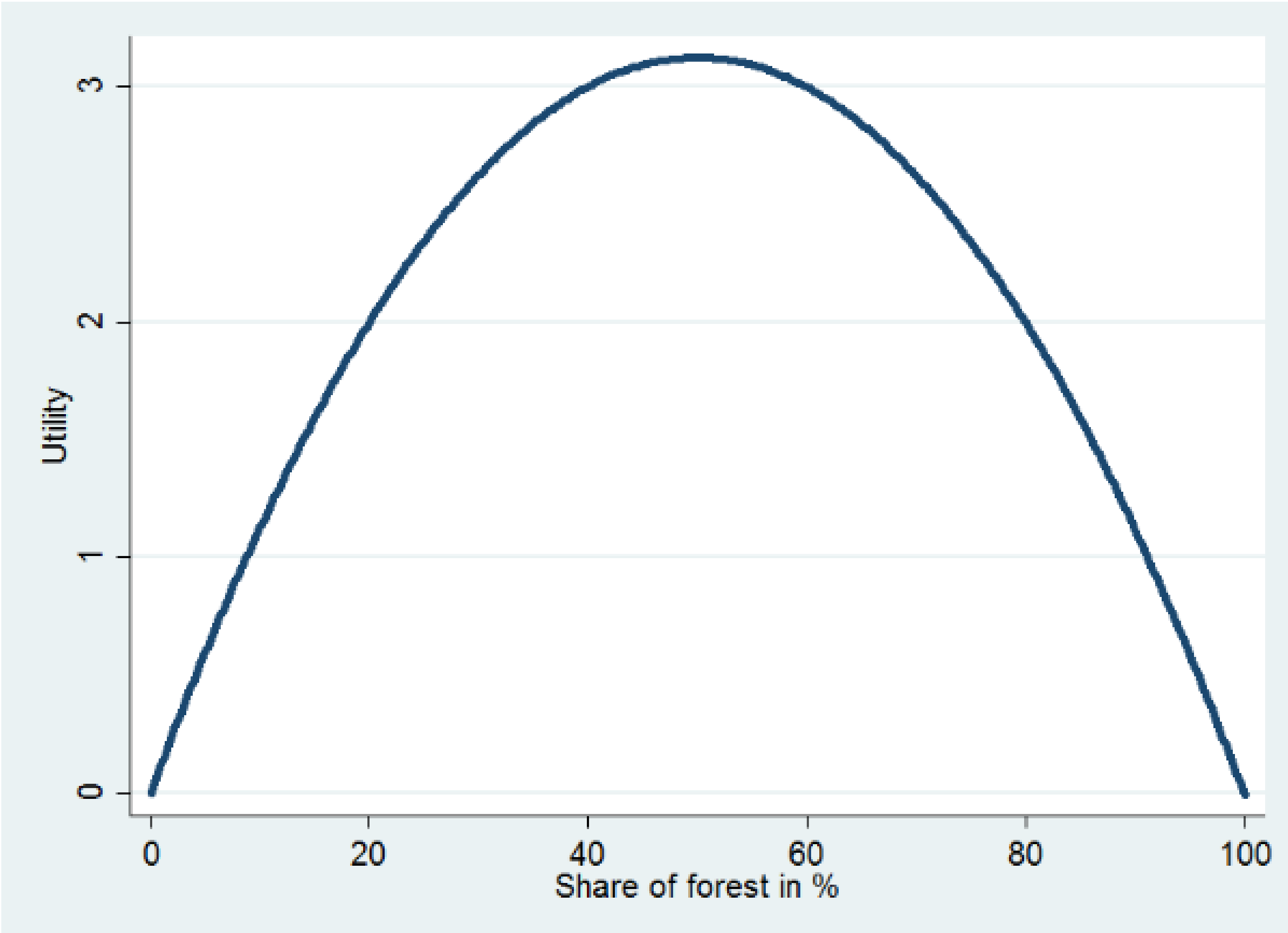
Step B: Model Estimation
a) Specify utility function

