LAND-SUITE a set of tools for landslide susceptibility zonation

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- **Introduction to LAND-SUITE**
- Hands on using a basic example

LAND-SUITE

- **What is LAND-SUITE**?
- **What's LAND-SUITE good at**?

LAND-SUITE does not want to substitute your **geomorphological inference/experience!**

LAND-SUITE wants to support you **in generating less subjective** (hopefully) **statistically-based susceptibility zonation.**

LAND-SUITE

LAND-SUITE (**LAND**slide - **SU**sceptibility **I**nferential **T**ool **E**valuator) is a suite of R tools designed to **support** the landslide susceptibility inference process. LAND-SUITE is composed by:

- **LAND-SE**: **LAND**slide - **S**usceptibility **E**valuation
- **LAND-SIP**: **LAND**slide - **S**usceptibility **I**nput **P**reparation
- **LAND-SVA**: **LAND**slide - **S**usceptibility **V**ariable **A**nalysis

LAND-SE

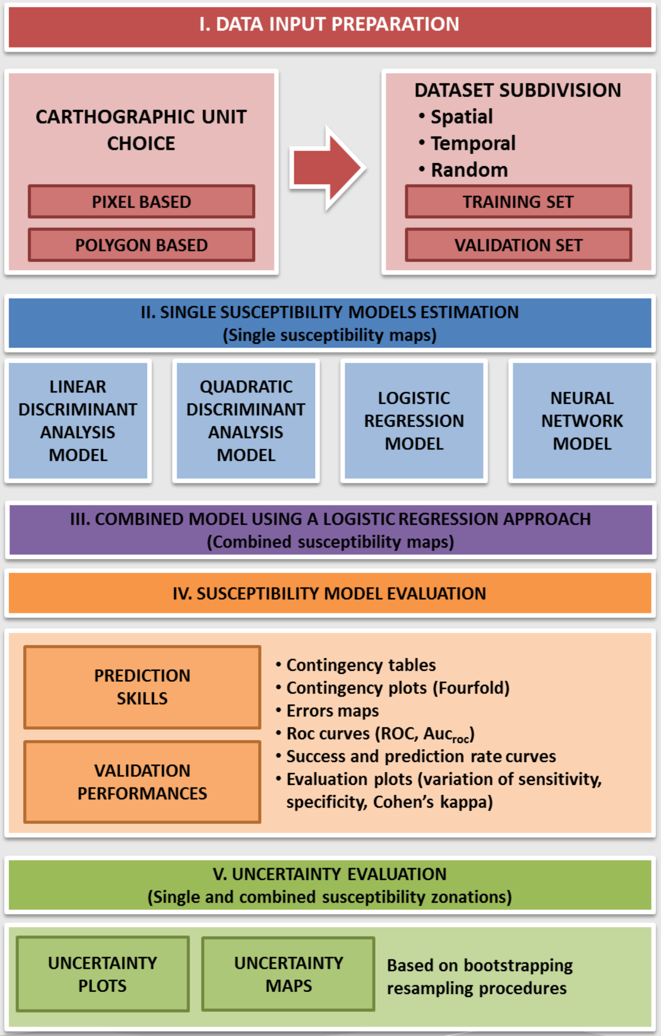
LAND-SE

LANDslide - **S**usceptibility **E**valuation

LAND-SE

LAND-SE (**LAND**slide - **S**usceptibility **E**valuation)

- Open source (R code) software for **regional** landslide susceptibility **modelling** and **zonation.**
- Model applications using different **cartographic units** (pixel, polygon).
- Improved susceptibility **model evaluation** tools.



Data Input Preparation

I. DATA INPUT PREPARATION

CARTHOGRAPHIC UNIT CHOICE

- PIXEL BASED
- POLYGON BASED

DATASET SUBDIVISION

- Spatial
- Temporal
- Random

- TRAINING SET
- VALIDATION SET

SW Input

In the supervised multivariate statistical approaches implemented in the software:

- the **dependent variable** (or grouping variable) **is** the **presence** (value=1) or **absence** (value=0) of **landslides** in the **mapping units** (derived from landslide inventory)
- the **independent variables** (explanatory variables) **are** obtained from **thematic information** (morphometry, land cover/use, lithology, etc.)

The **software** is **designed to use different mapping units**, **but reducible** to **point-like units** (pixels) or to **polygon-like subdivisions** (e.g. geomorphological, administrative, etc.)

SW Input

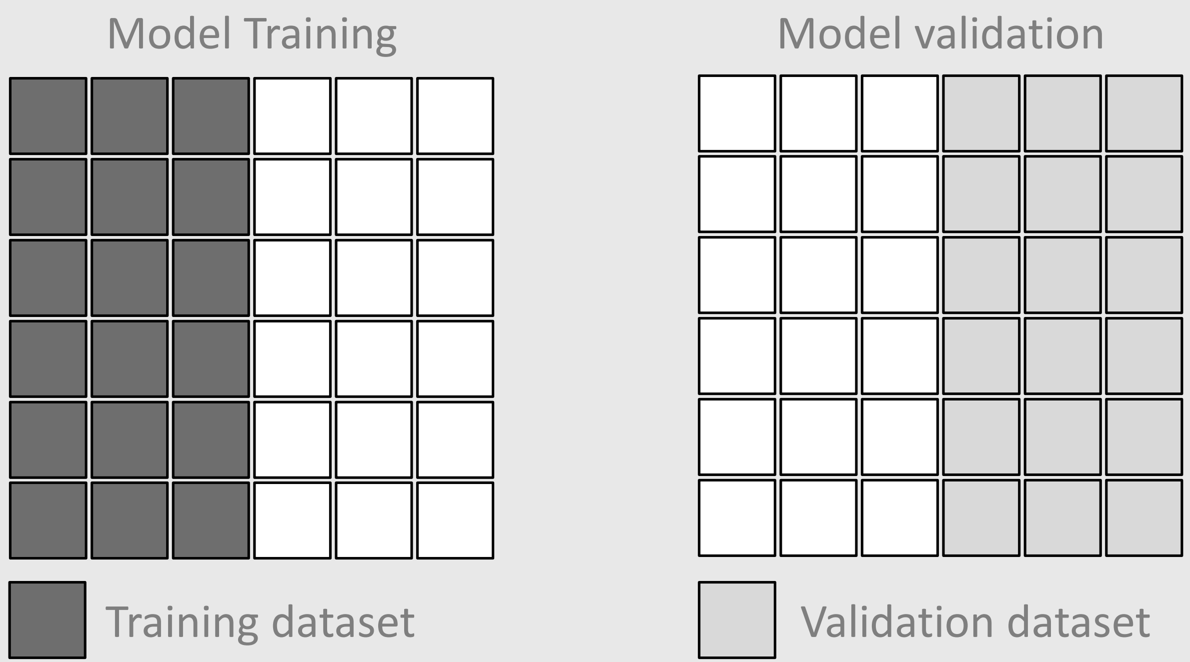
The **software** **requires** **in input two datasets, the training** and **the validation datasets** in **tabular format.**

ID | **Dependent Variable (grouping)** | **Independent variables (thematic information)**

SU_ID	FRAX	SUOLO1	SUOLO2	SUOLO3	SUOLO4	SUOLO5	DEM_AVG	DEM_STD	SLP_MEAN	SLP_STD
6	1	53.82	35.94	6.29	3.96	0	316.62	44.54	28.43	11.31
7	1	27.31	28.3	41.68	2.72	0	250.78	17.58	28.08	11.05
10	1	40.46	32.96	23.22	3.36	0	249.62	24.71	29.78	12.25
41	0	54.54	33.5	7.95	4.02	0	188.26	51.04	23.43	11.33
44	1	16.45	47.24	24.45	11.85	0	189.18	24.47	36.95	12.48
45	1	9.45	58.19	17.51	4.12	9.85	254.83	49.18	34.3	11.89
61	1	18.35	65.35	13.2	2.1	0	237.16	39.34	35.17	11.12
62	1	56.61	29.64	5.55	8.2	0	186.18	12.33	36.78	11.98
63	1	34.77	33.12	17.02	12.04	3.05	146.41	30.28	25.36	14.09
85	0	64.56	22.73	7.61	5.11	0	173.7	34.13	31.25	12.37
86	0	72.7	23.58	0.73	3	0	175.13	21.41	29.29	11.51
92	0	12.37	72.67	7.01	7.95	0	207.11	23.23	35.31	9.22
100	0	29.38	33.78	33.94	2.9	0	262.76	31.42	27.09	10.74

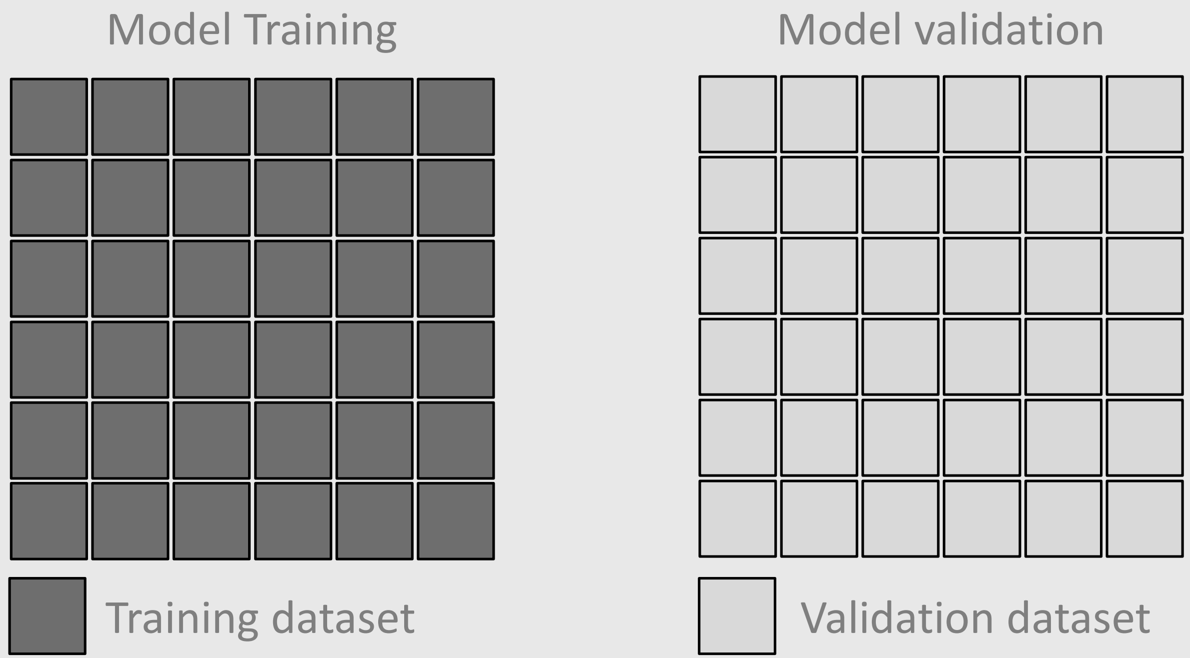
Training/Validation datasets subdivision

Spatial Validation



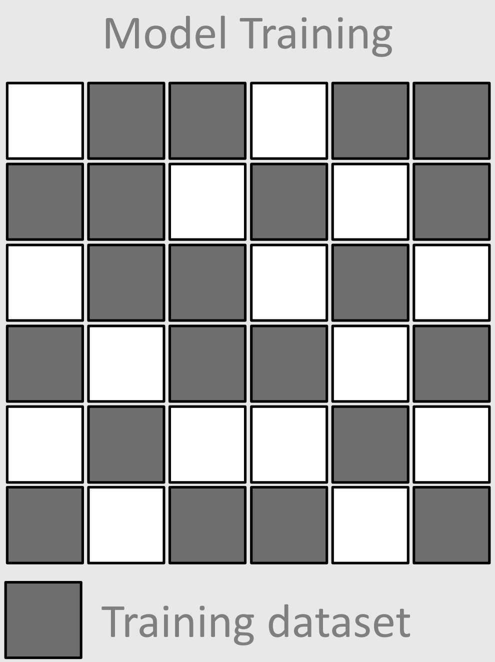
Training/Validation datasets subdivision

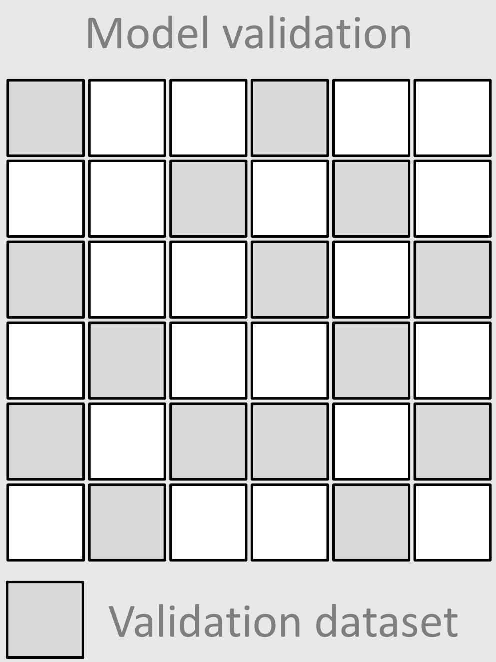
Temporal Validation



Training/Validation datasets subdivision

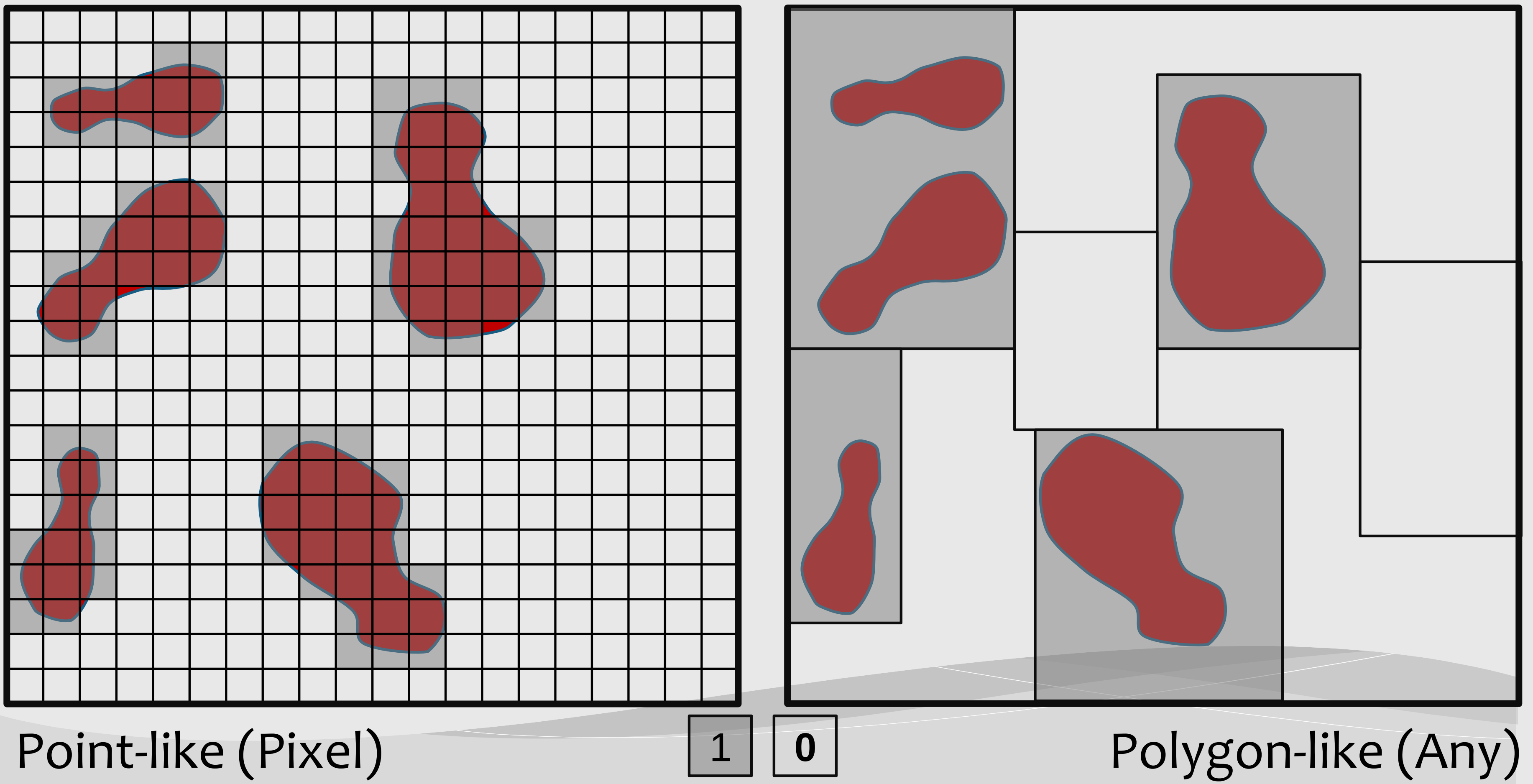
Cross Validation





Dependent variable

The **dependent variable** (or grouping variable) **is** the **presence** (value=1) or **absence** (value=0) of **landslides** in the **mapping units** . This is **derived from landslide inventories.**

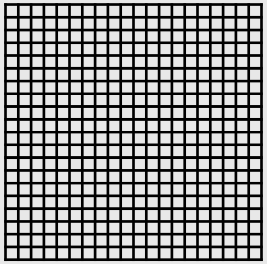


Independent variables

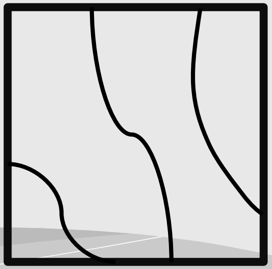
Independent variables (or explanatory variables) are **obtained from thematic information** (morphometry, land cover/use, lithology, etc.).

