Remote Sensing for Seismic Vulnerability Assessment of Built Environments

Christian Geiß, Joachim Post, Hannes Taubenböck et al.

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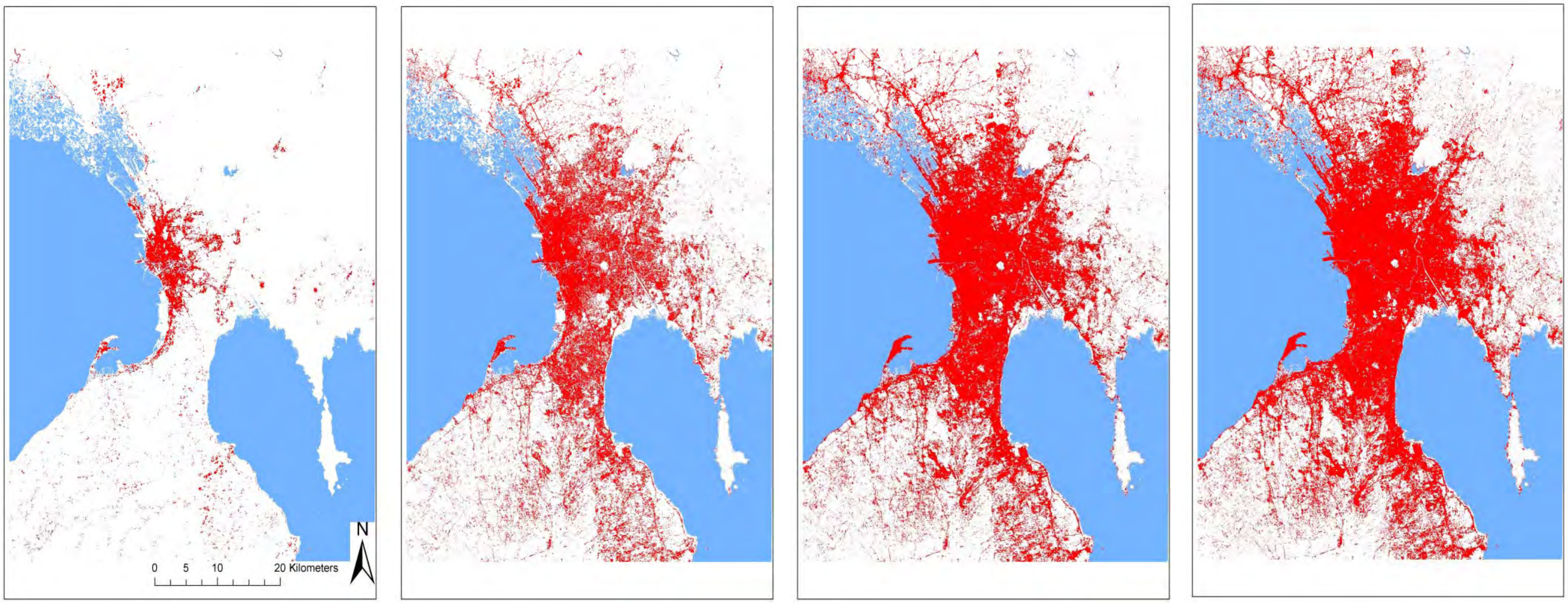
Motivation

- Rapid urbanization

Manila, 1975 **1990** **2000** **2010**



Taubenböck et al. 2012

Motivation

Conventional approaches to assess the seismic vulnerability of buildings face a challenging situation