- Random utility model
  - $U = V + \epsilon = f(X) + \epsilon$
  - $V = f(X) = \sum_1^N \beta_n X_n$
- For forest share, a quadratic (inverse U-shaped) function may be adequate
  - $V = \beta_{k1} X_k + \beta_{k2} {X_k}^2 + \sum_n^N \beta_n X_n$
  - Utility increases with diminishing rates…
  - …up to an optimum…
  - …and decreases with increasing rates

Step B: Model Estimation
a) Specify utility function



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Step B: Model Estimation
a) Specify utility function

- The price attribute is interacted with disposable income of respondent’s county
  - As a further source of spatial preference heterogeneity
  - Indicator on infrastructural development
- Many other spatial variables could be used
- Problems with multicollinearity

Step B: Model Estimation
a) Specify utility function

- Attributes share of forest (ShFor), share of maize on arable land (ShMai) and share of grassland on agricultural fields (ShGra) entered utility quadratically
- Estimation with Conditional Logit without DisInc Interaction
- And with Random Parameters Logit with DisInc Interaction
  - Alternative specific constant and all attributes normally distributed
  - Price attribute and interaction fixed

Step C: Prediction and Mapping
a) Predict MWTP depending on spatial variables

Merge land use data with population:

– Requires high resolution data on population

– Here 250x250m raster data

– Similar to step A, calculate for each raster cell the share of forest

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A Data preparation

a) Status quo of share of attributes

b) Incorporate status quo in attributes

B Model estimation