Thematic information can be **available** as:

- **continuous variables** generally **stored** in **raster format** (e.g. slope, curvature, elevation,…)



- **categorical variables** generally **stored** in **polygon format** (e.g. geology, land cover/use, etc.)



Independent variables

Continuous independent variables can be **used directly in the statistical susceptibility analyses, while categorical variables** are **generally transformed into dummy variables.**

A **dummy variable** can be **derived using different criteria:**

- **Heuristically** (based on personal judgment/experience) **assigning to different categories** an **index value** increasing/decreasing with the expected propensity to instability
- **Numerically calculating** the **relative landslide incidence** in each category
- **Numerically calculating** the **percentage** of each **category in the mapping unit** (generally adopted when using polygon-like mapping units)

Susceptibility Estimation

II. SINGLE SUSCEPTIBILITY MODELS ESTIMATION
(Single susceptibility maps)

LINEAR DISCRIMINANT ANALYSIS MODEL	QUADRATIC DISCRIMINANT ANALYSIS MODEL	LOGISTIC REGRESSION MODEL	NEURAL NETWORK MODEL

III. COMBINED MODEL USING A LOGISTIC REGRESSION APPROACH
(Combined susceptibility maps)

SW Landslide Susceptibility

Each **single model** **gives in output** the **probability** of a **given mapping unit** (e.g. a pixel, a slope unit, etc.) of **being classified as 1** (i.e. as unstable)

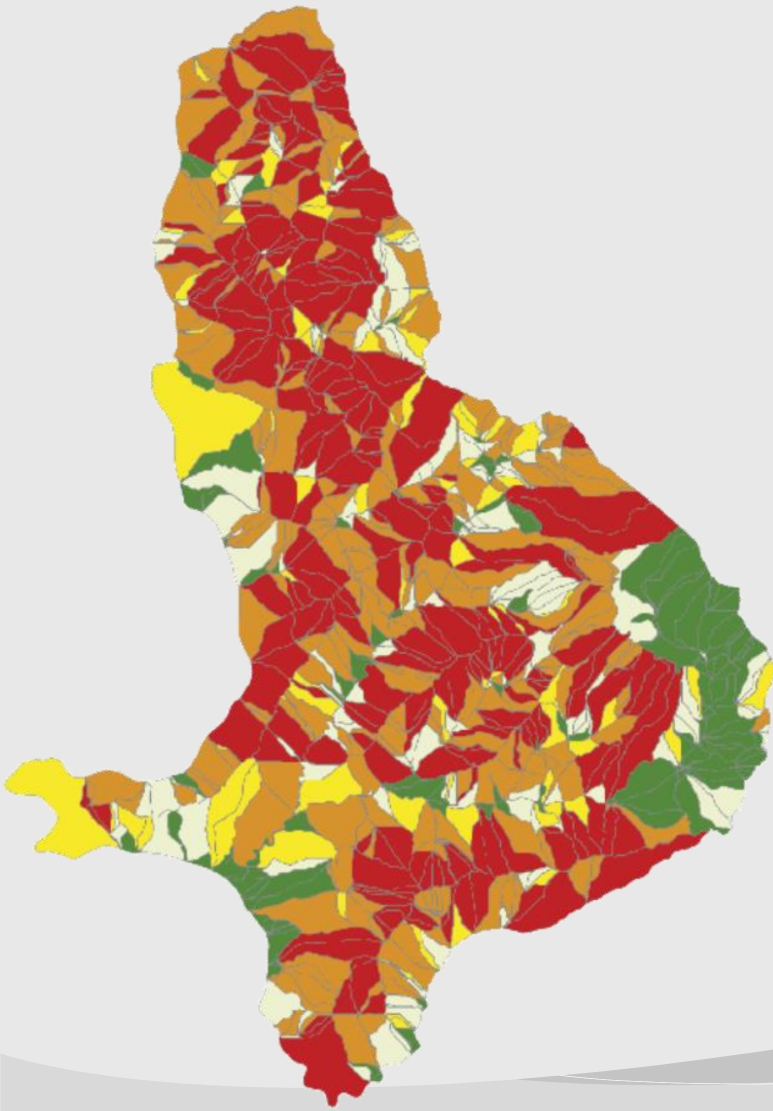
But **how** **to decide** which is the **best "optimal" model** for your analysis?

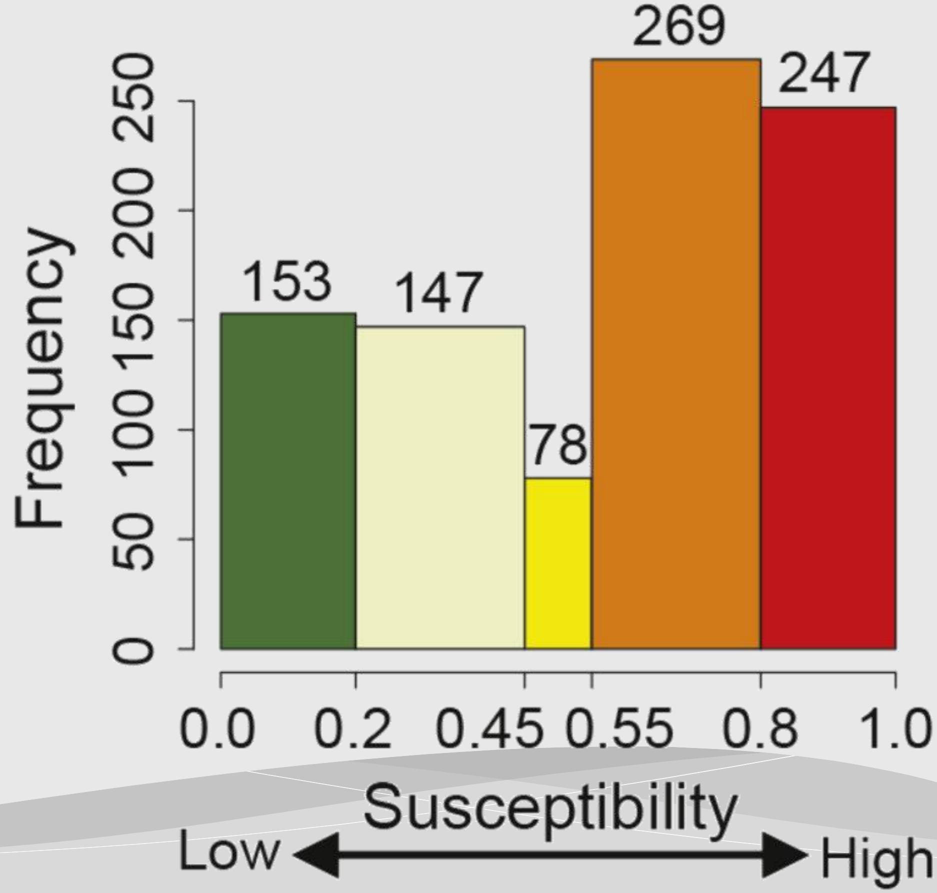
SW Landslide Susceptibility

The **software** **integrates** **four** different **supervised multivariate** statistical **approaches** to assess landslide susceptibility:

- a **linear discriminant** analysis model (**LDA**);
- a **quadratic discriminant** analysis model (**QDA**);
- a **logistic regression** model (**LRM**);
- a self-optimizing **neural network** model (**NNM**).

Susceptibility Maps & Histograms





Selection of the optimal model

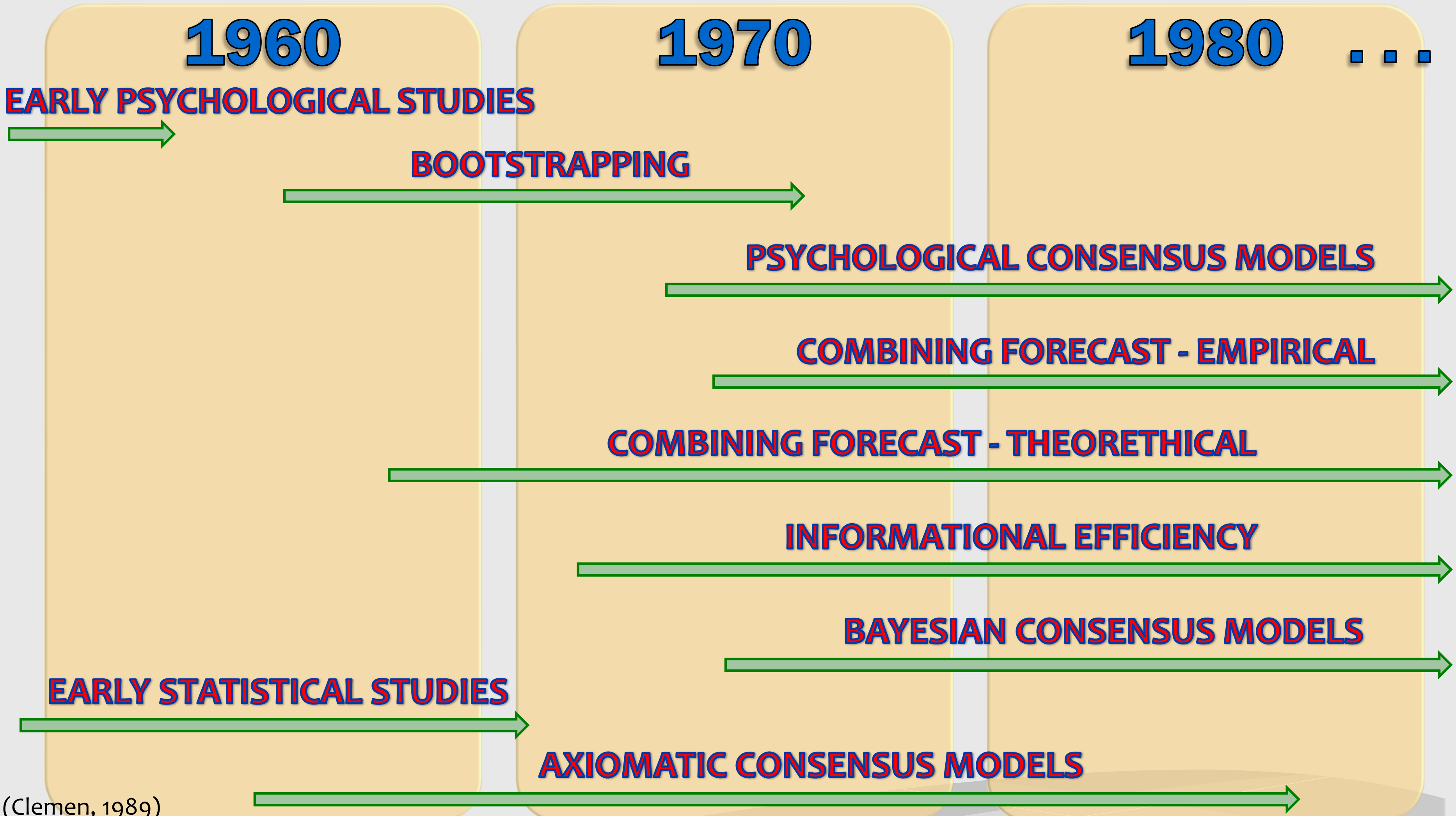
But **how** **to decide** which is the **best "optimal" model** for the susceptibility analysis?

As shown by the **literature review** **there isn't** a **model that outperforms** **among all the others, but** it is **possible** to **combine** **them.**

Combination Model Criteria

The basic idea of **combining forecast implicitly assumes** that **one model could not identify the underlying process**, but **different forecasting models could be able to capture different aspects** of the **information available for prediction** (input data).