„First Assessment - Street Surveying“

Istanbul: 75 engineers 1 year

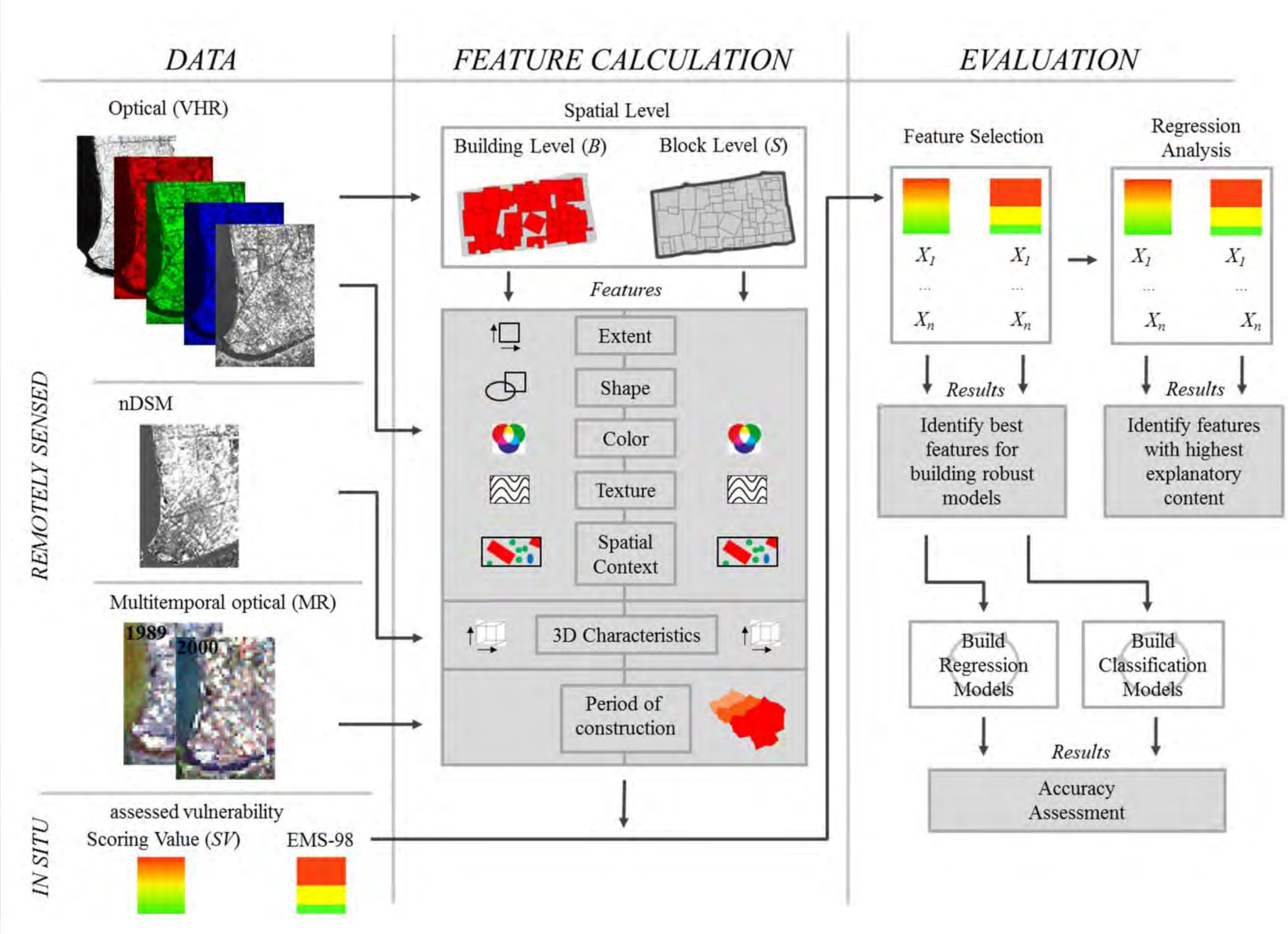
„Smith rebound hammer test“, Padang 2008

Research Questions

- *Which features* can be derived from satellite remote sensing data that *best explain* seismic building vulnerability?

- *How suitable* are features derived from satellite remote sensing data for *estimating seismic building vulnerability* levels?

Evaluation Scheme



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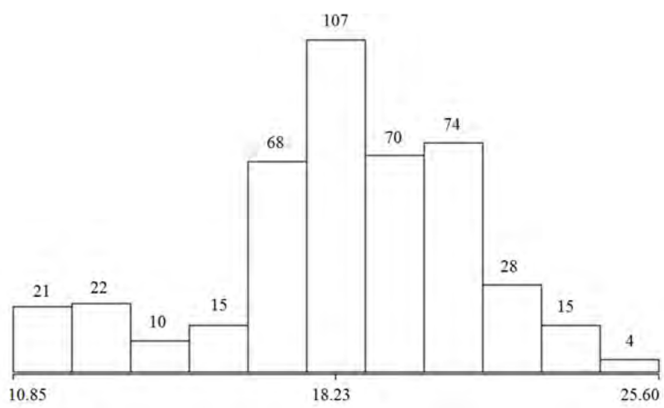
Experiment Setting and Data

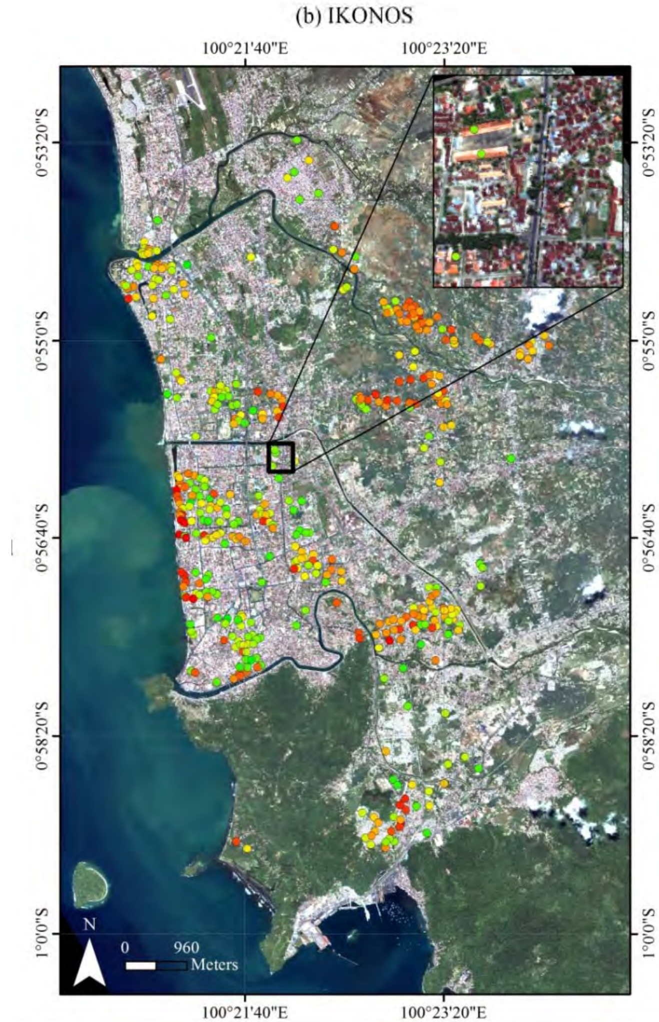
Detailed assessment by civil engineers *in situ*

