Accounting for uncertainty in non-industrial private forest (NIPF) owner segmentation

Univerza v Ljubljani Biotehniška fakulteta Oddelek za gozdarstvo in

obnovljive gozdne vire

Andrej Ficko & Andrej Boncina

University of Ljubljana, Biotechnical Faculty, Department of Forestry and Renewable Forest Resources, Vecna pot 83, 1000 Ljubljana, Slovenia Main sources of uncertainty in NIPF owner segmentation:

In survey-based customer segmentation: two main sources:

- 1) uncertainty about whether responses reflect the real opinion of a respondent or are biased (respondent uncertainty);
- 2) uncertainty of the researcher about the number of customer segments, their meaning, and customer membership (analyst uncertainty).

- Analyst uncertainty (e.g. Expectation Maximization (EM) clustering (Dempster et al., 1977):
 - → Ficko & Boncina (2013). Forest Policy and Economics, 27, 34-43.
 - \rightarrow Book of abstracts (Umea conference).
- This presentation: focus on methods for accounting for respondent uncertainty.

Responses may be biased!

Common response styles identified in social or marketing science literature:

- 1. the acquiescence response style (ARS) = the tendency to agree with the item irrespective of the content of that item;
- 2. the disacquiescence response style (DARS) = consistent disagreement with the items irrespective of their content;
- and extreme responding (ERS) = a preference for extreme response categories.

How can respondent uncertainty in NIPF owner segmentation be accounted for?

- 1. **measured** directly with a follow-up rating question on certainty immediately after the valuation question (Shaikh et al., ²⁰⁵ Several se
 - e.g. On a scale of 1 to 10, how certa answer to the previous [valuation] qu
- 2. **simulated** by skewing the distribution of the responses or by recoding the responses of Conservative Conservative data

Self-reported

uncertainty!

How can respondent uncertainty in NIPF owner segmentation be accounted for?

- 3. diagnosed as latent response style behavior by means of several techniques (a review of Stat. power! Stat.
 - Structural equation modeling (SEM), e.g. Billiet & McClendon (2000).

Case study for a demonstration of 2 approaches

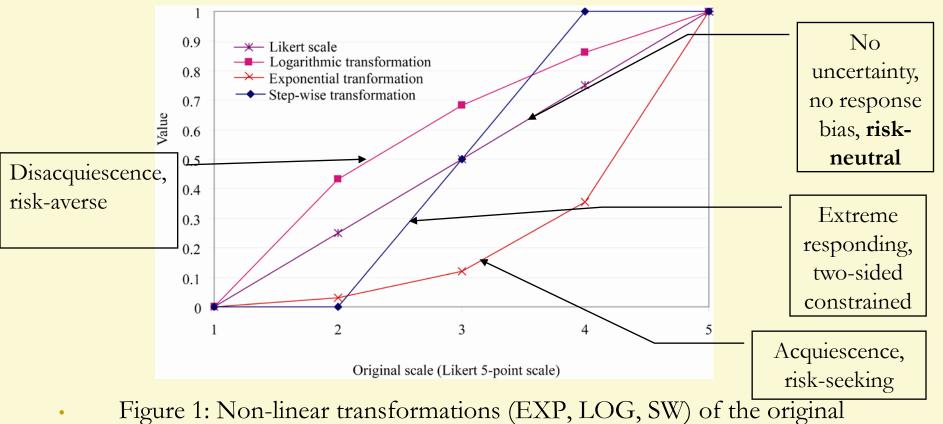
- N = 364 face-to-face interviews
- N = 19 items questioning about the relevance of certain types of information (Likert scale)

Manifest variables (vi):	
v ₁	Costs of forest operations
v2	Profitability of forest management
V3	Possibilities for hiring wood harvesting companies and the cost
V4	Possibilities for mechanized harvesting
₩5	Bucking techniques
V6	Wood prices and wood markets
V7	Possible cut for each individual parcel
v ₈	Silvicultural measures
V9	Forest protection and bark beetle prevention
v ₁₀	Current market price of forest land
v ₁₁	Property boundaries
v ₁₂	Locations of all parcels
v ₁₃	Possibilities and costs of forest road building
V14	Rights and duties of forest possession
v15	Public rights on owner's holding
V16	Game species and population densities
V17	Management restrictions due to nature protection
v ₁₈	Allowable cut
v19	Contact with a person in charge of cutting approval