Forecast combination literature



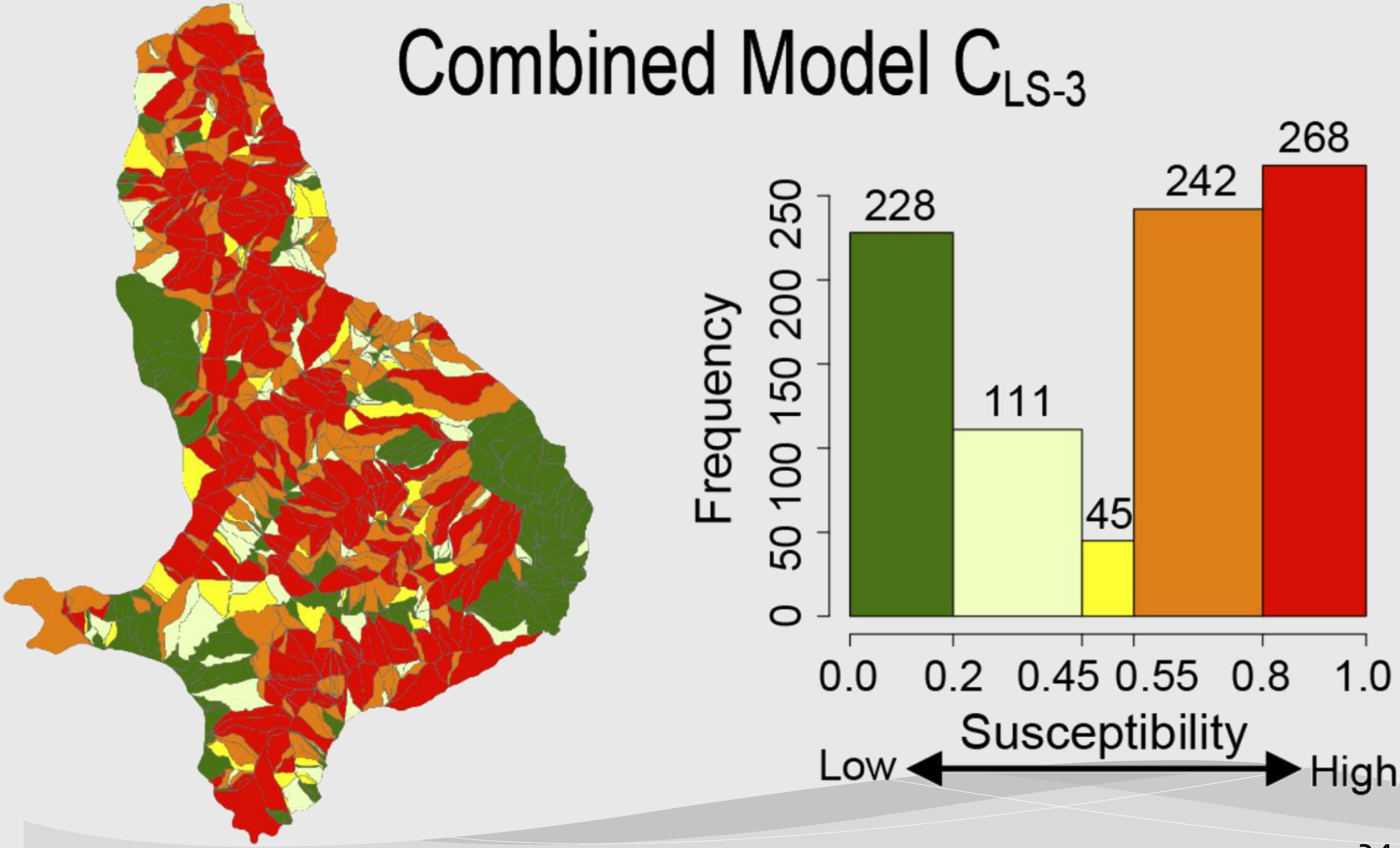
(Clemen, 1989)

Combination Model Criteria

The **software includes** a **model** (CFM) **to combine** the **single modelling susceptibility** results (LDA, QDA, LRM, NNM or some of them).

A **logistic regression approach** was **selected** for the **combination schema,** where the **grouping variable** is the **presence** or **absence** of **landslides** in the mapping units (the same of single susceptibility models) and the **explanatory variables** are the **susceptibility prediction** obtained **from** the **single models**.

Susceptibility Maps & Histograms



Susceptibility Model Evaluation

IV. SUSCEPTIBILITY MODEL EVALUATION

PREDICTION SKILLS

VALIDATION PERFORMANCES

- Contingency tables
- Contingency plots (Fourfold)
- Errors maps
- Roc curves (ROC, Auc_{roc})
- Success and prediction rate curves
- Evaluation plots (variation of sensitivity, specificity, Cohen's kappa)

Contingency table/Confusion matrix

Contingency tables (or confusion matrixes) are used in the field of machine learning and specifically to the problem of statistical classification, to visualize or classified of the performance of an classification algorithm. In the case of a binary classifier table is a table with 2X2 values

		PREDICTED 0	PREDICTED 1	
OBSERVED	1	True Negative (TN)	False Positive (FP)	Observed Negative
OBSERVED	0	False Negative (FN)	True Positive (TP)	Observed Positive
		Predicted Negative	Predicted Positive	

true positive (TP)

eqv. with hit

true negative (TN)

eqv. with correct rejection

false positive (FP)

eqv. with false alarm, Type I error

false negative (FN)

eqv. with miss, Type II error

Quantitative metrics

		PREDICTED 0	PREDICTED 1	
OBSERVED	1	True Negative (TN)	False Positive (FP)	Observed Negative
	0	False Negative (FN)	True Positive (TP)	Observed Positive
		Predicted Negative	Predicted Positive	

sensitivity, **recall**, **hit rate**, or **true positive rate (TPR)**

$$\mathrm{TPR} = \frac{\mathrm{TP}}{P} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}$$

specificity or **true negative rate (TNR)**

$$\mathrm{TNR} = \frac{\mathrm{TN}}{N} = \frac{\mathrm{TN}}{\mathrm{FP}+\mathrm{TN}}$$

precision or **positive predictive value (PPV)**

$$\mathrm{PPV} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}$$

negative predictive value (NPV)

$$\mathrm{NPV} = \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FN}}$$

fall-out or **false positive rate (FPR)**

$$\mathrm{FPR} = \frac{\mathrm{FP}}{N} = \frac{\mathrm{FP}}{\mathrm{FP}+\mathrm{TN}} = 1-\mathrm{TNR}$$

false discovery rate (FDR)

$$\mathrm{FDR} = \frac{\mathrm{FP}}{\mathrm{FP}+\mathrm{TP}} = 1-\mathrm{PPV}$$

miss rate or **false negative rate (FNR)**

$$\mathrm{FNR} = \frac{\mathrm{FN}}{P} = \frac{\mathrm{FN}}{\mathrm{FN}+\mathrm{TP}} = 1-\mathrm{TPR}$$

accuracy (ACC)

$$\mathrm{ACC} = \frac{\mathrm{TP}+\mathrm{TN}}{P+N}$$

F1 score

is the harmonic mean of precision and sensitivity

$$F_1 = \frac{2\mathrm{TP}}{2\mathrm{TP}+\mathrm{FP}+\mathrm{FN}}$$

Matthews correlation coefficient (MCC)

$$\mathrm{MCC} = \frac{\mathrm{TP}\times\mathrm{TN}-\mathrm{FP}\times\mathrm{FN}}{\sqrt{(\mathrm{TP}+\mathrm{FP})(\mathrm{TP}+\mathrm{FN})(\mathrm{TN}+\mathrm{FP})(\mathrm{TN}+\mathrm{FN})}}$$

Informedness or Bookmaker Informedness (BM)

$$\mathrm{BM} = \mathrm{TPR}+\mathrm{TNR}-1$$

Markedness (MK)

$$\mathrm{MK} = \mathrm{PPV}+\mathrm{NPV}-1$$

Cohen's Kappa

$$\kappa \equiv \frac{p_o - p_e}{1-p_e} \qquad p_0 \equiv \mathrm{ACC} \qquad p_e = p_{rap} + p_{ran}$$

$$p_{rap} = \frac{\mathrm{TP}+\mathrm{FP}}{TP+TN+FP+FN}\cdot\frac{\mathrm{TP}+\mathrm{FN}}{TP+TN+FP+FN}$$

$$p_{ran} = \frac{\mathrm{TN}+\mathrm{FN}}{TP+TN+FP+FN}\cdot\frac{\mathrm{TN}+\mathrm{FP}}{TP+TN+FP+FN}$$

Obtaning Contingency Table

OBSERVED	PREDICTED PROBABILITY	PREDICTED CLASSIFIED Probability >= Threshold Classified as 1 (e.g. Threshold =0.5)	OUTCOME
1	0.9	1	TP
1	0.8	1	TP
1	0.4	0	FN
1	0.7	1	TP
1	0.9	1	TP
1	0.2	0	FN
0	0.1	0	TN
0	0.4	0	TN
0	0.3	0	TN
0	0.1	0	TN
0	0.6	1	FP
0	0.8	1	FP

TP: True Positive   TN: True Negative   FP: False Positive   FN: False Negative

Obtaning Contingency Table

ACC = (4 + 4) / (4 + 2 + 2 + 4) = 0.67 (67%)

TPR = 4 / (4 + 2) = 0.67 (67%)

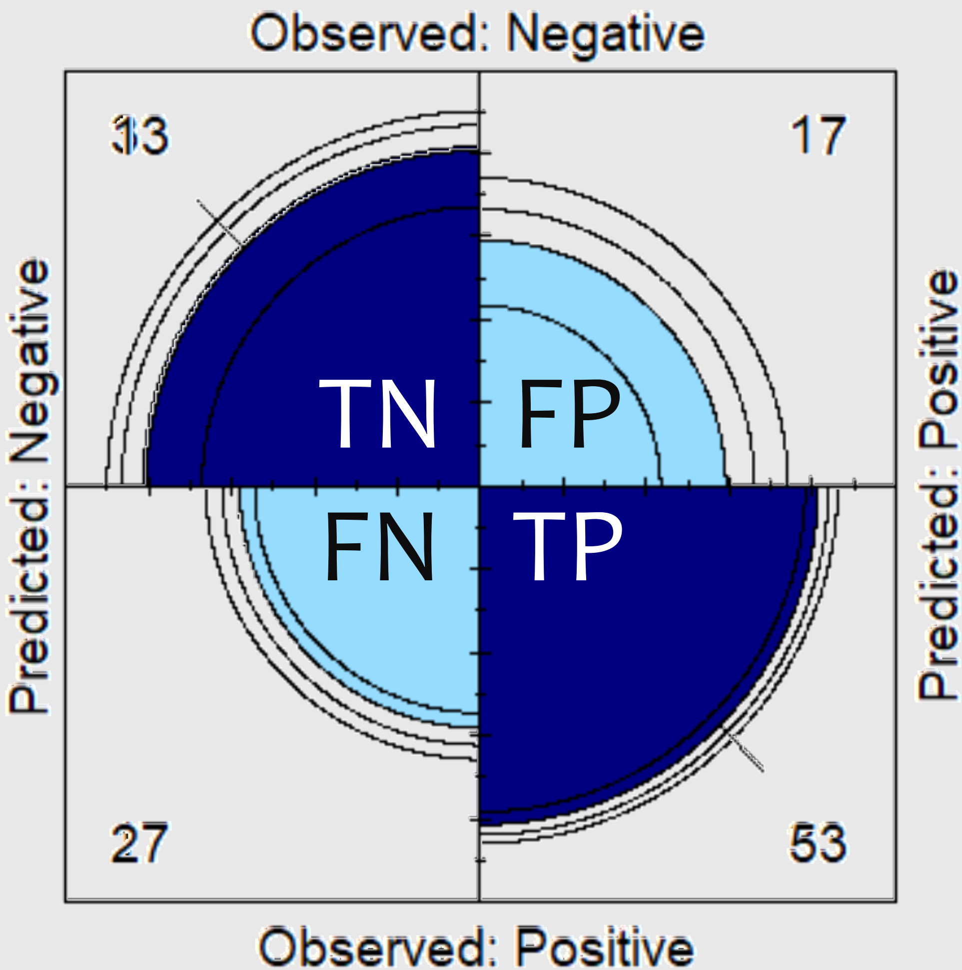
TNR = 4 / (4 + 2) = 0.67 (67%)

FPR = 1 - TNR = 0.33 (33%)

		PREDICTED 0	PREDICTED 1	
OBSERVED	1	TN=4 (33%)	FP=2 (17%)	Observed Negative N_{OBS}=6
OBSERVED	0	FN=2 (17%)	TP =4 (33%)	Observed Positive P_{OBS} =6
		Predicted Negative N_{PRE} =6	Predicted Positive P_{PRE} =6	