Scoring Value (SV)

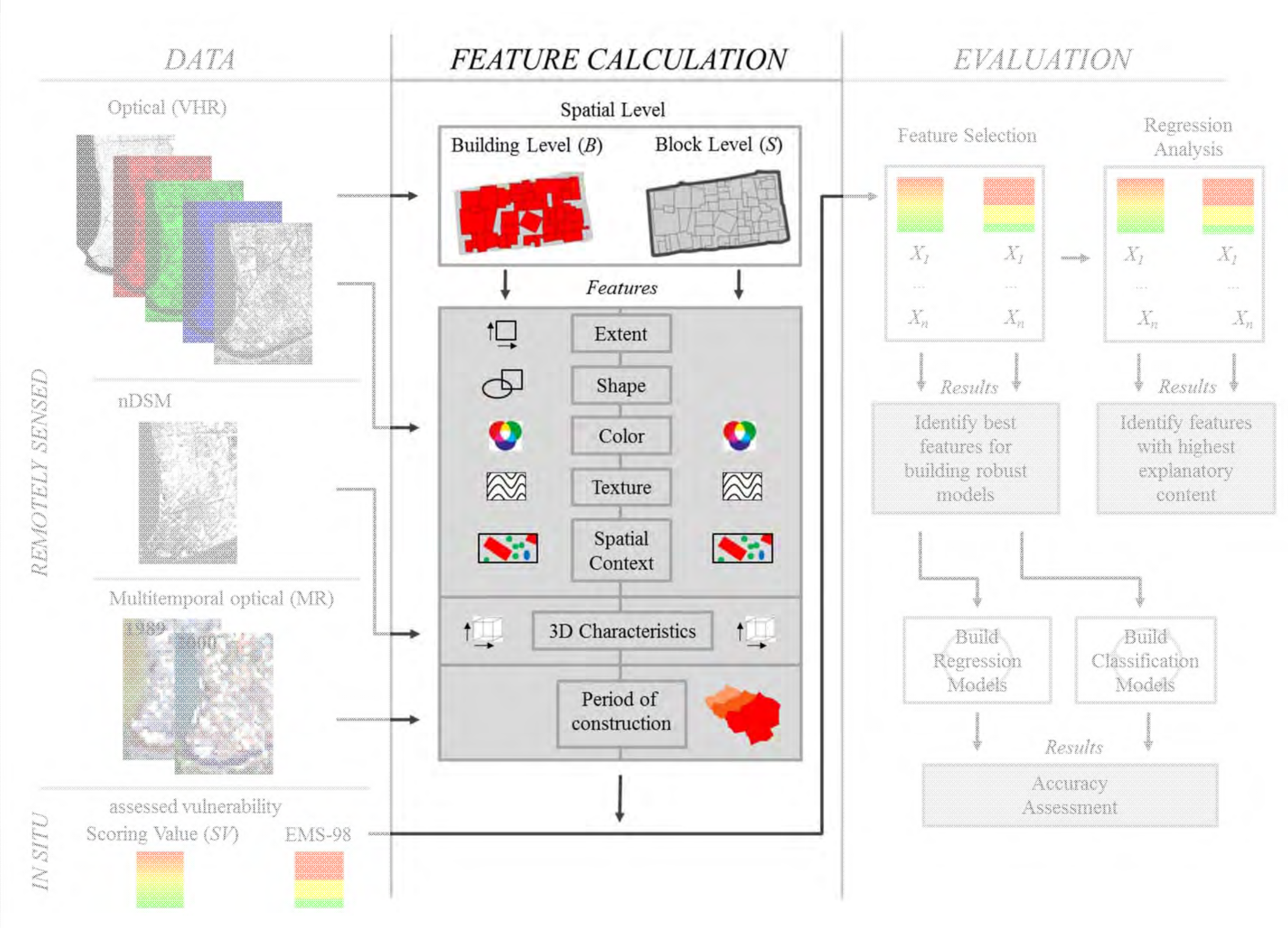


EMS-98

Initial classification	*Number*	*Aggregated classification*	*Number*
A-B	7	A-**B**	242
B	235		
B-C	26	B-**C**	149
C	123		
C-D	32	C-**D**-E	43
D-E	3		
E	8		