Clustering of owners into decision-making types

1. Simulating the respondent uncertainty

•by skewing the distribution of the responses or by recoding the responses



response values

K-means clustering of owners: membership similarities

A) k-means cluste:	ring	Pair	Information								
		LIN					counting	theoretic			
	<u>C1</u> .	1	2	3	4	5	measure of	measure of			
	∭ .	1	2		-		similarity	similarity			
		17,3	17,0	4,1	29,1	32,4	Cramer's V	Asymetric NMI			
LOG	1	12,4	0,5	0	0	8,2	0.605*	0.376*			
	2	3	3,8	1,1	5,5	1,9					
	3	0	0	1,9	0	0,3					
	4	1,9	1,4	1,1	23,6	22					
	5	0	11,3	0	0	0					
SW	1	7,7	0,8	0	0	7,4	0.452*	0,269*			
	2	3,8	4,9	1,4	6,6	4,9					
	3	3,6	0,8	1,4	2,2	0,8					
	4	1,6	0,3	1,1	19,2	19,2					
	5	0,5	10,2	0,3	1,1	0					
EXP	1	9,6	1,6	2,2	4,4	4,7	0.405*	0.219*			
	2	1,1	10,7	0	3,8	2,5					
	3	1,6	3,3	1,9	1,4	8,8					
	4	0	1,4	0	10,2	2,5					
	5	4,9	0	0	9,3	14					
RD	1	0,8	12,6	0	0,8	0	0.524*	0.330*			
	2	10,4	0,3	0	0,8	8,8					
	3	1,6	0,8	2,2	0	3					
	4	3	2,5	1,4	8,5	2,5					
	5	1,4	0,8	0,5	19	18,1					
* denotes approx. significance at p = 0.001											

Table 1. Similarities in the classification of NIPF owners (N=364) when respondent uncertainty is ignored or riskneutral behavior is assumed(LIN) and the classification under 4 different assumptions of response styles.

•Similarity between the original response-based clustering and the biased response-based clustering is low!

•If strong bias in the responses truly existed, taking the responses as unbiased would only reduce 21.9% to 37.6% of the uncertainty about the true clusters in the case of risk-seekers and risk avoiders, respectively.

K-means clustering of owners: PCs similarities

A) k-means clustering										
			er of s ent pair	Percentage of significantly different PCs,						
		LIN		pairs of all pairs						
	<u>C1</u> .	1	2	3	4	5				
LOG	1	n.s.	N/A	-	-	n.s.				
	2	n.s.	n.s.	1	n.s.	n.s.				
	3	-	N/A	n.s.	N/A	N/A	3/84 = 3.6%			
	4	1	1	n.s.	n.s.	n.s.				
	5	-	n.s.	-	-	-				
SW	1	n.s.	n.s.	-	-	1				
	2	n.s.	n.s.	n.s.	n.s.	n.s.				
	3	n.s.	n.s.	n.s.	n.s.	n.s.	6/120 = 5.0%			
	4	1	N/A	1	1	2				
	5	n.s.	n.s.	N/A	n.s.	-				
EXP	1	4	4	5	2	5				
	2	3	2	-	5	3				
	3 4		4	4	3	5	77/120 = 64.2%			
			3	-	4	6				
	5	4	-	-	2	5				
RD	1	1	2	-	n.s.	-				
	2	5	N/A	N/A	2	5				
	3	1	1	n.s.	-	6	46/120 = 38.3%			
	4	1	4	1	3	3	1			
	5	1	2	n.s.	4	3				

Table 1. Similarities in the classification of NIPF owners (N=364) when respondent uncertainty is ignored or riskneutral behavior is assumed (LIN) and the classification under 4 different assumptions of response styles.

Pairwise comparison of means of clustering variables confirmed the extent of the influence of risk-seeking behavior to cluster assignment; more than 60% of all pairs of clustering variables significantly differed when EXP was compared to LIN !