TP: True Positive TN: True Negative FP: False Positive FN: False Negative

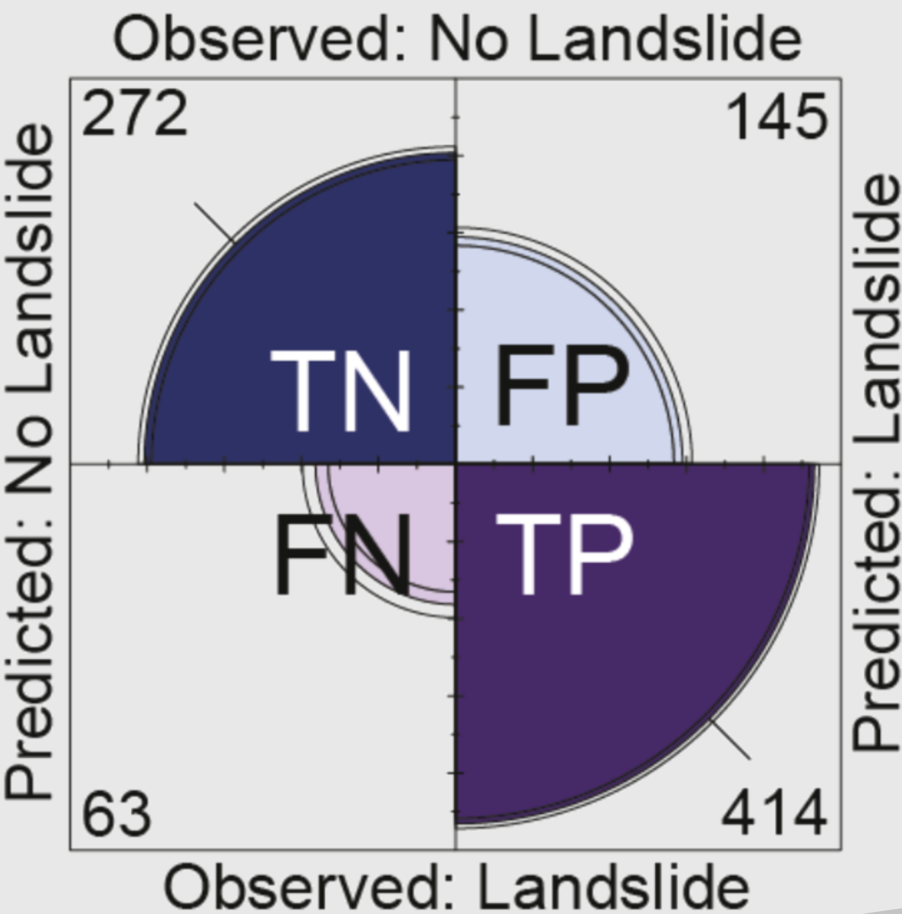
Contingency Plots

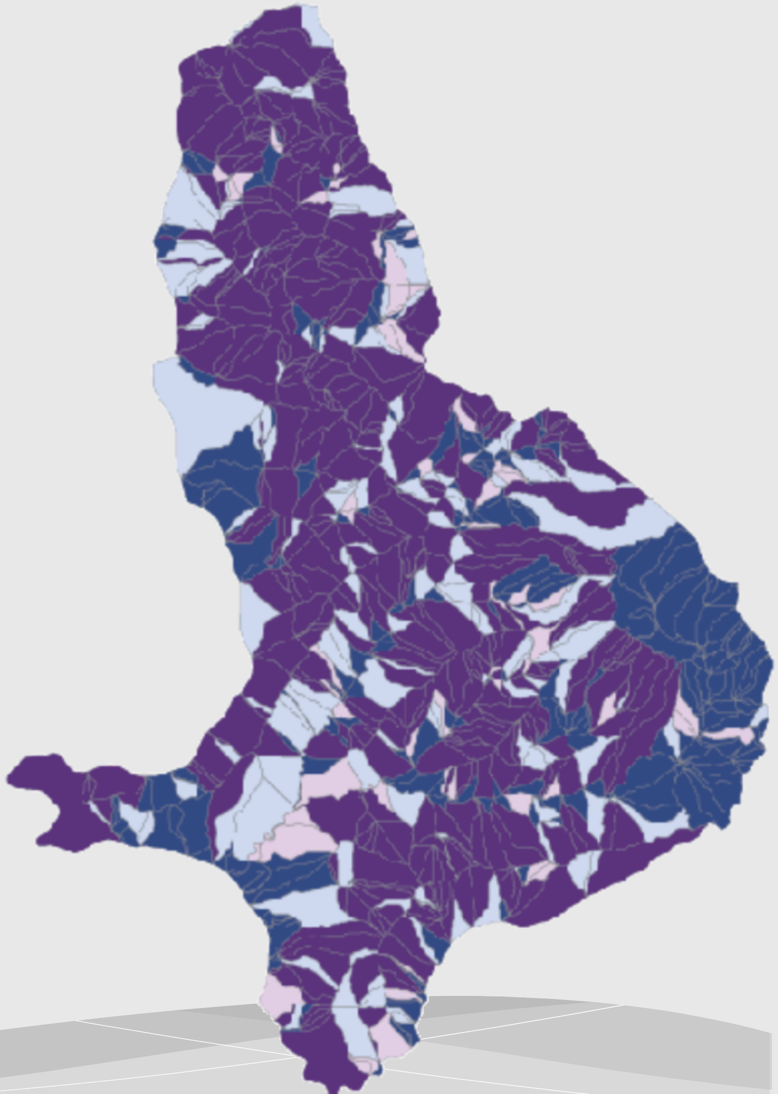


TP: True Positive TN: True Negative FP: False Positive FN: False Negative

Contingency Plots & Error maps

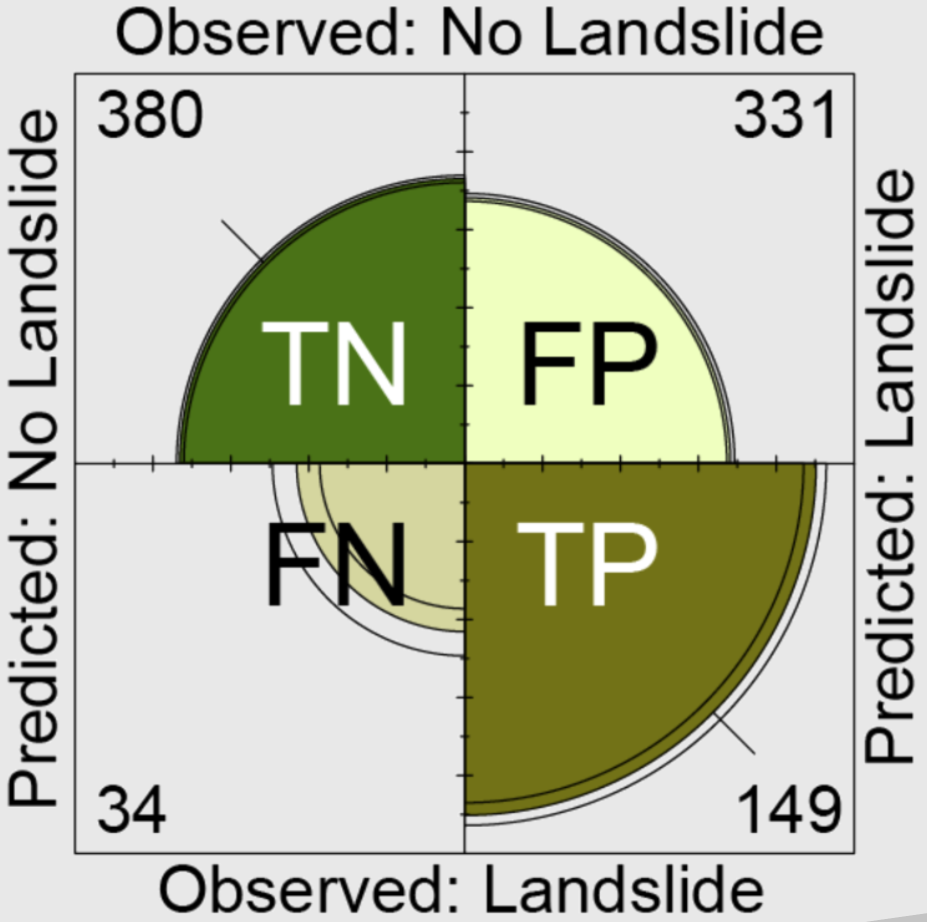
TRAINING

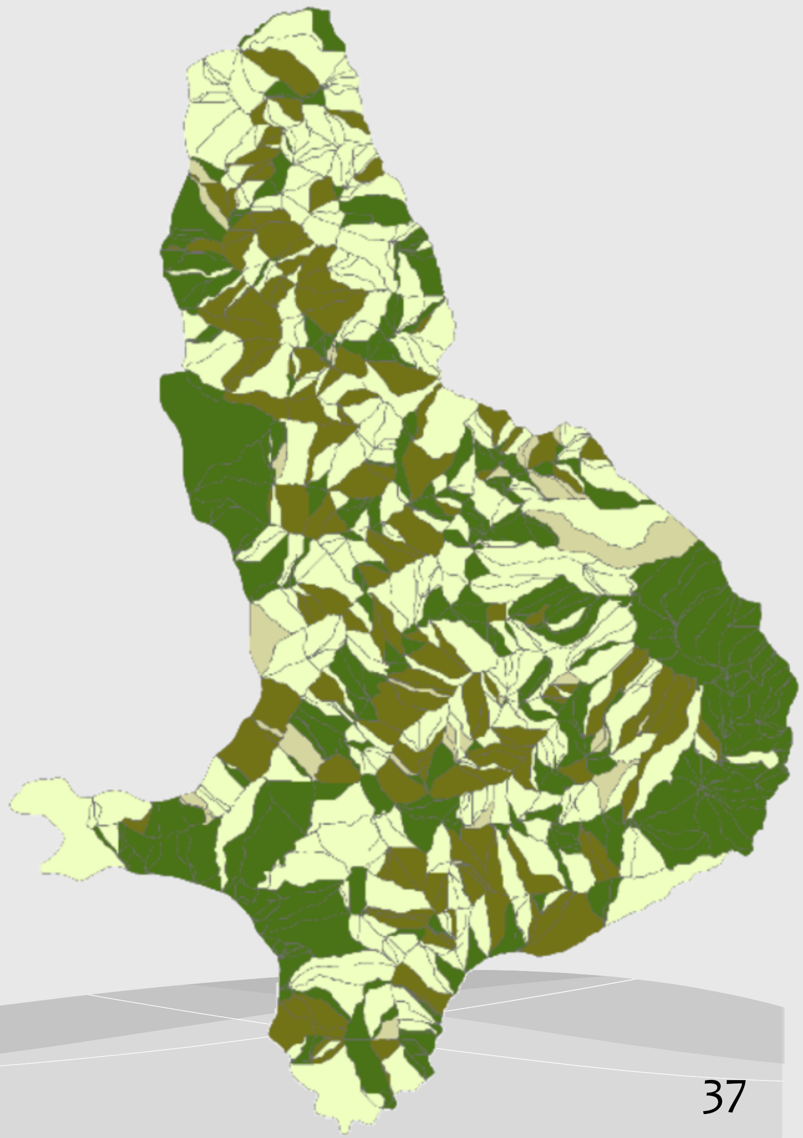




Contingency Plots & Error maps

VALIDATION

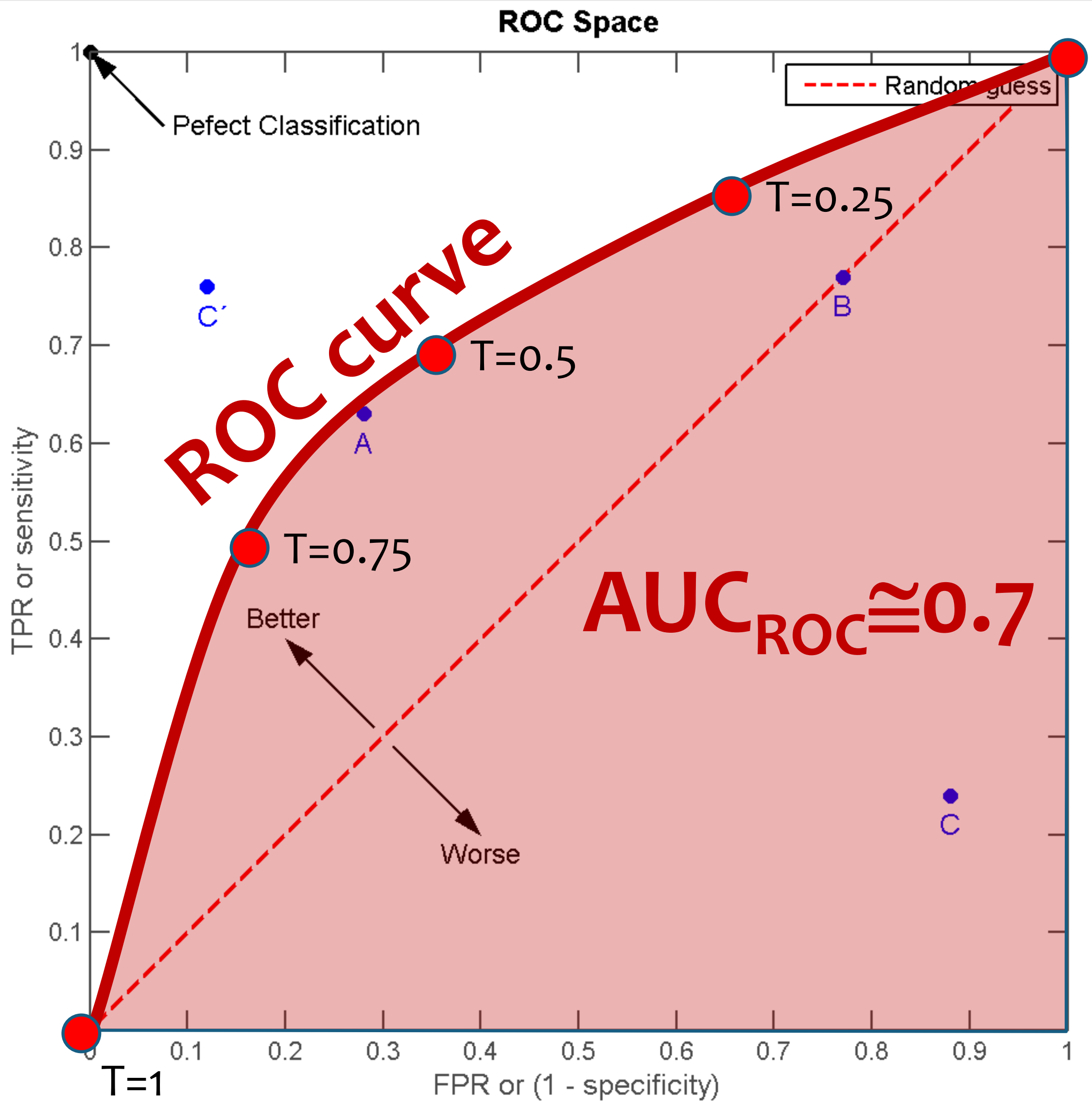




Changing probability threshold

OBSERVED	PREDICTED PROBABILITY	PRED CLASS T=0		PRED CLASS T=0.25		PRED CLASS T=0.5		PRED CLASS T=0.75		PRED CLASS T=1	
1	0.9	1	TP	1	TP	1	TP	1	TP	0	FN
1	0.8	1	TP	1	TP	1	TP	1	TP	0	FN
1	0.4	1	TP	1	TP	0	FN	0	FN	0	FN
1	0.7	1	TP	1	TP	1	TP	0	FN	0	FN
1	0.9	1	TP	1	TP	1	TP	1	TP	0	FN
1	0.2	1	TP	0	FN	0	FN	0	FN	0	FN
0	0.1	1	FP	0	TN	0	TN	0	TN	0	TN
0	0.4	1	FP	1	FP	0	TN	0	TN	0	TN
0	0.3	1	FP	1	FP	0	TN	0	TN	0	TN
0	0.1	1	FP	0	TN	0	TN	0	TN	0	TN
0	0.6	1	FP	1	FP	1	FP	0	TN	0	TN
0	0.8	1	FP	1	FP	1	FP	1	FP	0	TN
		TPR=1 TNR=0 FPR=1		TPR=0.83 TNR=0.33 FPR=0.67		TPR=0.67 TNR=0.67 FPR=0.33		TPR=0.5 TNR=0.83 FPR=0.17		TPR=1 TNR=1 FPR=0	

ROC space



T=0 TPR=1 TNR=0 FPR=1

T=0.25 TPR=0.83 TNR=0.33 FPR=0.67

T=0.5 TPR=0.67 TNR=0.67 FPR=0.33

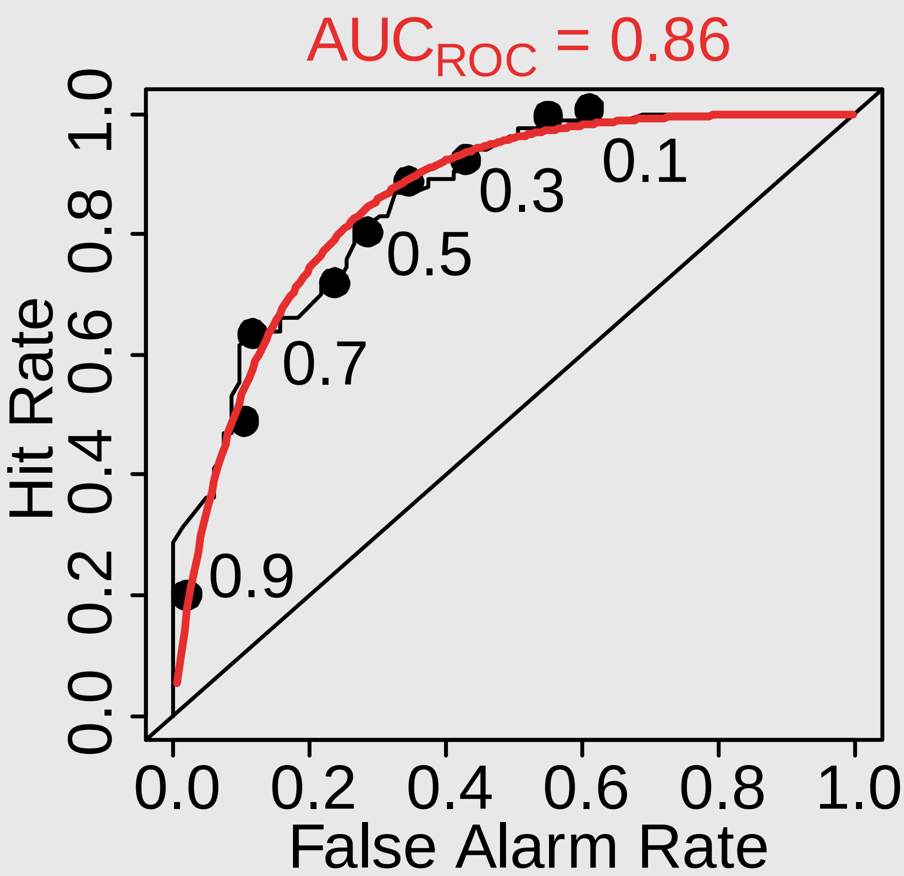
T=0.75 TPR=0.5 TNR=0.83 FPR=0.17

T=1 TPR=1 TNR=1 FPR=0

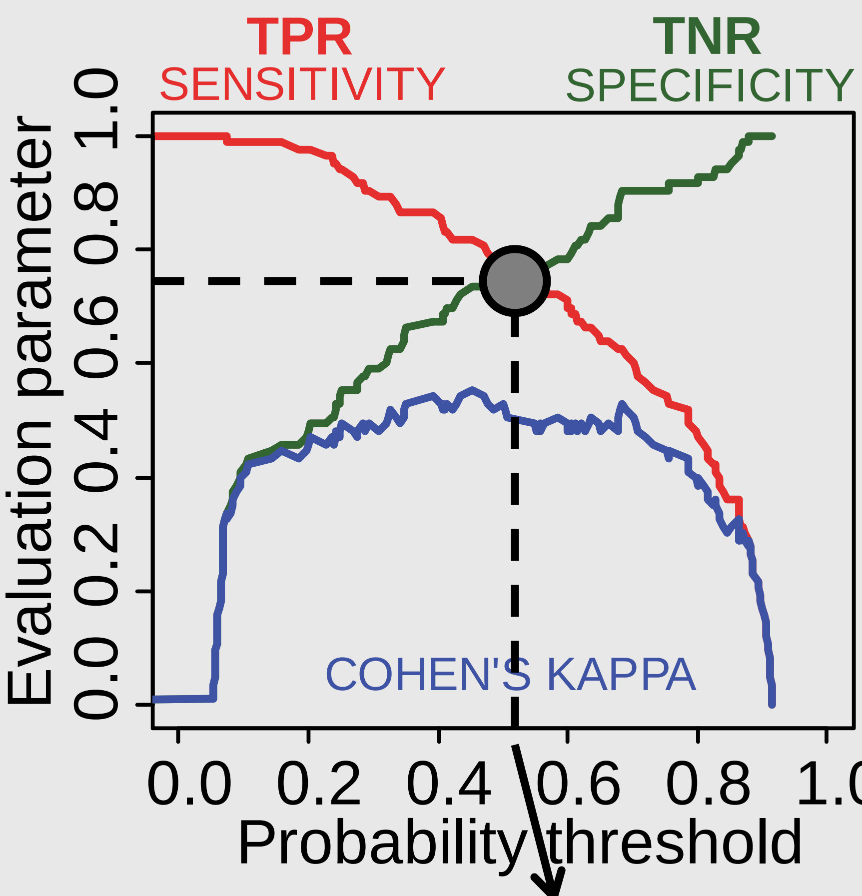
Accessibile @ https://en.wikipedia.org/wiki/Receiver_operating_characteristic