Evaluation Scheme



METHODS
Feature Calculation

Spatial Level

Building Level

Block Level

METHODS
Feature Calculation

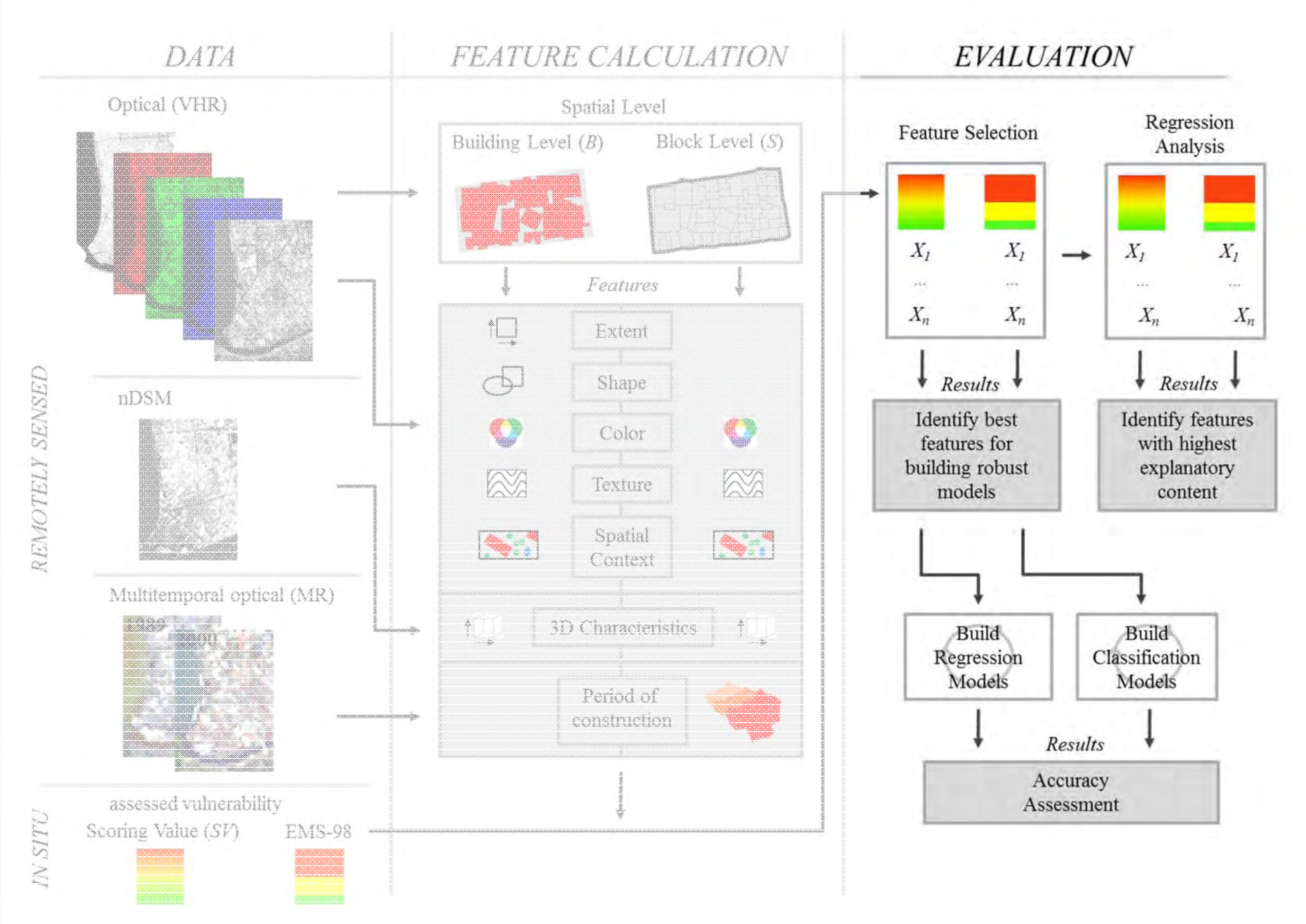
132-dimensional feature vector,
whereby 73 features are related to individual buildings,
and 59 provide block level information.

a) features that went into the calculation of the *in situ* values when they can be quantified by means of remote sensing data

b) features frequently utilized in previous studies on remote sensing based building vulnerability assessment

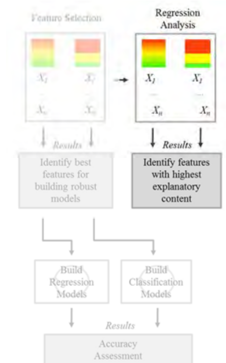
c) features that were used to discriminate urban built-up structures by means of remote sensing previously

METHODS



DATA
FEATURE CALCULATION
EVALUATION
Optical (VHR)
nDSM
Multitemporal optical (MR)
REMOTELY SENSED
IN SITU
assessed vulnerability
Scoring Value (SV)
EMS-98
Spatial Level
Building Level (B)
Block Level (S)
Features
Extent
Shape
Color
Texture
Spatial Context
3D Characteristics
Period of construction
Feature Selection
Regression Analysis
X_1
...
X_n
Results
Identify best features for building robust models
Identify features with highest explanatory content
Build Regression Models
Build Classification Models
Accuracy Assessment

RESULTS
Regression Analysis



SCORING VALUE (SV)

Height and geometry most important determinants (significant at 99.9% level)

R^2 of 0.262;