2. Diagnosing the respondent uncertainty

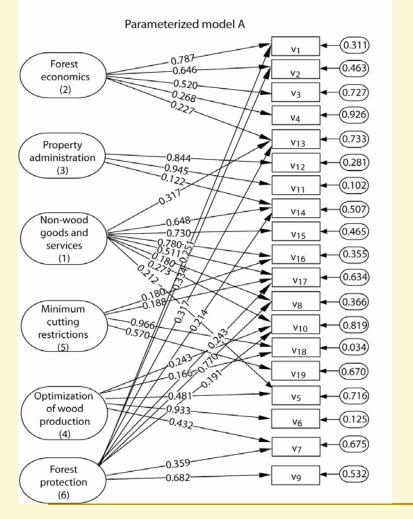
If a substantial number of respondents systematically favors positive response categories

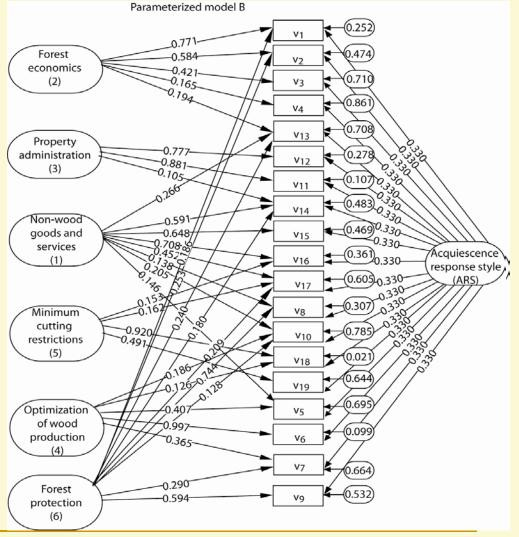
			1000 111024			"- ²	·P	<u>1</u> 4_1.00		
irres	4 👪 Mont	e Carlo Analy	sis: Likert_6.sta						? _ 🗙	321
	📲 Iteratio	on Results: Lik	(ert_6.sta						?	
beha	ltn #	Discrepancy	RCos Lami	oda MAXCON	I NRP NRC	NAIC	StepLe	in		
	× 0	11.2478	23 0.454890	1.000000	0.500000	Θ	0	1	0.000	6
(× 1	1.7506	71 0.208656	1.000000	0.144778	Θ	0	0	0.129	E
facto	× 2	1.1484	79 0.203136	1.000000	0.106561	Θ	Θ	0	0.097	actor
	× 3	0.95460		1.000000	0.038297	Θ	Θ	0	0.059	5
(D:11)	× 4	0.9288		1.000000	0.003040	0	0	1	0.020	5
	× 5	0.92289		1.000000	0.001634	0	0	1	0.010	2
	× 0	1.5054		1.000000	0.001634	0	0	1	0.000	
	× 1	0.9714	56 0.035150	1.000000	0.009679	0	0	1	0.059	1
Story	- ×									
Structure	-									
	Executing	Maximum Likeliho	ood Estimation.							1 6
Stati	-		eplication 205 of 100)				Cance	ОК	
	5									465
	4							-		. 587
	5 0,35	3 0,606	0,127	5 0,698	0,184	50		2 -0,	14538 -0,1	2597

Decision support systems for sustainable forest management

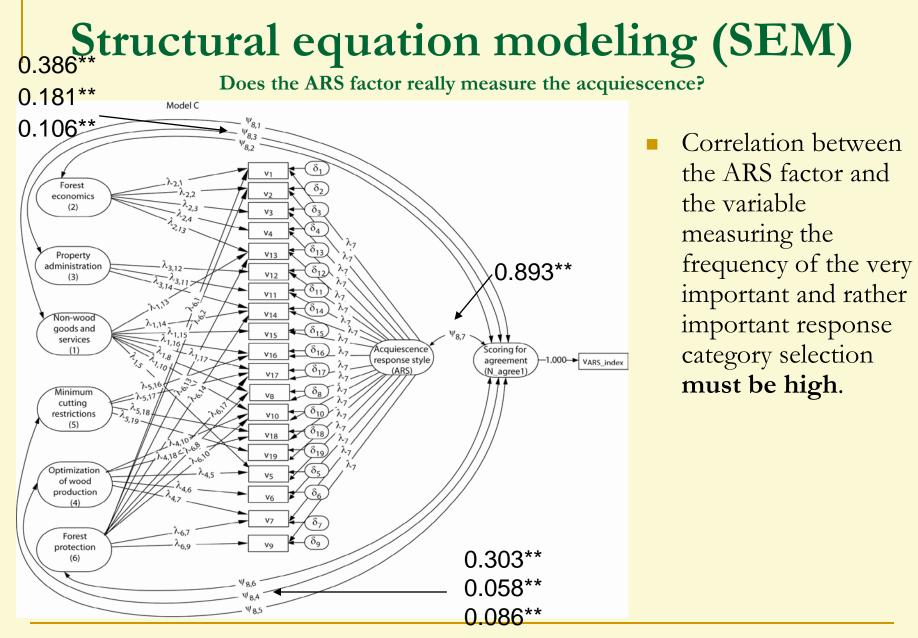
Structural equation modeling (SEM)

Which model replicates the correlation matrix better?