ROC Plot / Evaluation plot

ROC Plot



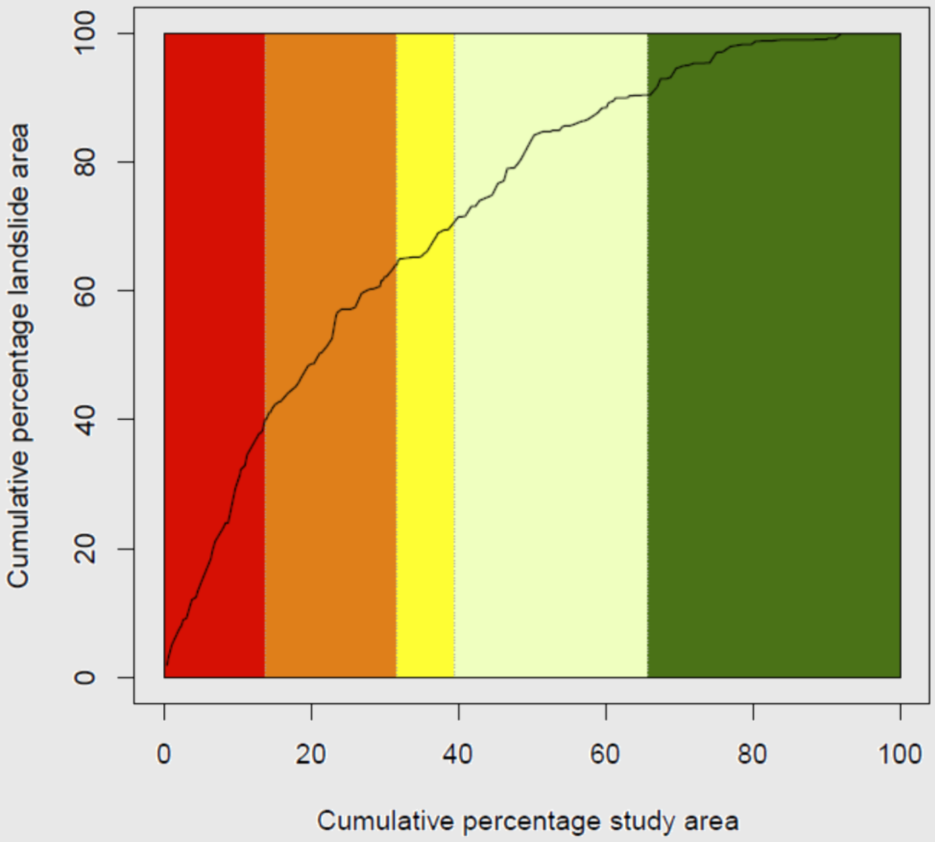
Evaluation Plot



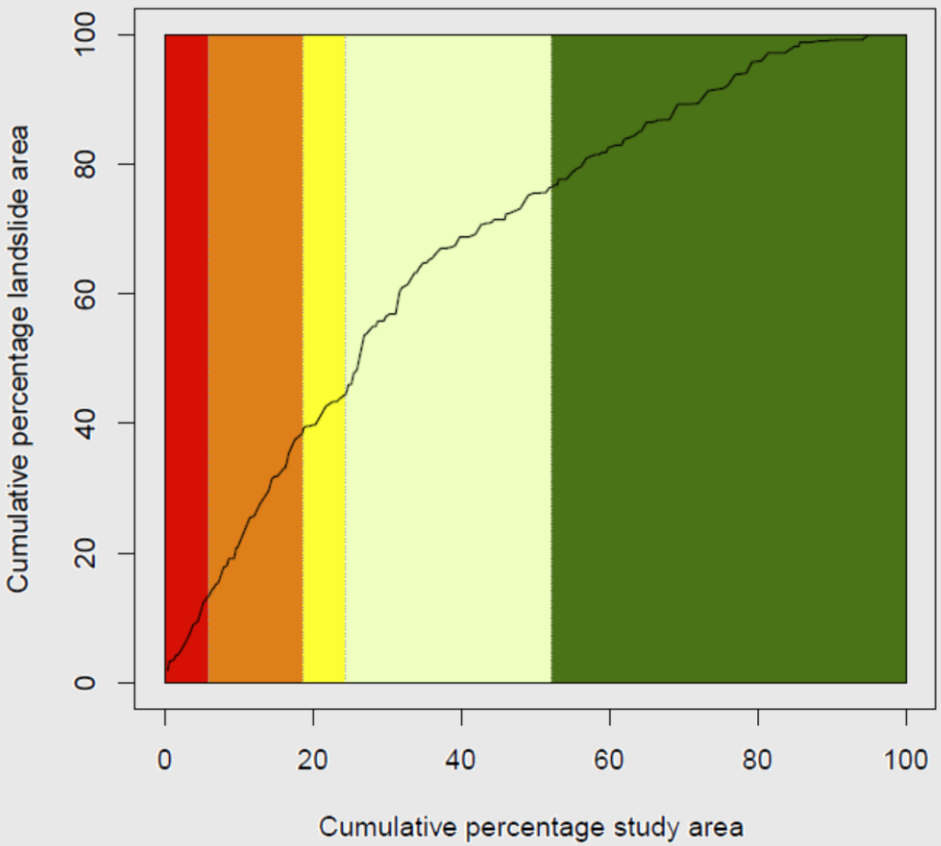
Optimal Binary Classification Threshold

Success/Prediction Rate Curves

Success rate curve

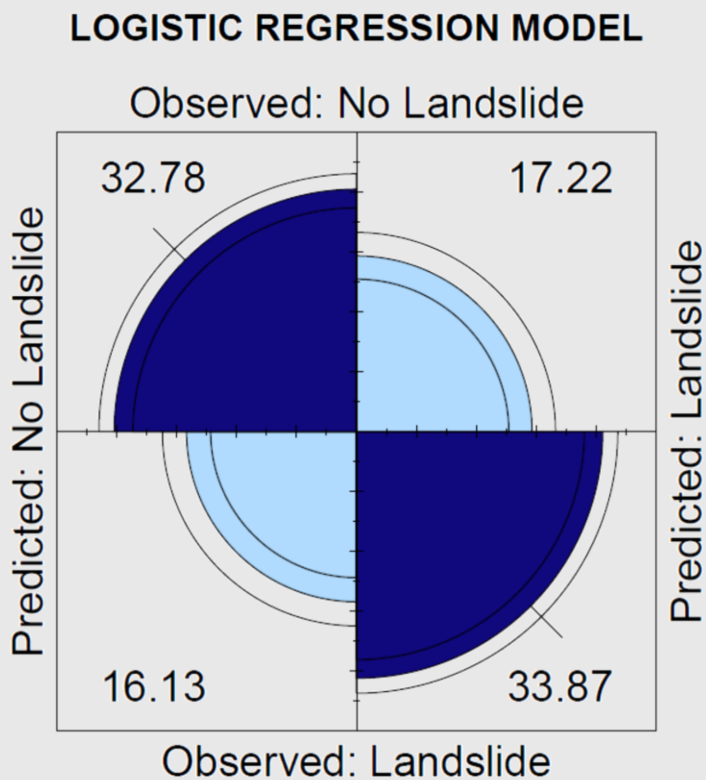


Prediction rate curve

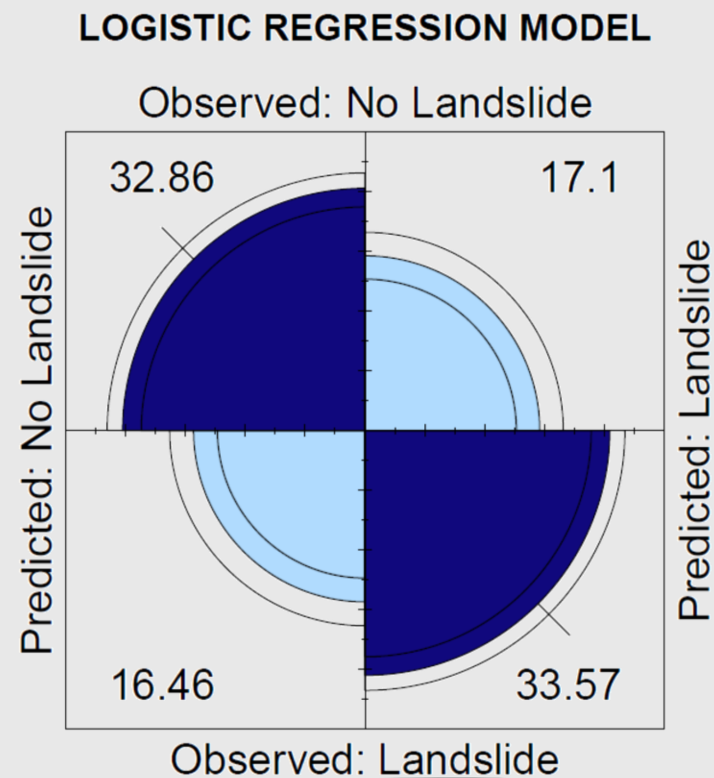


Effect random sampling on training

Sample 1:
50% of **1** (unstable pixels) and
50% of **0** (stable pixels)



Sample 2:
50% of **1** (unstable pixels) and
50% of **0** (stable pixels)



Effect random sampling on training

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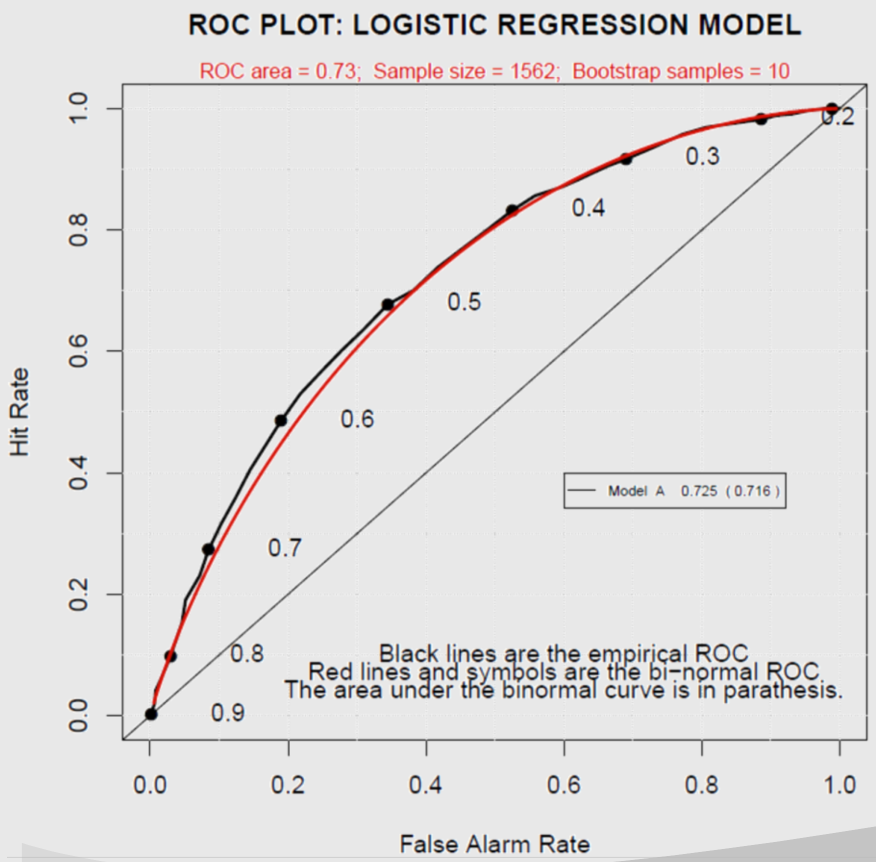
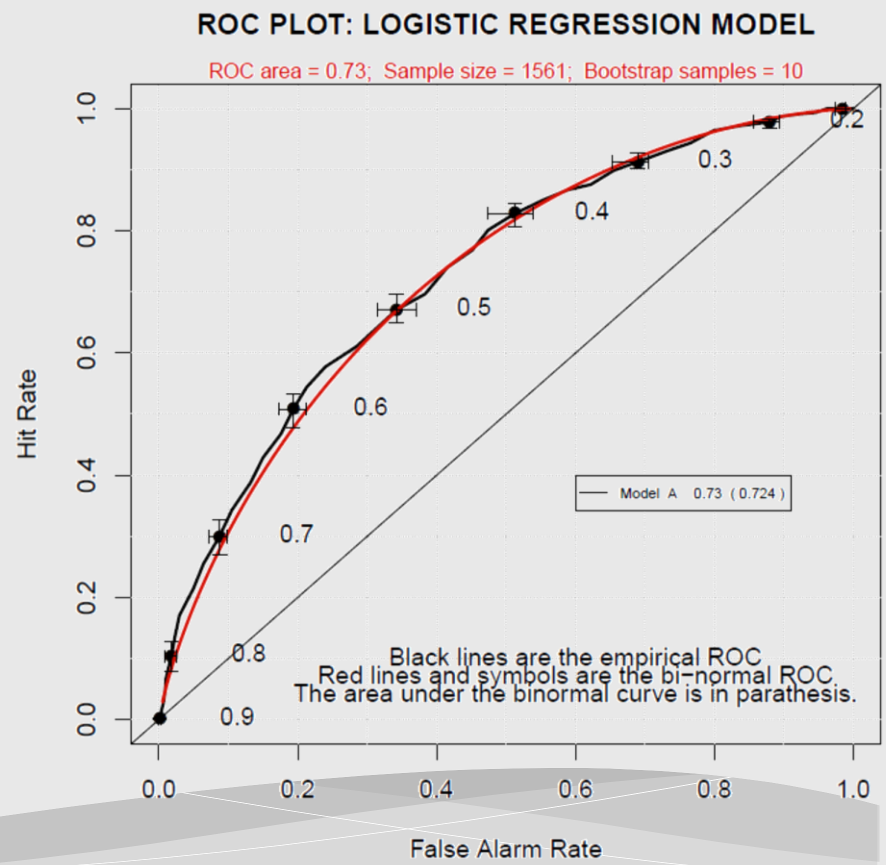