Additional features raise the model's R^2 value to 0.32

Spectral features enhance model performance but are rarely significant

Feature	Model 1		Model 2		Model 3		Model 4	
[illegible]			[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
			3.31487***	.888291	3.354441***	.8640369	3.112394***	.8651691
			5.073578***	1.123404	5.063067***	1.081441	4.660547***	1.063173
Roof Type B			.1545023	.2558068	.1839185	.2544025	.2649701	.2615001
GLCM Homogeneity B pan					1.07571	1.315121	.4871516	1.336938
GLCM Homogeneity B nir					1.350518*	.5738469	.7967434	.6515387
						170.6297	190.7972	217.2341
						9.150705	-1.461658	10.16228
M(3)/M(4) B							1.167996	1.689854
M(2)/[M(1)+M(2)+M(3)+M(4)] B							12.98874*	6.32278
								105.0541
M(2)/M(4) S							[illegible]	1.412028
Number of observations	434		434		434		434	
R^2	0.167		0.262		0.288		0.320	

*P < 5%, **P < 1%, ***P < 0.1%

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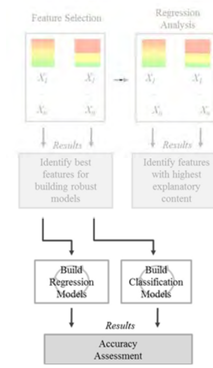
RESULTS
Supervised Regression

SCORING VALUE (SV)

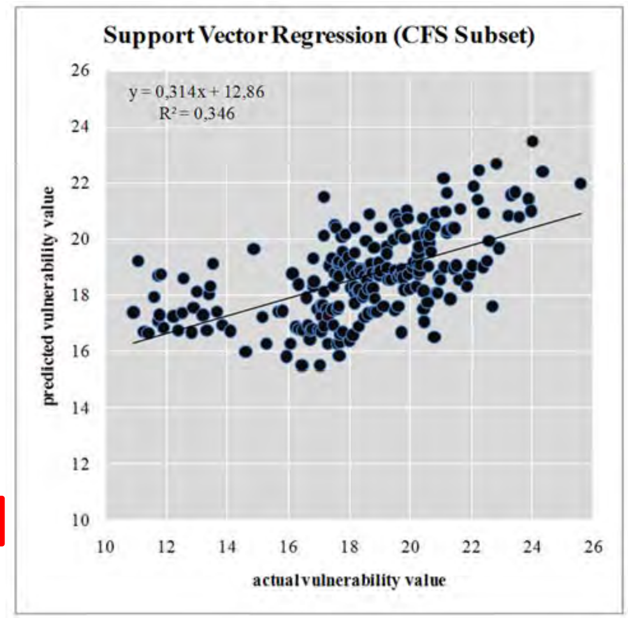


Multi-linear Regression

Used features	*MAE*	*MAPE*	*ME*	*MPE*	*StDev*	*RStDev*	*R*	*RMSE*
All features	2.33	13.32	–0.56	–3.02	2.56	14.32	0.43	2.98
Relief-F W(A)>0	2.02	11.84	–0.11	–0.58	2.07	11.29	0.48	2.62
CFS subset	1.84	10.99	–0.17	–0.91	1.52	8.33	0.56	2.41
CFS subset (*R*<0.8)	1.80	10.81	–0.20	–1.10	1.45	7.96	0.58	2.37

Support Vector Regression

Used features	*MAE*	*MAPE*	*ME*	*MPE*	*StDev*	*RStDev*	*R*	*RMSE*
All features	1.88	11.26	0.02	0.13	1.91	10.37	0.53	2.48
Relief-F W(A)>0	1.79	11.07	0.43	2.31	1.72	9.13	0.57	2.42
CFS subset	1.72	10.61	0.23	1.25	1.54	8.28	0.59	2.36
CFS subset (*R*<0.8)	1.73	10.67	0.24	1.31	1.63	8.73	0.59	2.36