Decision support systems for sustainable forest management



Decision support systems for sustainable forest management

- After adding the ARS factor to model A, the **model fit improved** (χ^2 =404.45, df=136). The difference in the χ^2 statistics between model A and B is highly significant, p < 0.001.
- Fit indices of B vs. A are higher: RMSEA=0.07, GFI=0.93, AGFI=0.90, CFI=0.94, TLI=0.93, χ²/df=3.0).
- The model with the ARS factor (Model B) explains the data significantly better than the model with content factors only (Model A). → acquiescence response style diagnosed.

Correcting the raw data for acquiescence (an improved approach) **Correlation matrix** of a dataset V13 V4 V5 v_6 V7 v8 V۹ v_{10} v_{11} v_{12} V_{14} V_1 v_2 V3 Acquiesce \mathtt{v}_1 .55 .41 .12 .14 .29 .15 1 .20 .09 .27 .15 .13 .33 perfectly fitting to v_2 .08 .27 .13 .28 .53 1 .33 .20 .07 .16 .24 .11 .15 model with the the items V3 .22 .31 .14 .38 .10 .10 .11 .11 .16 1 .20 .11 .14 ARS factor (B) V4 .07 .17 .10 .14 .06 .07 .18 .16 1 .10 .06 .10 We genera ٧s .53 .31 .11 .20 .20 .18 .19 .17 .23 -.02 -.04 .00 .00 1 .10 .14 del V6 .51 .12 .03 -.02 .01 -.04 .51 1 .08 .11 .12 .09 .10 .13 .31 .12 A and 100 V_7 .10 .00 .26 .49 .28 .22 .18 .23 .17 .08 20 .07 -.01 1 .16 .14 .24 .12 . 10 58 .23 .01 .22 21 .18 .17 V8 .25 -.01 .03 .01 1 .41 .32 .17 .22 .28 .11 .08 B - A We selecte V۹ .23 .21 .03 -.01 -.02 .18 .15 .15 .31 .19 .22 .09 -.01 .24 .11 .12 Э V_{10} .00 -.05 .16 .23 .13 .17 .19 .03 .03 .28 .23 .27 .32 .06 .04 .19 .19 .14 1 the model V11 .05 .05 .01 .07 .07 .03 -.08 .81 .21 .15 .13 .04 .11 .06 .03 -.04 .06 1 .30 V12 .03 .03 -.04 .00 .01 .08 -.08 .81 .18 .15 .05 .02 .06 .28 .11 .11 .04 1 .06 correlation V13 .29 .25 .14 .08 .03 .38 .23 15 .27 .09 .06 1 .33 .23 .31 .24 .13 .10 .05 -.01 -.06 V14 .08 .28 .18 .20 .22 .20 .29 .45 .50 .37 .10 .07 1 -.04 .13 -.01 .10 Correlation matrix .00 .24 .00 .00 .17 .43 1 .56 .33 .11 .10 -.02 -.06 .14 -.01 .15 .03 .48 .03 .08 .29 .03 .24 .56 .39 1 .26 .14 of a dataset .10 .12 .22 .15 .15 .01 .00 .18 .33 .29 .01 -.01 .03 .36 1 .32 .20 perfectly fitting to .16 -.01 -.03 .11 -.07 -.08 .01 -.01 .02 -.02 .16 .26 .01 .18 .25 1 .56 model with the .03 .01 .01 -.07 .07 .13 .02 .04 .02 -.04 .04 -.09 -.02 -.04 .01 .55 1 content factors

Decision support systems for sustainable forest management

only (A)

Correcting the raw data for acquiescence (an improved approach)

- Subtracting the correlation matrix of model A from the correlation matrix of model B (B-A) = the effect of ARS on correlations (Net ARS matrix).
- The correlation matrix of raw data minus the Net ARS matrix = correlation matrix corrected for acquiescence.
- PCA analysis with the correlation matrix corrected for acquiescence.
- Monte Carlo generation of the 364 responses with the desired corrected correlations between the 19 items: not successful in 1000 attempts (the resulted correlations not accurate enough).