Sample 2:
50% of **1** (unstable pixels) and
50% of **0** (stable pixels)



Effect random sampling on training

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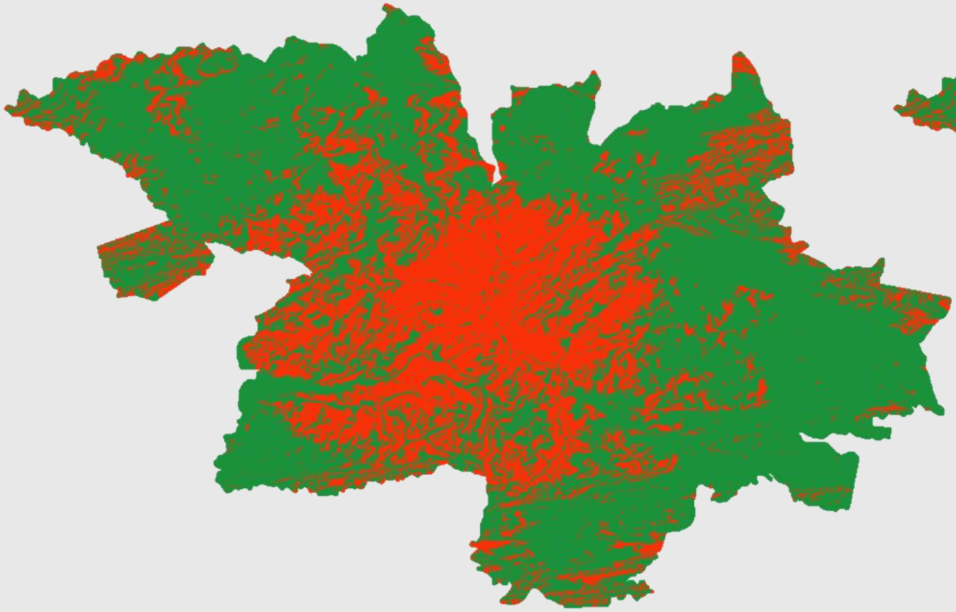
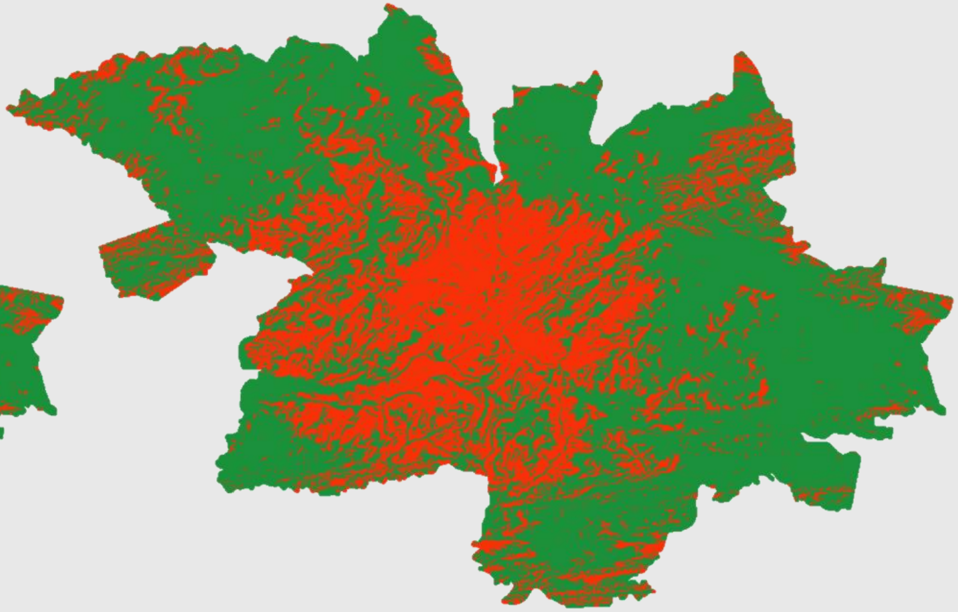
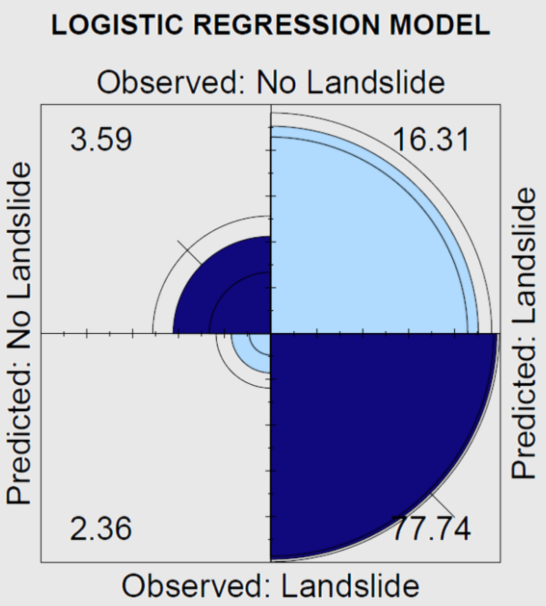


Sample 2:
50% of **1** (unstable pixels) and
50% of **0** (stable pixels)

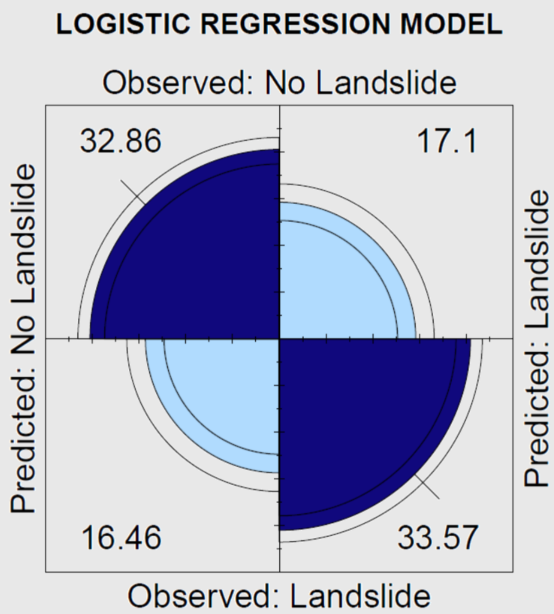


Effect of balancing on training

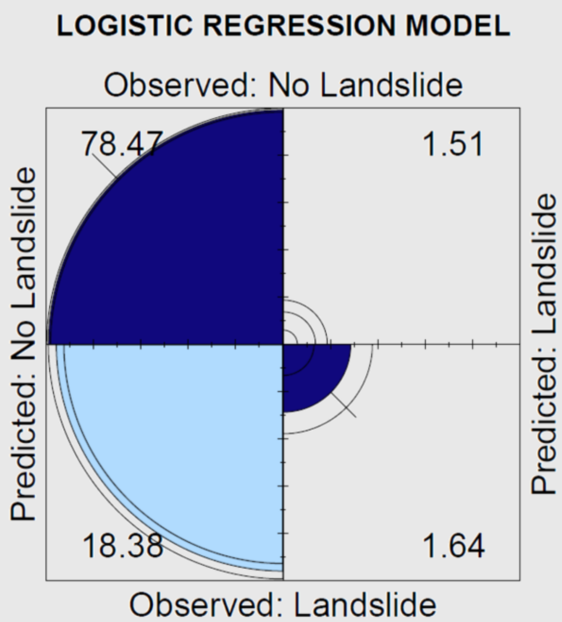
Sample 1:
80% of **1** (unstable pixels)
20% of **0** (stable pixels)



Sample 2:
50% of **1** (unstable pixels)
50% of **0** (stable pixels)



Sample 3:
20% of **1** (unstable pixels)
80% of **0** (stable pixels)

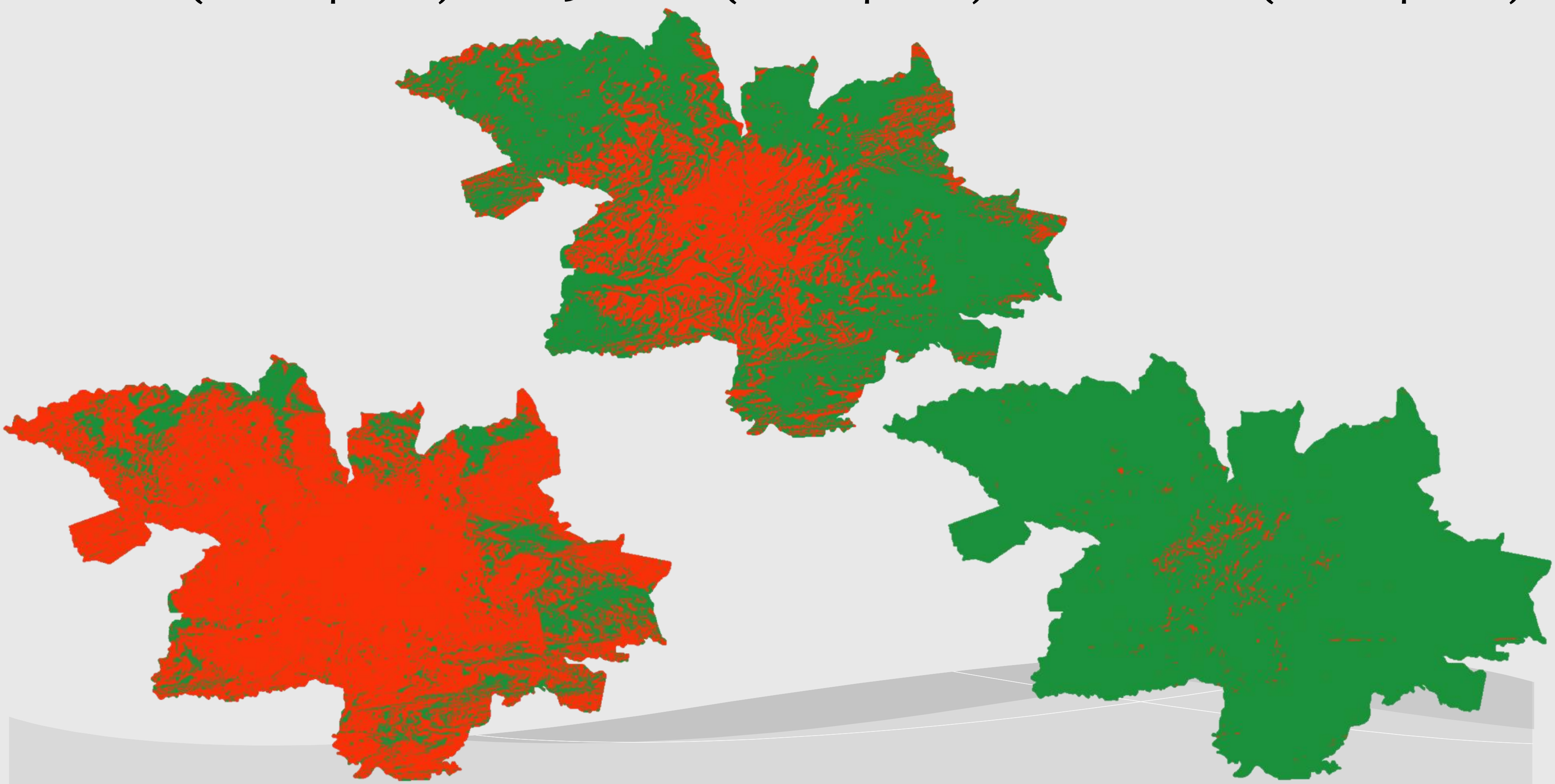


Effect of balancing on training

Sample 1:
80% of **1** (unstable pixels)
20% of **0** (stable pixels)

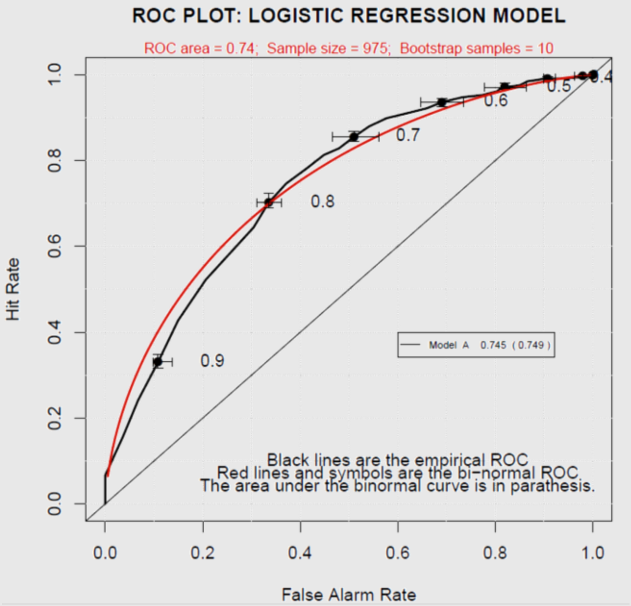
Sample 2:
50% of **1** (unstable pixels)
50% of **0** (stable pixels)

Sample 3:
20% of **1** (unstable pixels)
80% of **0** (stable pixels)

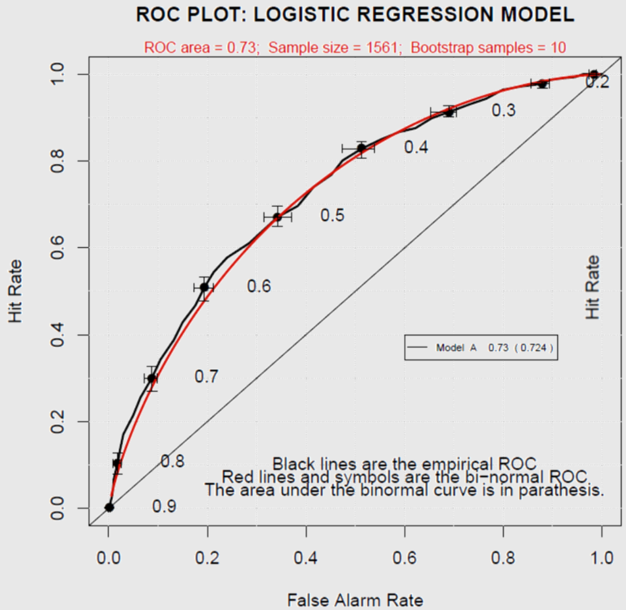


Effect of balancing on training

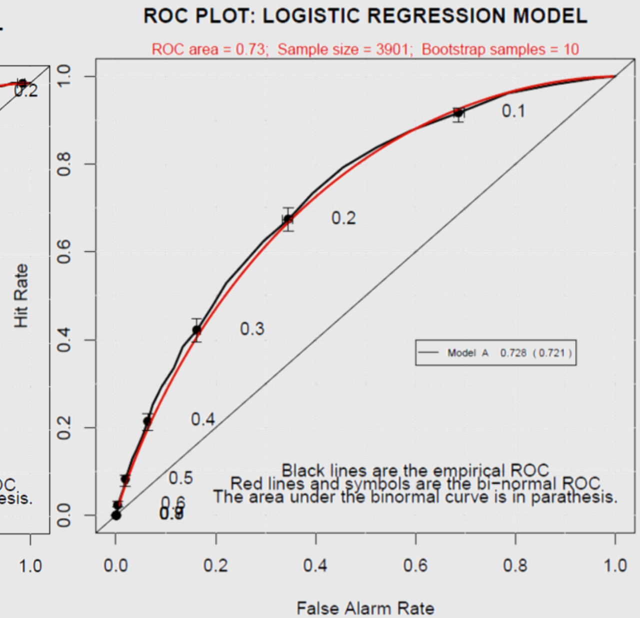
Sample 1:
80% of **1** (unstable pixels)
20% of **0** (stable pixels)