a) Specify utility function

b) Estimate the utility parameters

c) Derive MWTP function

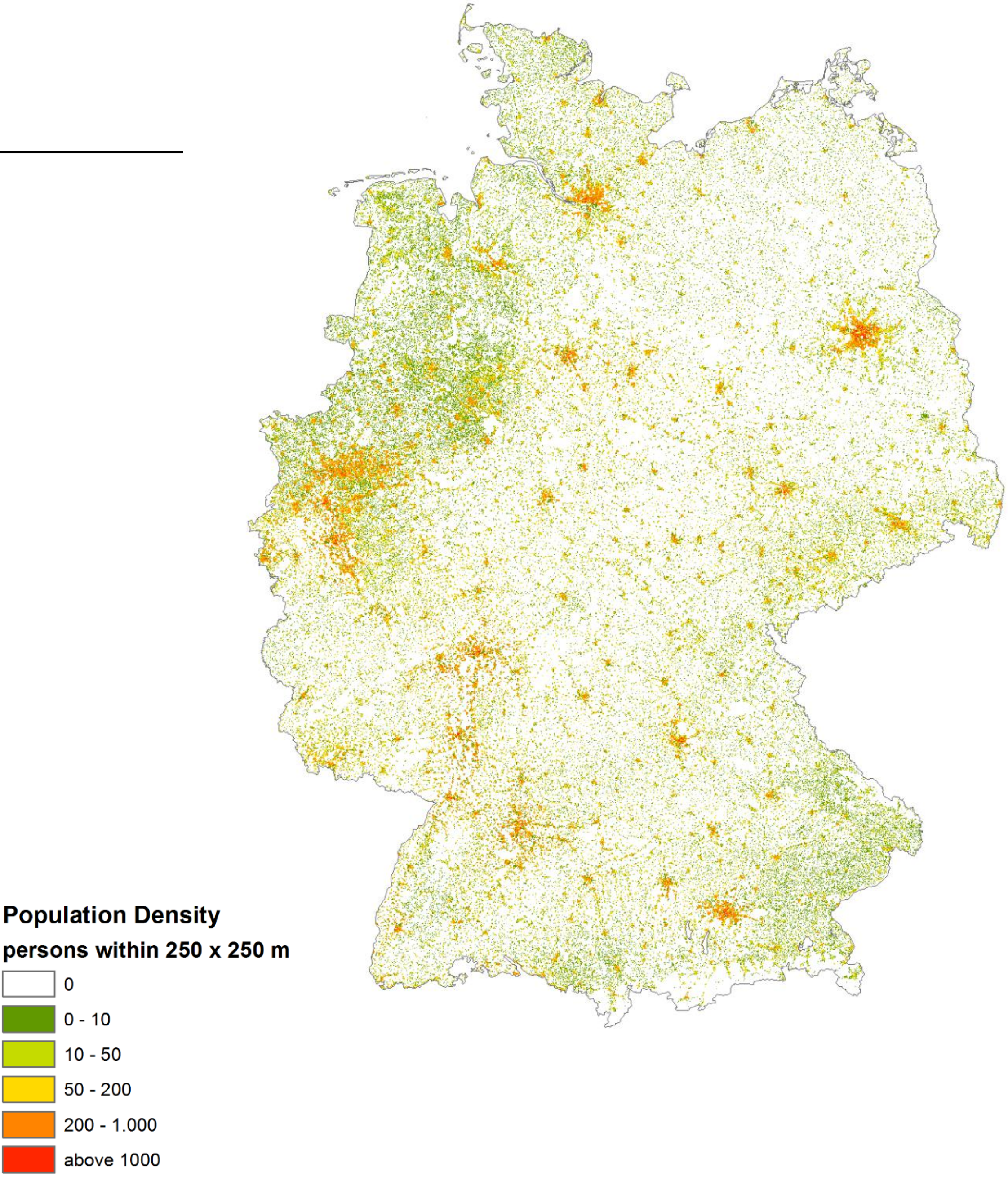
C Prediction and mapping

a) Predict MWTP depending on spatial variables

b) Multiply the MWTP with the population

c) Map the MWTP values

d) Aggregate on administrative units


Population Density
persons within 250 x 250 m
0
0 - 10
10 - 50
50 - 200
200 - 1.000
above 1000

Step C: Prediction and Mapping
a) Predict MWTP depending on spatial variables

- For each raster cell ($k = 1 \ldots K$), substitute the forest share and disposable income into MWTP function
- $MWTP_k\ (ShFor, DisInc) = -\frac{\beta_1 + 2\beta_2\ ShFor_k}{\beta_{price} + \beta_{\mathrm{DisInc}} * DisInc_k}$
- Examples:
- $MWTP_{ShFor}\ (7.5) = -(.125 + 2 * -.00125 * 7.5)/-.0124 = 8.65€$
- $MWTP_{ShFor}\ (95) = -(.125 + 2 * -.00125 * 95)/-.0124 = -9.07€$

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Step C: Prediction and Mapping
c) Map the MWTP values

– Map the MWTP values

– Multiply the MWTP with the number of inhabitants and create a map with these aggregate values

– Map further statistics, e.g. the standard deviation of MWTP in each county

Step C: Prediction and Mapping
d) Aggregate on administrative units

- Sometimes, MWTP between administrative regions is relevant
  - To distribute funds
  - To identify regions that require more support
  - To inform local policy makers

- German counties as an example

Step C: Prediction and Mapping
d) Aggregate on administrative units

- For each county, calculate the distribution of forest share across the population

- For simplicity, we used a discrete distribution
  - 7.5 for 5%-10%, 15 for 10-20% etc.