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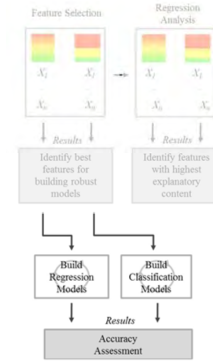
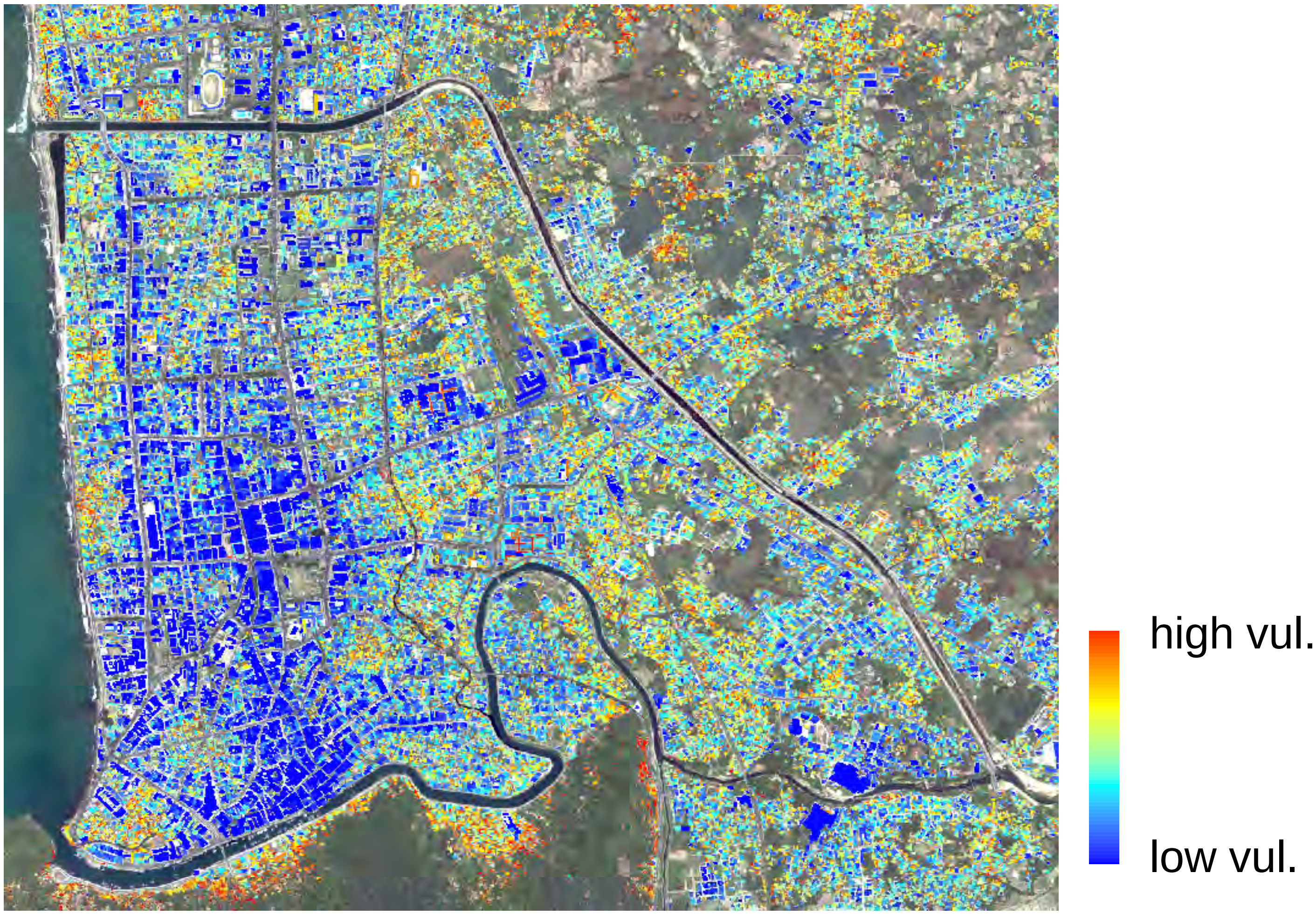
RESULTS
Applied Regression Model





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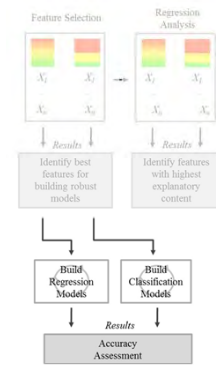
RESULTS
Supervised Regression and Classification



EMS-98

Overall Accuracy: 65.4%
***Kappa* statistic: 0.36**

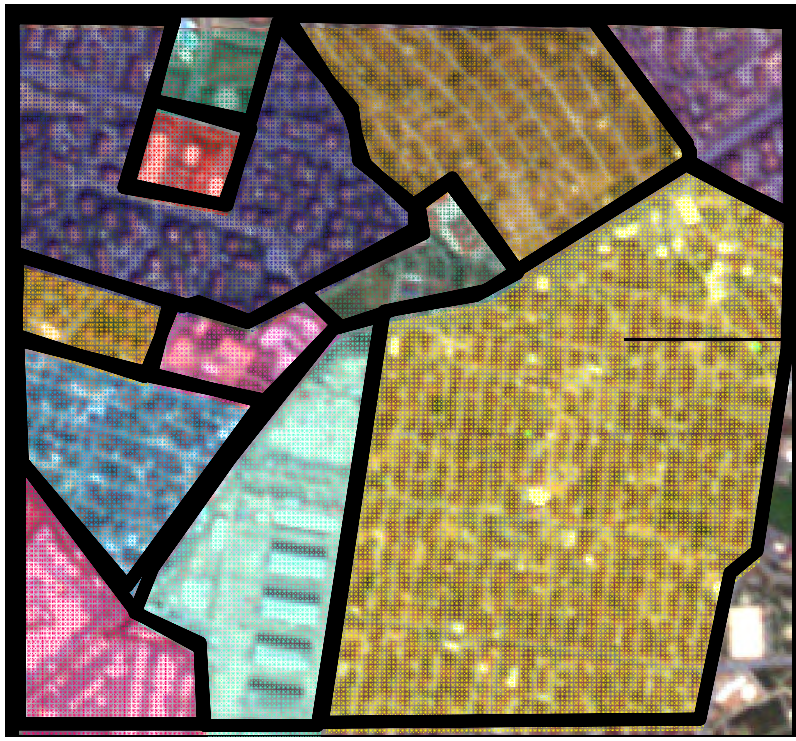
Class	User's Accuracy (Precision)	Producer's Accuracy (Recall)	ROC Area
A-B	0.696	0.793	0.666
B-C	0.661	0.554	0.686
C-D-E	0.294	0.227	0.601
Weighted Average	0.643	0.654	0.645