Sample 2:
50% of **1** (unstable pixels)
50% of **0** (stable pixels)

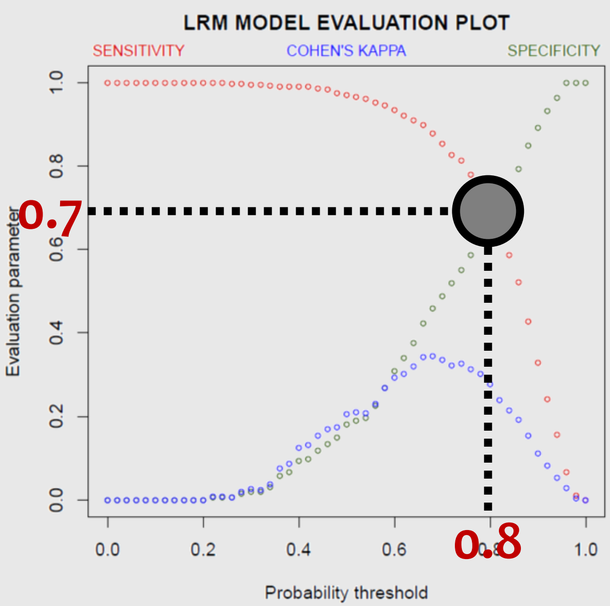


Sample 3:
20% of **1** (unstable pixels)
80% of **0** (stable pixels)

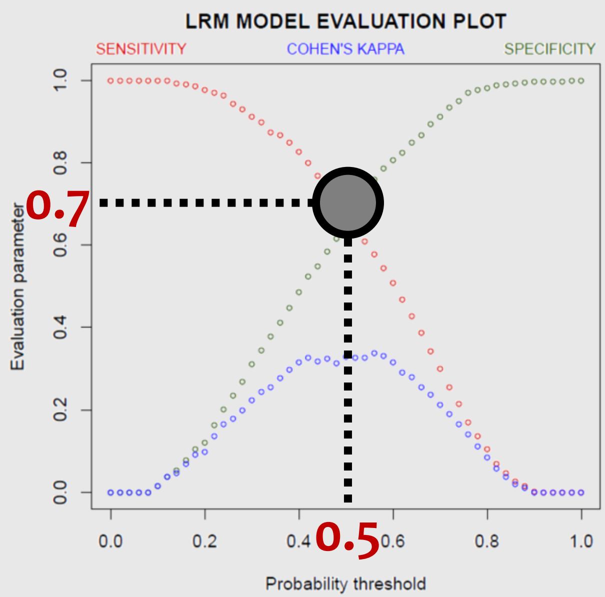


Effect of balancing on training

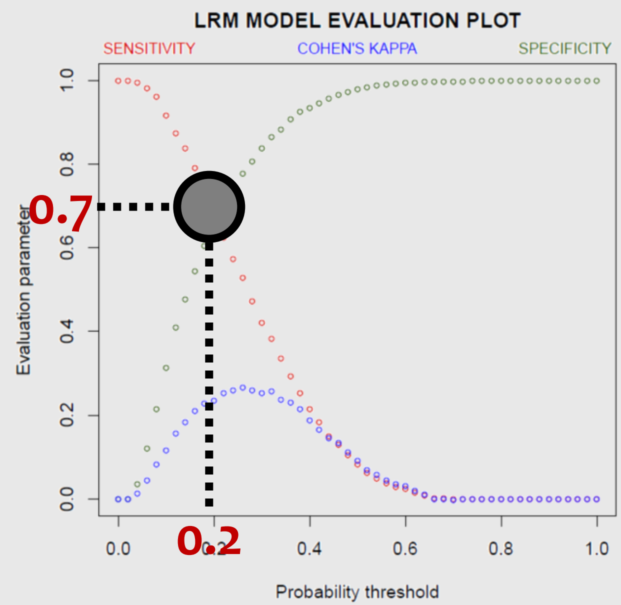
Sample 1:
80% of **1** (unstable pixels)
20% of **0** (stable pixels)



Sample 2:
50% of **1** (unstable pixels)
50% of **0** (stable pixels)



Sample 3:
20% of **1** (unstable pixels)
80% of **0** (stable pixels)



Effect of balancing on training

Sample 1:
80% of **1** (unstable pixels)
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50% of **1** (unstable pixels)
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Sample 3:
20% of **1** (unstable pixels)
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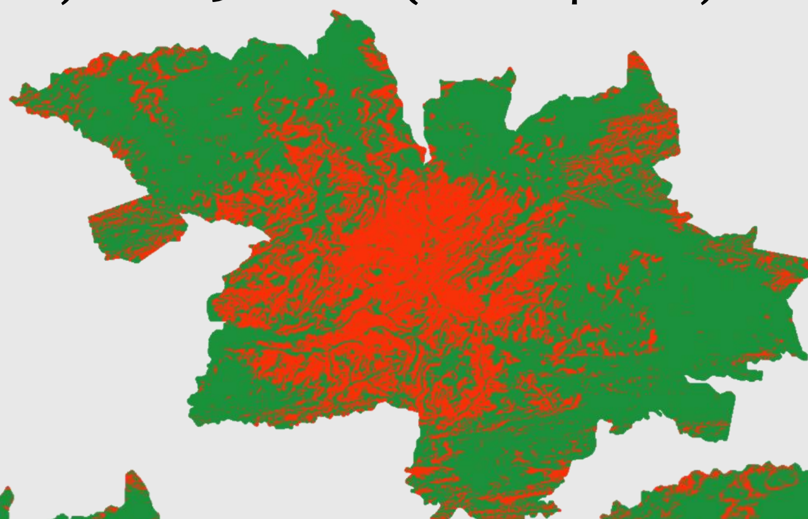
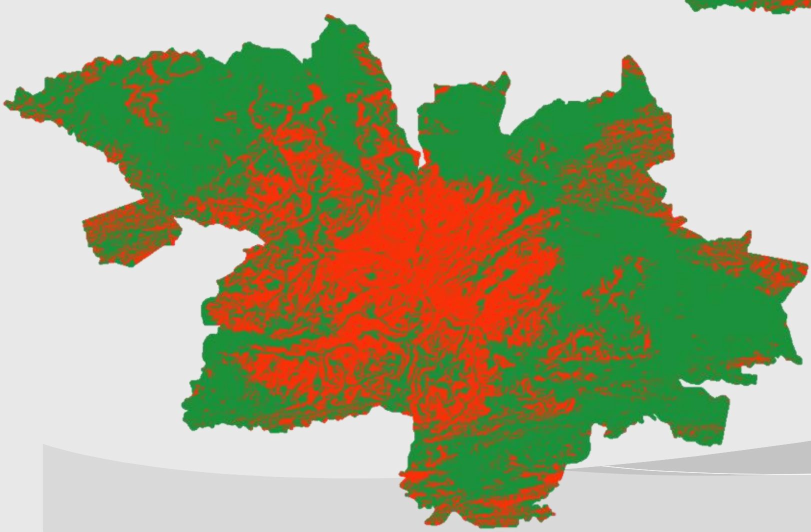




Model Uncertainty Evaluation

V. UNCERTAINTY EVALUATION
(Single and combined susceptibility zonations)

UNCERTAINTY PLOTS

UNCERTAINTY MAPS

Based on bootstrapping resampling procedures

Uncertainty evaluation

The **model** is **able to estimate** the **uncertainty** using a **statistical sampling/resampling techniques**.

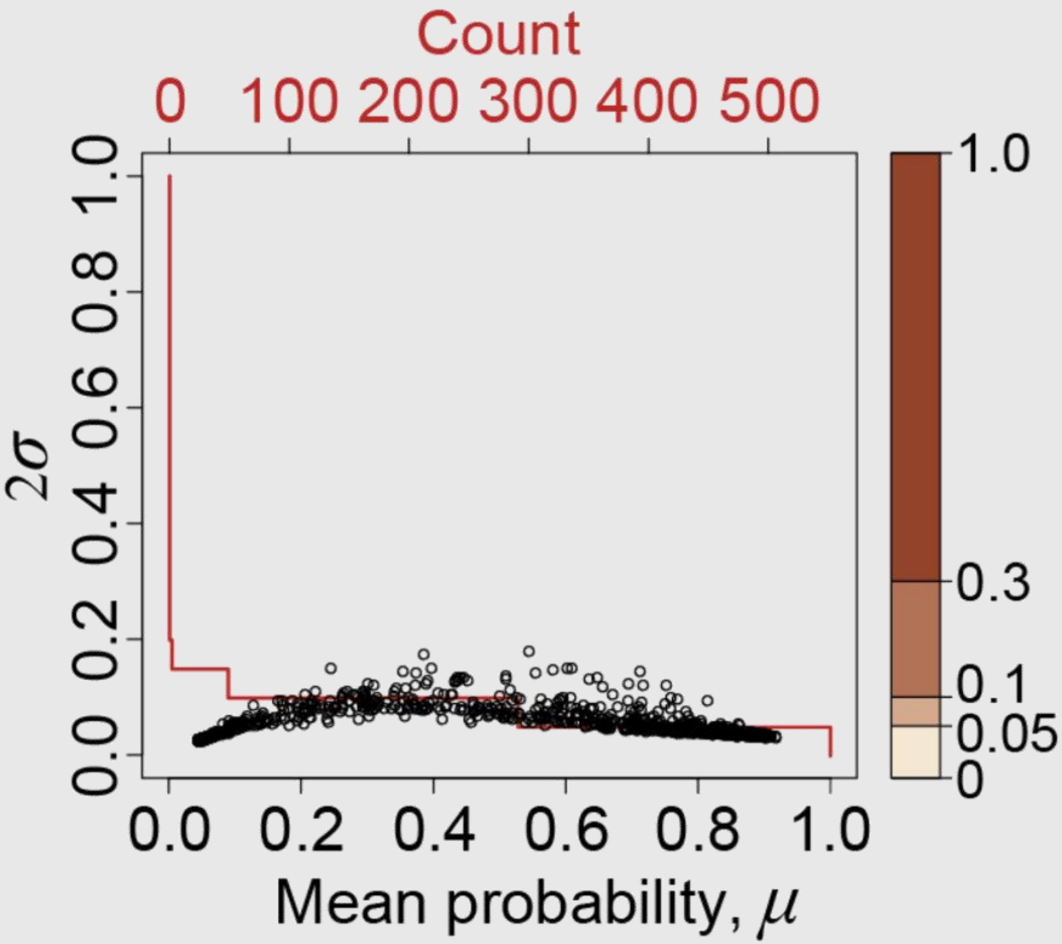
Susceptibility estimation is **performed multiple times**, each time **introducing** a **perturbation on** the **input data.**

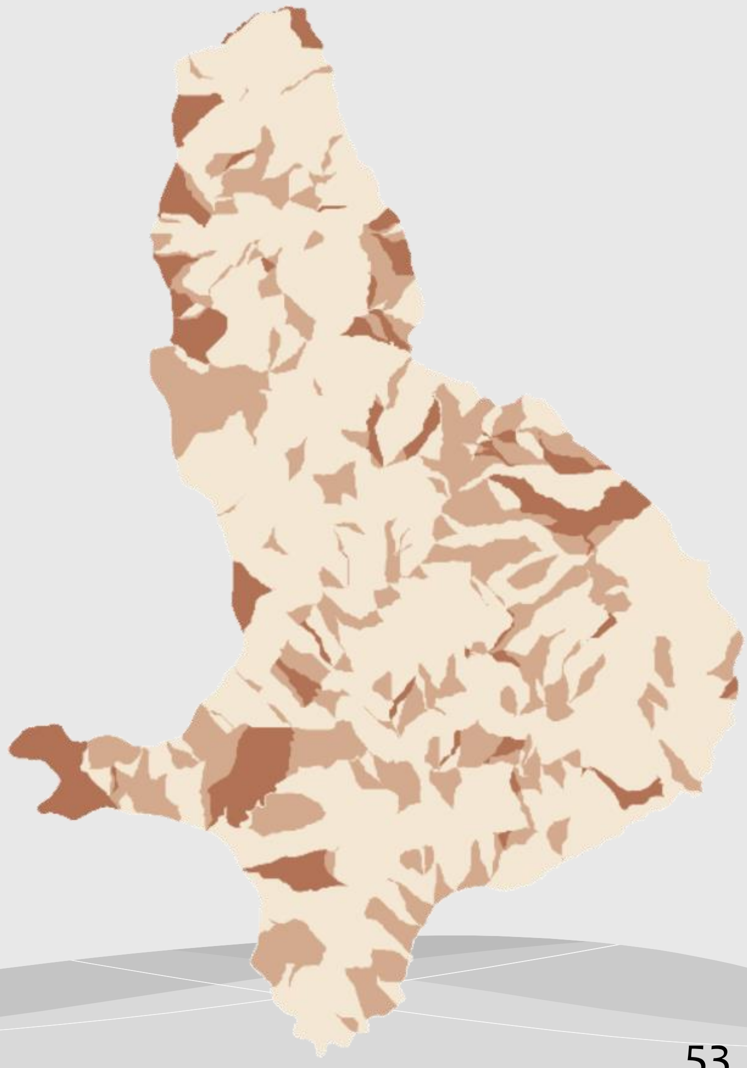
Uncertainty evaluation

Statistics (i.e. **mean** and **standard deviation) on** the final **susceptibility values** are **calculated for each mapping unit.**

A **parabolic uncertainty model fitting** such **susceptibility statistics** is then **used to estimate uncertainty for each mapping unit.**