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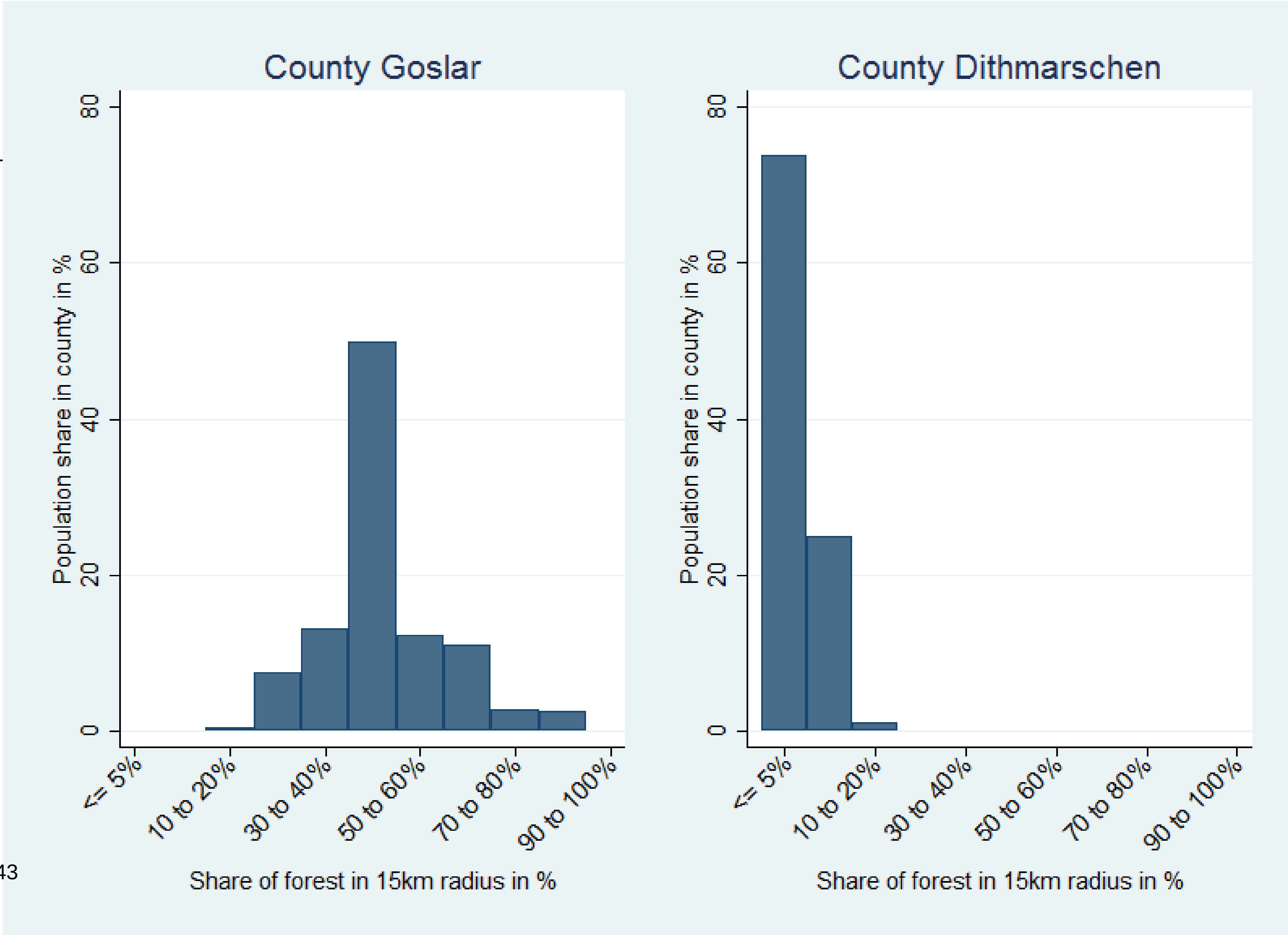

County Goslar
County Dithmarschen
Population share in county in %
0
20
40
60
80
<= 5%
10 to 20%
30 to 40%
50 to 60%
70 to 80%
90 to 100%
Share of forest in 15km radius in %