Large-area Assessment

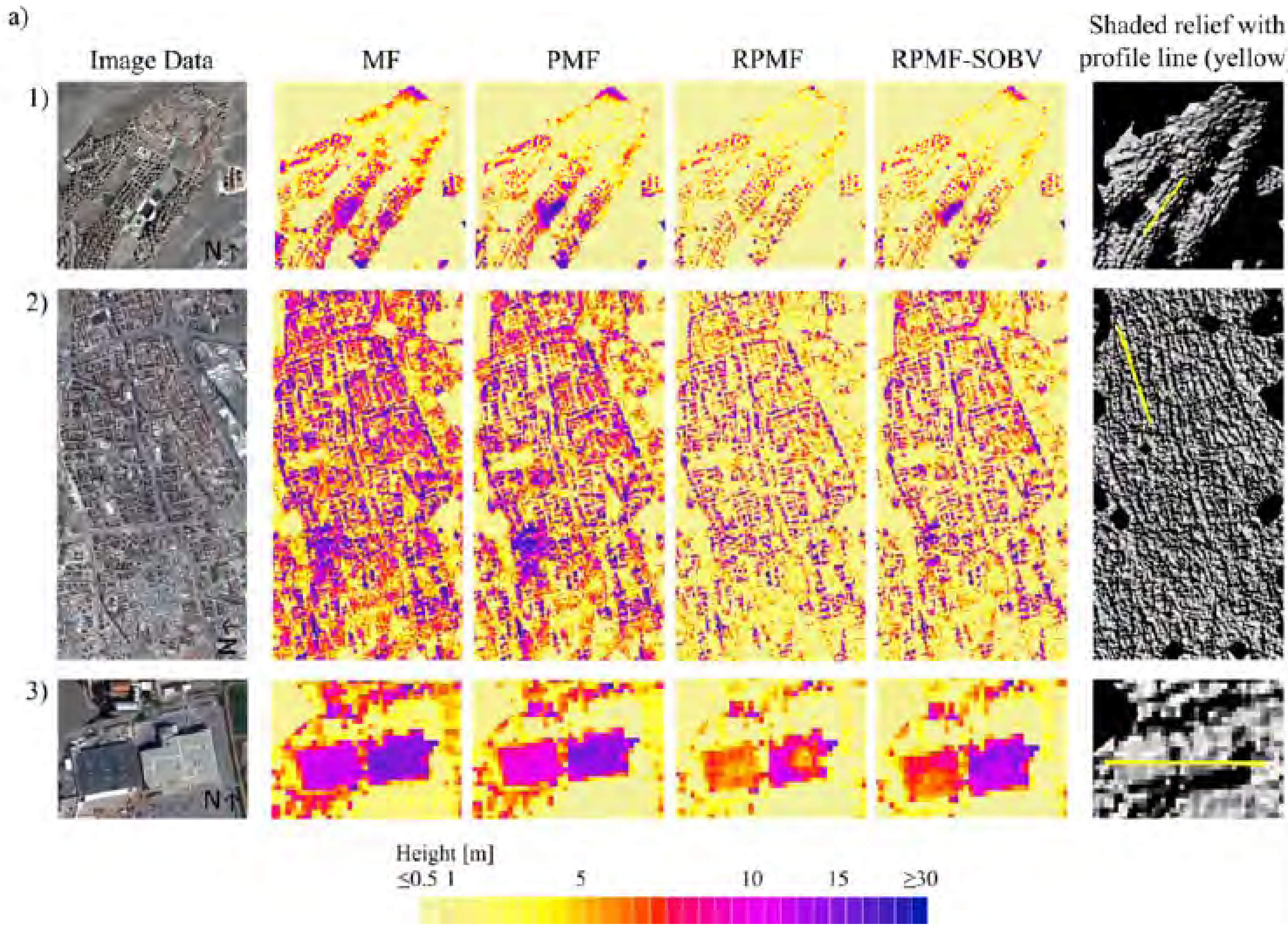
data with coarser spatial resolution but larger spatial coverage (TanDEM-X, RapidEye)

urban structures determined by large industrial/ commercial buildings (highly vulnerable)

urban structures determined by tall detached residential buildings (slightly vulnerable)