Conclusions

	(a) Raw data ^b							(b) Data corrected for acquiescence						
								Content factors						
Manifest variable	1	2	3	4	5	6	1	2	3	4	5	6		
V1	-0.03	0.81	0.11	0.01	0.00	0.21	-0.07	0.82	0.03	-0.01	-0.02	0.16		
v ₂	0.07	0.72	0.14	0.10	-0.03	0.29	0.03	0.77	0.07	0.08	-0.03	0.25		
V3	0.12	0.72	0.05	0.00	0.12	-0.24	0.02	0.69	-0.02	-0.08	0.03	-0.34		
V ₄	0.24	0.48	-0.23	0.15	0.08	-0.10	0.13	0.42	-0.26	0.00	-0.07	-0.21		
V3	0.21	-0.03	0.05	0.71	0.12	0.04	0.20	-0.09	-0.01	0.69	0.06	-0.04		
Vi	0.00	0.07	0.11	0.85	0.10	0.01	-0.05	0.02	0.04	0.86	0.08	-0.06		
V7	0.06	0.03	0.19	0.58	-0.02	0.43	-0.01	0.04	0.11	0.63	-0.01	0.41		
Vs	0.21	0.05	0.00	0.14	0.12	0.78	0.19	0.06	-0.04	0.08	0.04	0.78		
V9	0.05	0.13	-0.07	0.04	0.14	0.77	-0.02	0.10	-0.11	-0.04	0.03	0.78		
V10	0.31	0.18	0.14	0.41	-0.22	0.20	0.32	0.11	0.04	0.42	-0.21	0.19		
V11	0.14	0.06	0.90	0.10	0.12	0.03	0.08	0.02	0.93	0.05	0.06	-0.01		
V12	0.09	0.08	0.90	0.09	0.09	-0.03	0.03	0.02	0.93	0.02	0.02	-0.06		
V13	0.35	0.29	0.22	-0.07	-0.06	0.45	0.34	0.32	0.11	-0.08	-0.09	0.43		
V1+	0.72	0.08	0.22	0.04	-0.11	0.28	0.73	0.06	0.19	0.04	-0.14	0.25		
V13	0.80	0.03	0.08	0.08	0.12	-0.01	0.81	-0.03	0.03	0.03	0.05	-0.05		
V11	0.82	0.05	0.08	0.06	0.17	0.03	0.84	-0.02	0.02	0.02	0.13	-0.01		
V17	0.62	0.03	0.08	0.10	0.18	0.26	0.62	0.01	0.02	0.06	0.20	0.24		
V _{1S}	0.15	0.00	0.13	0.15	0.84	0.01	0.10	-0.03	0.04	0.14	0.87	-0.06		
V19	0.06	0.06	0.14	-0.01	0.81	0.19	0.02	0.01	0.05	-0.07	0.85	0.11		
<u>Eigenvalue</u>	4.5	1.8	1.6	1.6	1.4	1.3	3.3	2.2	1.8	1.8	1.5	1.5		
Cumulative variance explained (%)	23.6	33.3	41.9	50.1	57.4	64.1	17.3	28.8	38.3	47.6	55.7	63.3		

 Acquiescence had no effect on substantive construct in this case.

 The cumulative variance explained decreased from 64.1% to 63.3% when the responses were corrected for the ARS.

*Bolded loading indicates a value greater than 0.50.

PCA when acquiescence is left in the responses (Ficko & Boncina, 2013a)

Lessons – learned & research recommendations

- Response style can threaten the validity of clustering results
 Junvalid typologies
- Researchers: Pay attention to stimuli of response style (e.g. survey design, looking for socially desirable behavior, personal characteristics)
- Use of advanced methods (e.g. probabilistic clustering, mixed-methods, other methods from social sciences) → more simple typologies, owners not forced into a priori groups
- Towards more harmonized approach to NIPF owner segmentation to compare the typologies also statistically.

Thank you all for the opportunity to work with the FORSYS community and to share your experiences, and for accepting this presentation.