Step C: Prediction and Mapping
d) Aggregate on administrative units

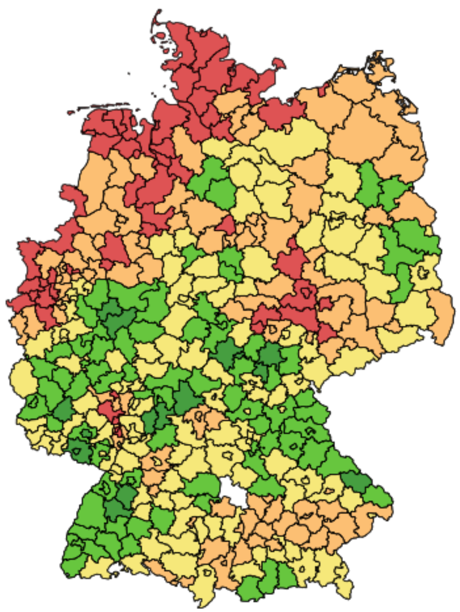
- For each county calculate the average MWTP per person
  - Weighted average
  - $Av.MWTP = \sum fr_i * MWTP_i$

- Example Ditmarschen (DisInc=19833)
  - $Av.MWTP = 0.73 * 9.77 + 0.25 * 8.74 + 0.012 * 7.2 = 9.48\ Euro$
- Example Goslar (DisInc=19016)
  - $Av.MWTP = 0.55\ Euro$

Step C: Prediction and Mapping
d) Aggregate on administrative units

Share of forest and MWTP

N



a)

Share of forest [%]

- ≤ 13
- > 13-25
- > 25-38
- > 38-50
- > 50

Sources: Federal Statistical Office, Kleinräumige Einwohnerdisaggregation (small-scale Inhabitantdisaggregation) © BBSR Bonn 2013, Base: LOCAL © Nexiga GmbH 2013, ATKIS Basis DLM © BKG/GeoBasis DE 2013

1:8.333.598

0 100 200 300 400 500 km

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Results

– In general, higher MWTP where forest share is low

– But: Population density is very important

– MWTP hotspots are in the north of Germany

– Eastern Midlands are already equipped with large forests

Estimation Results: Conditional Logit

Observations	33291
Pseudo R^2	0.103
AIC	21890.5
BIC	21983.1
Chi Squared	2514.1
Lok-Lik. (Null)	-12191.3
Log-Lik.	-10934.3