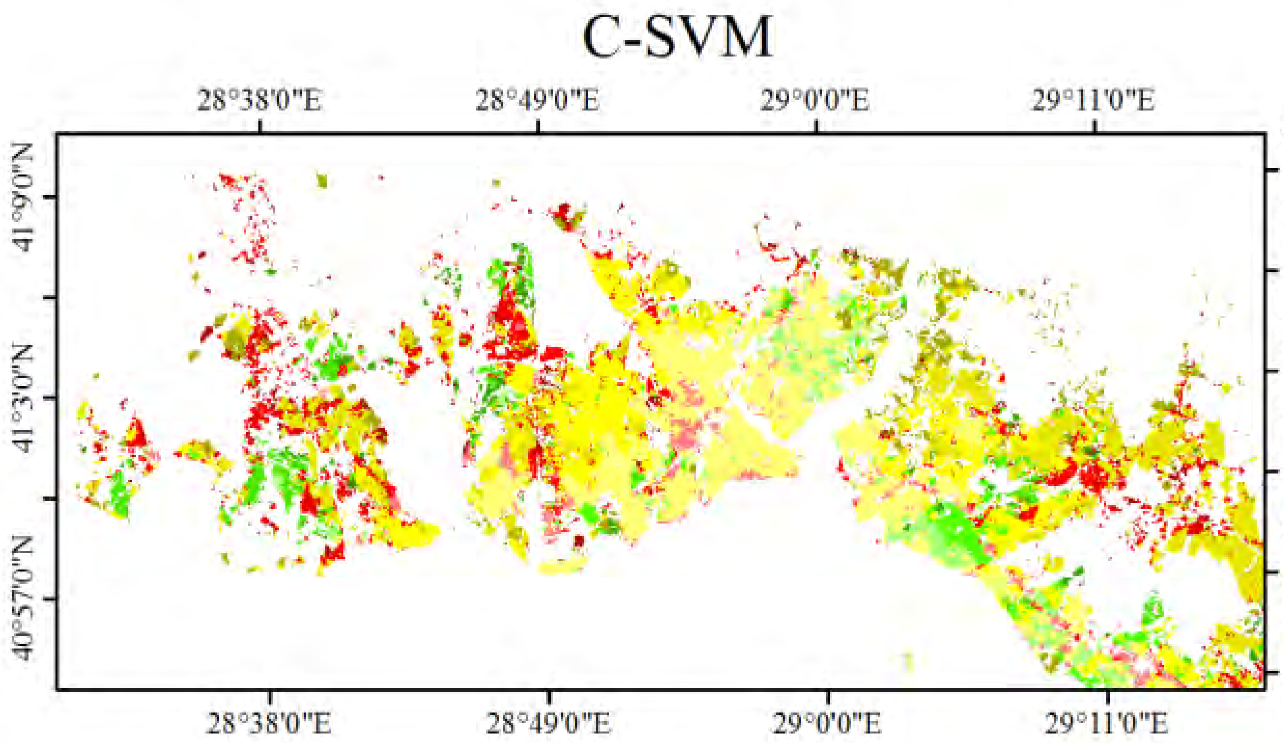


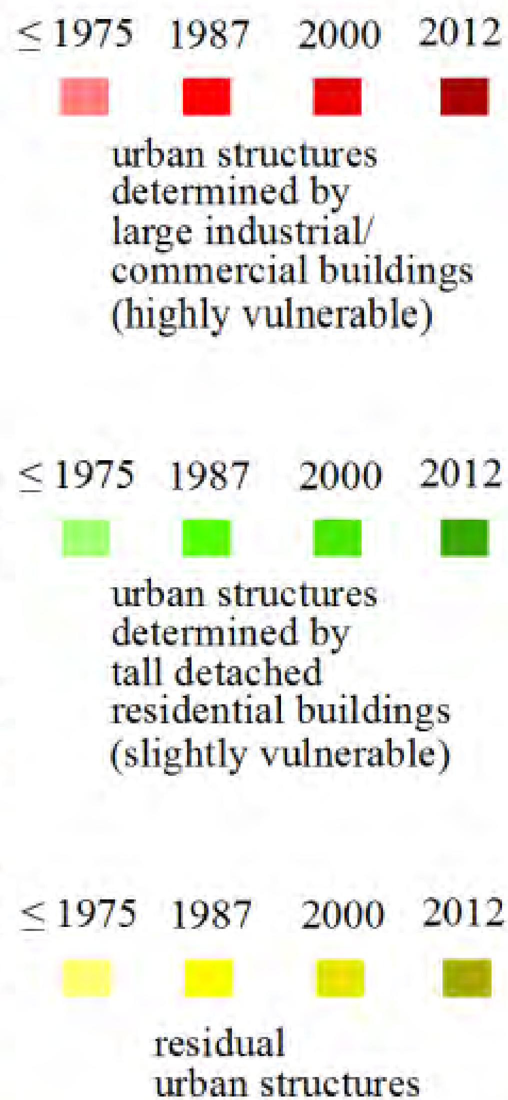
Polygon()
X_1
X_2
X_3
…


a)
Image Data
MF
PMF
RPMF
RPMF-SOBV
Shaded relief with profile line (yellow)
1)
2)
3)
Height [m]
≤0.5 1
5
10
15
≥30

Large-area Assessment

Overall Accuracy: 85.6%
***Kappa* statistic: 0.77**





Conclusions & Outlook

- relation between urban morphology drawn from remote sensing and seismic building vulnerability exists

- estimations feature accuracies that may allow for a valuable support with respect to seismic vulnerability assessment

- define common scales and benchmark accuracies that need to be met

User: Can I make decisions based on the results?

Scientist: What accuracies do you need in order to make decisions?

References

Mück M, Taubenböck H, Post J, Wegscheider S, Strunz G, Sumaryono S, Ismail F (2013) Assessing building vulnerability to earthquae and tsunami hazard using remotely sensed data. Natural Hazards 68(1):97-114.

Taubenböck H, Esch T, Felbier, A, Wiesner M, Roth A, Dech S (2012) Monitoring urbanization in mega cities from space. Remote Sensing of Environment 117:162-176

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