Estimation Results: Random Parameters Logit

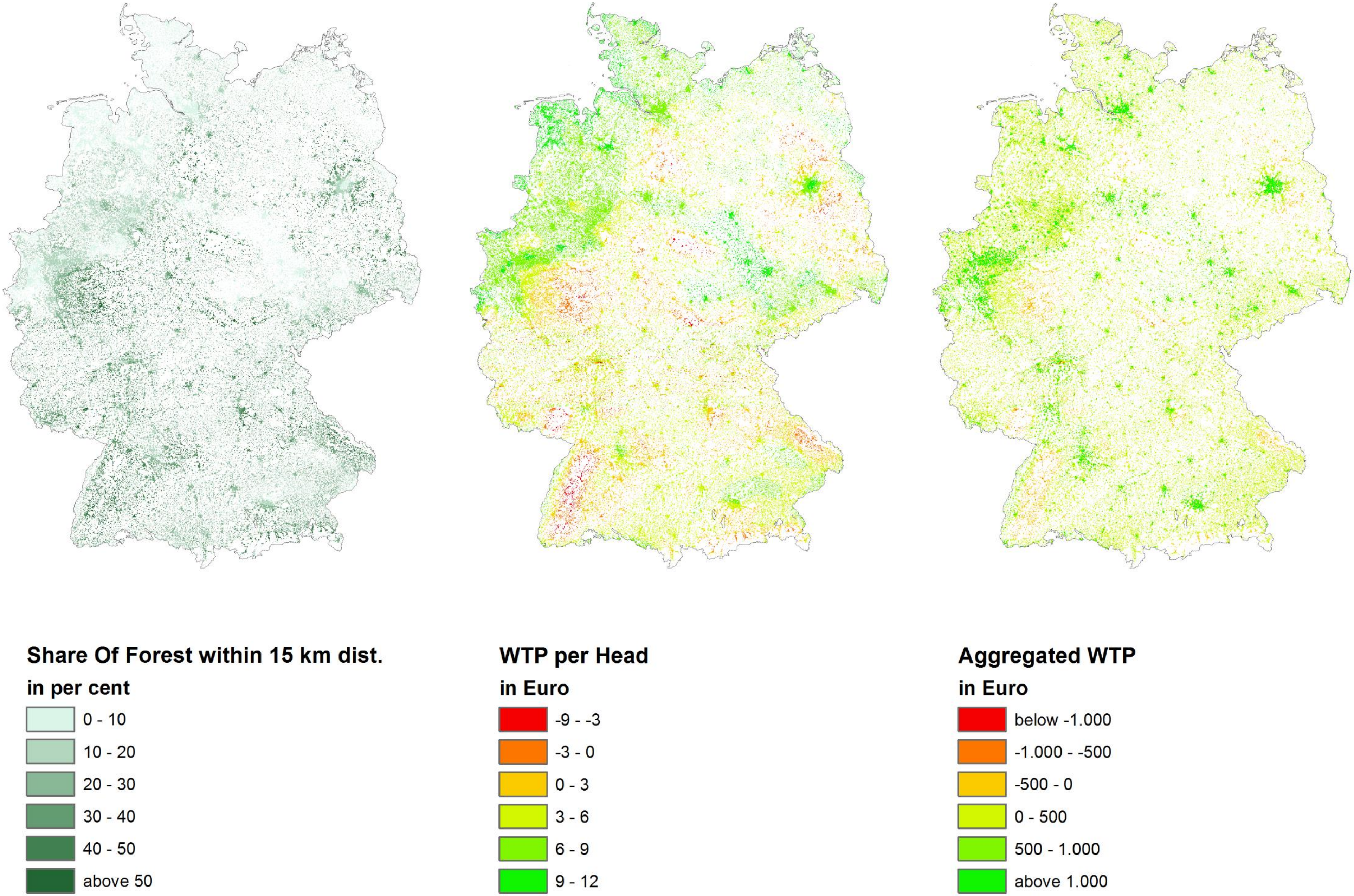
Observations	33291
AIC	16204
BIC	16389
Chi Squared	5696
Lok-Lik. (Null)	-10928
Log-Lik.	-8080

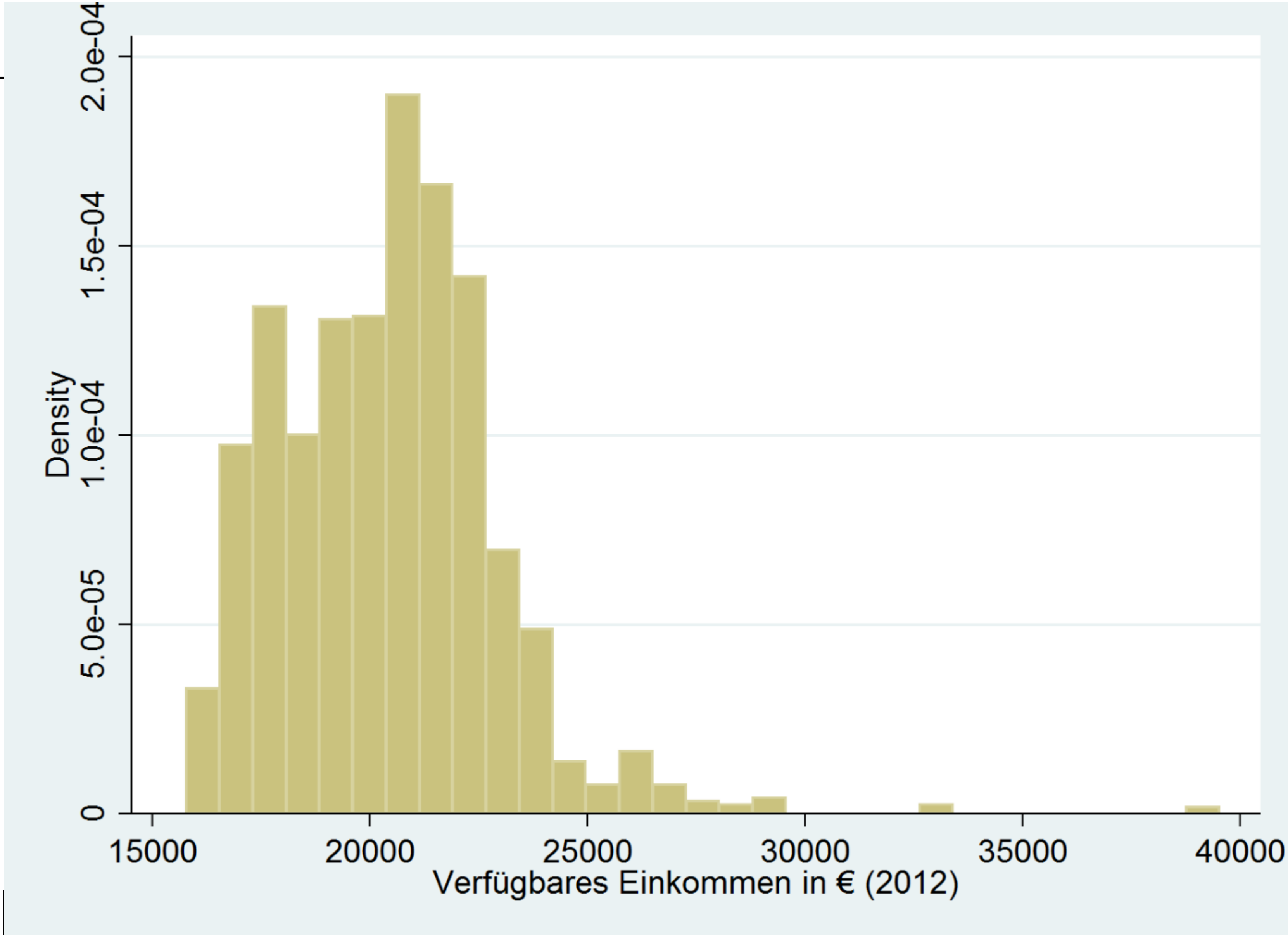
Introduction: Need for valuation

- Land use conflicts and need for land use changes
  - Interaction with climate change
  - New political perspective on nature conservation
    - E.g. Convention on Biological Diversity, European Water Framework Directive
- Sustainable land use requires incorporation of all costs and benefits
  - On farm level
  - Climate effects
  - Societal effects e.g. landscape, aesthetic value

Introduction: Discrete choice experiments

- DCEs to inform policy decisions
  - Several studies on land use conducted in Europe (van Zanten et al. 2014)
  - Can be integrated into cost-benefit analysis


Share Of Forest within 15 km dist.
in per cent
0 - 10
10 - 20
20 - 30
30 - 40
40 - 50
above 50
WTP per Head
in Euro
-9 - -3
-3 - 0
0 - 3
3 - 6
6 - 9
9 - 12
Aggregated WTP
in Euro
below -1.000
-1.000 - -500
-500 - 0
0 - 500
500 - 1.000
above 1.000



Density
2.0e-04
1.5e-04
1.0e-04
5.0e-05
0
15000
20000
25000
30000
35000
40000
Verfügbares Einkommen in € (2012)

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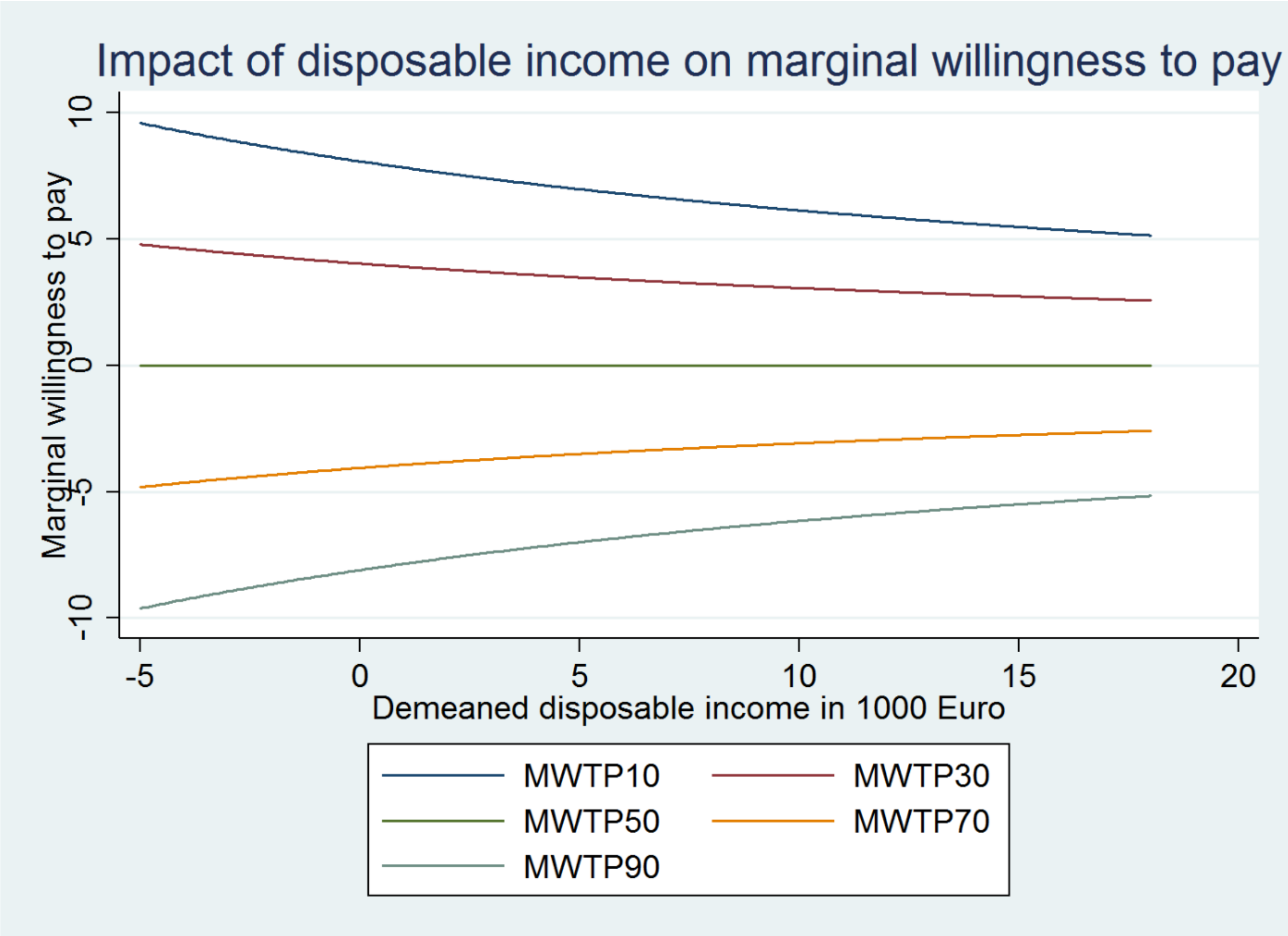
Step B: Model Estimation
a) Specify utility function

- Estimate the parameters of the utility function with discrete choice model

- Any discrete choice model can be used
  - Conditional logit, mixed logit, latent class logit
  - $\Pr(j) = \frac{\exp(V_j),}{\sum \exp(V_i)}$

Step B: Model Estimation
a) Specify utility function



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