Uncertainty Plots & maps



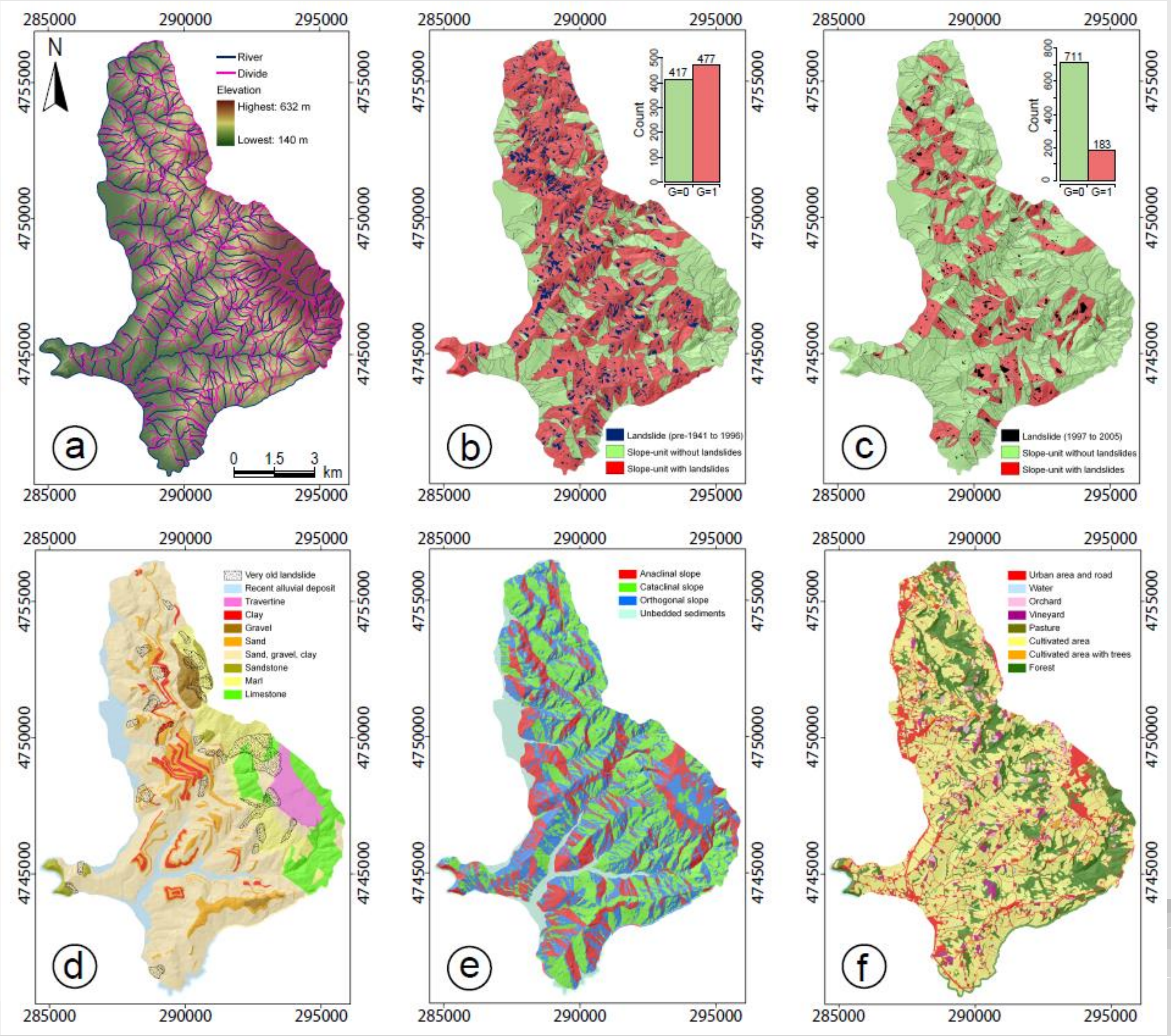


SW Output

The **model outputs** are:

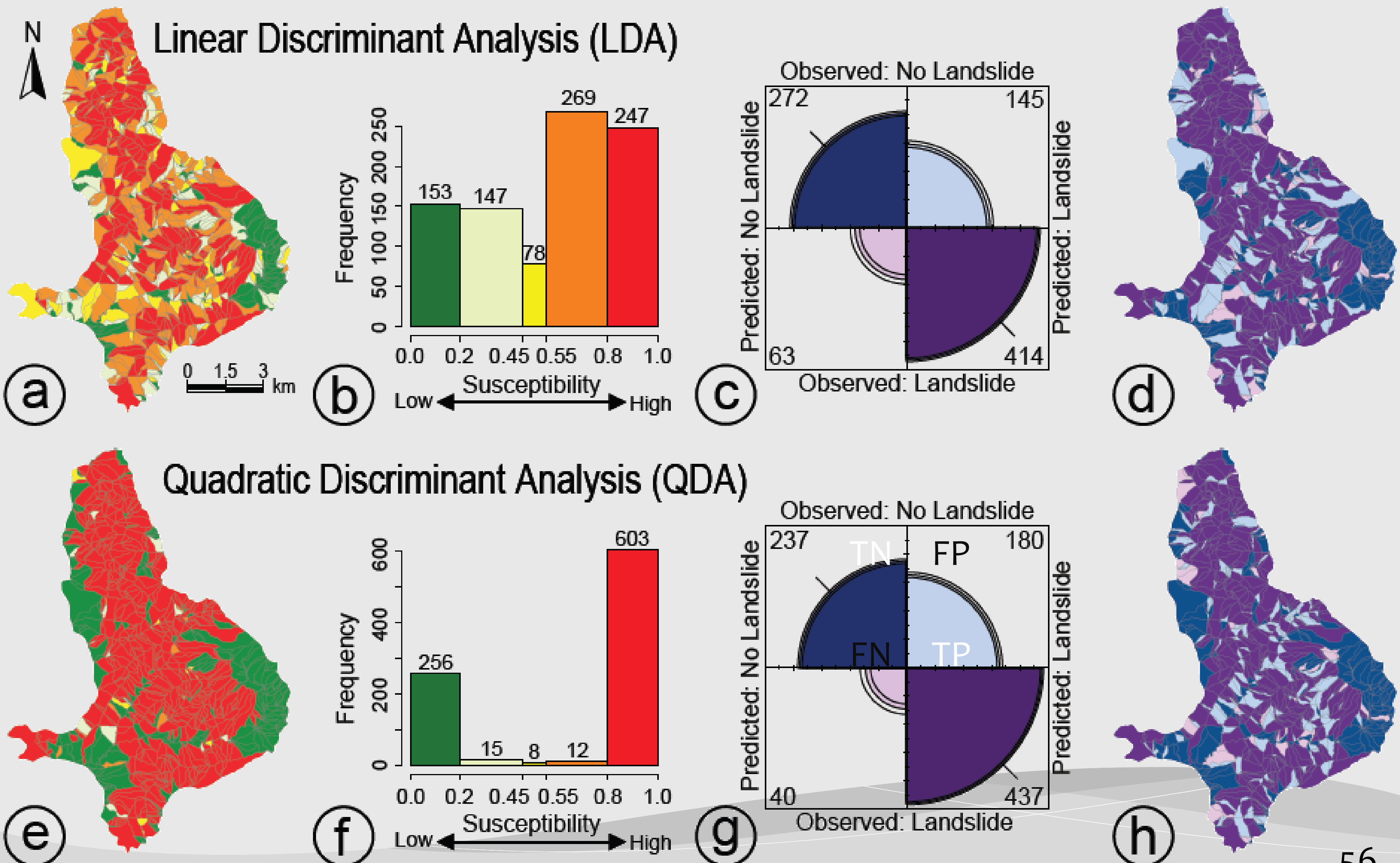
- **textual results** **stored** in **.txt format**
- **plots and graphics** **stored** in **.pdf format**
- **geographical results** **stored** in **geographical formats** such as shapefile or geotiff (.shp or .tif)

SW Input

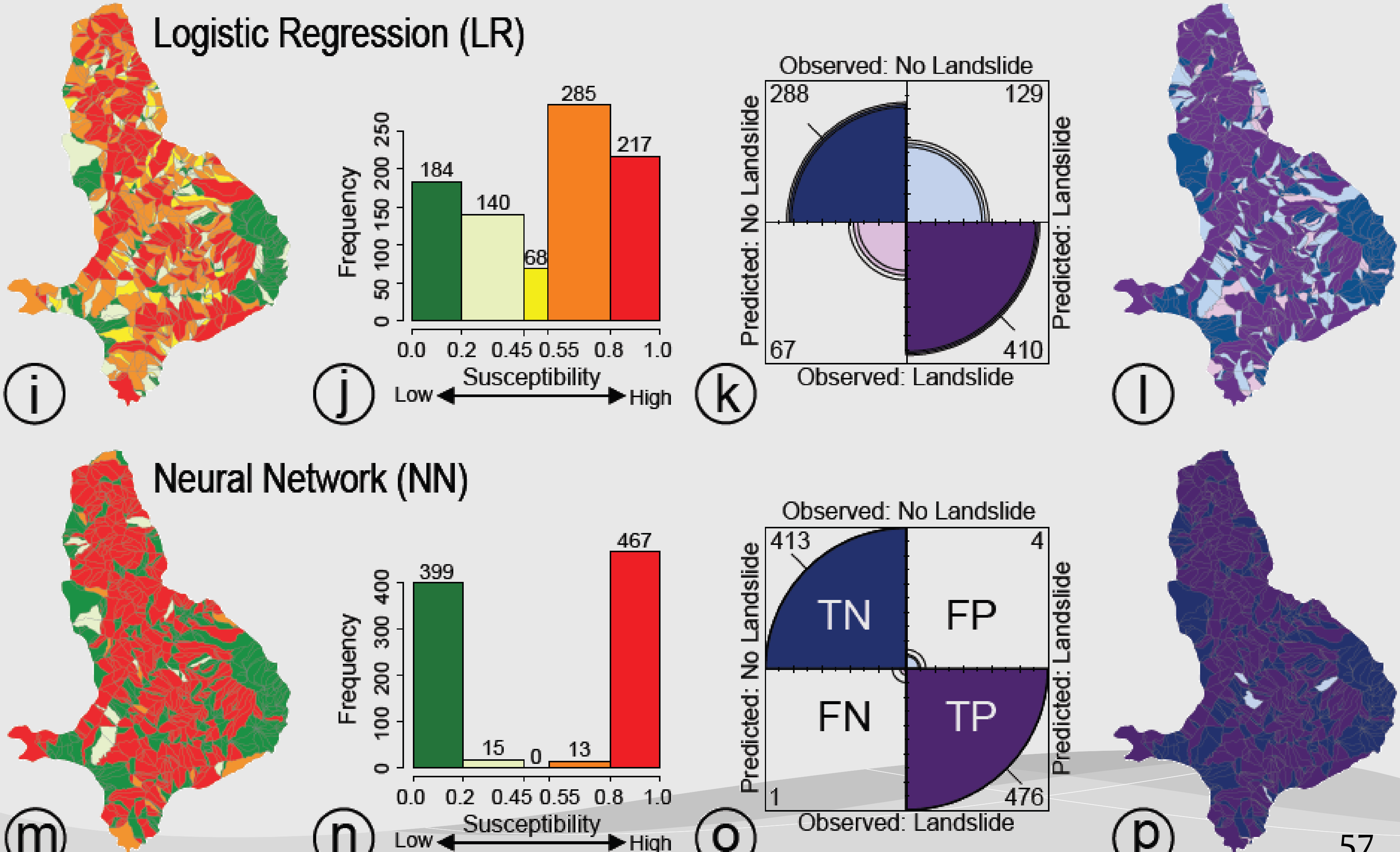


River
Divide
Elevation
Highest: 632 m
Lowest: 140 m
0 1.5 3 km
Count
G=0 G=1
417
477
Landslide (pre-1941 to 1996)
Slope-unit without landslides
Slope-unit with landslides
711
183
Landslide (1997 to 2005)
Slope-unit without landslides
Slope-unit with landslides
Very old landslide
Recent alluvial deposit
Travertine
Clay
Gravel
Sand
Sand, gravel, clay
Sandstone
Marl
Limestone
Anaclinal slope
Cataclinal slope
Orthogonal slope
Unbedded sediments
Urban area and road
Water
Orchard
Vineyard
Pasture
Cultivated area
Cultivated area with trees
Forest
a
b
c
d
e
f
285000
290000
295000
4745000
4750000
4755000

Single Models Training

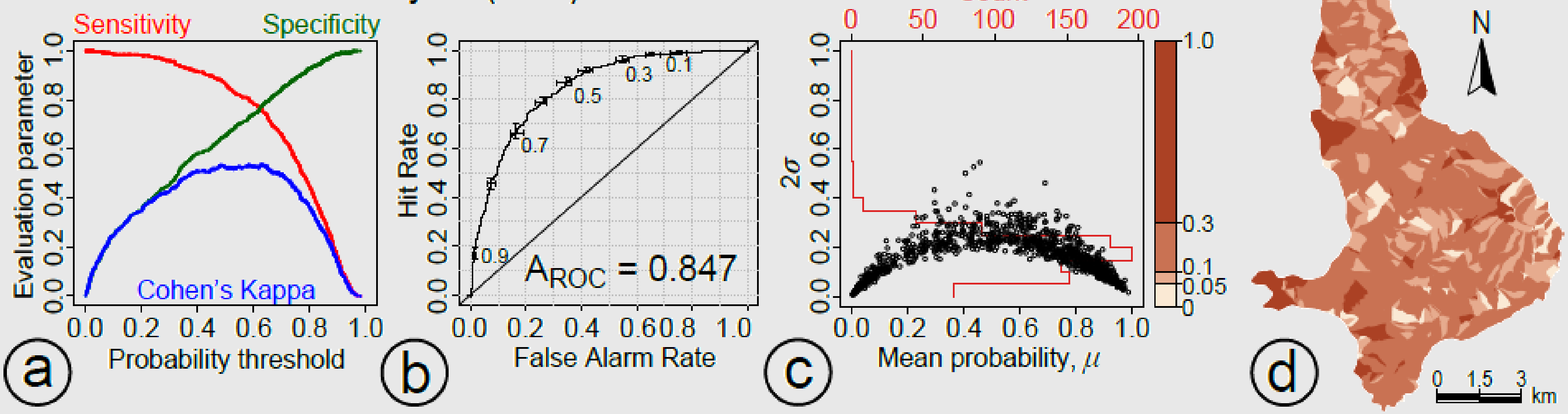


Single Models Training

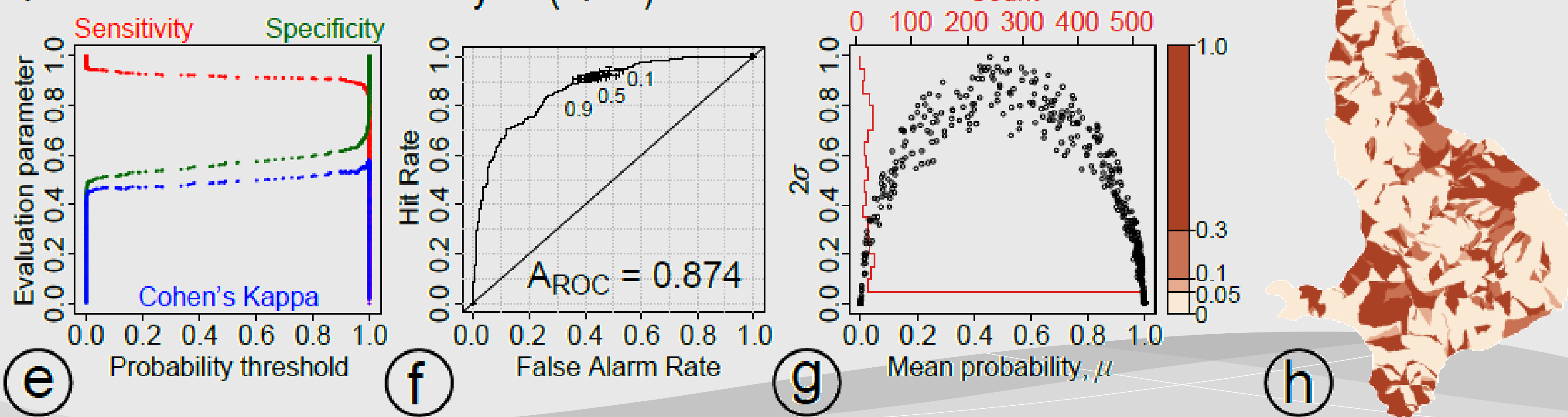


Single Models Training Evaluations

Linear Discriminant Analysis (LDA)



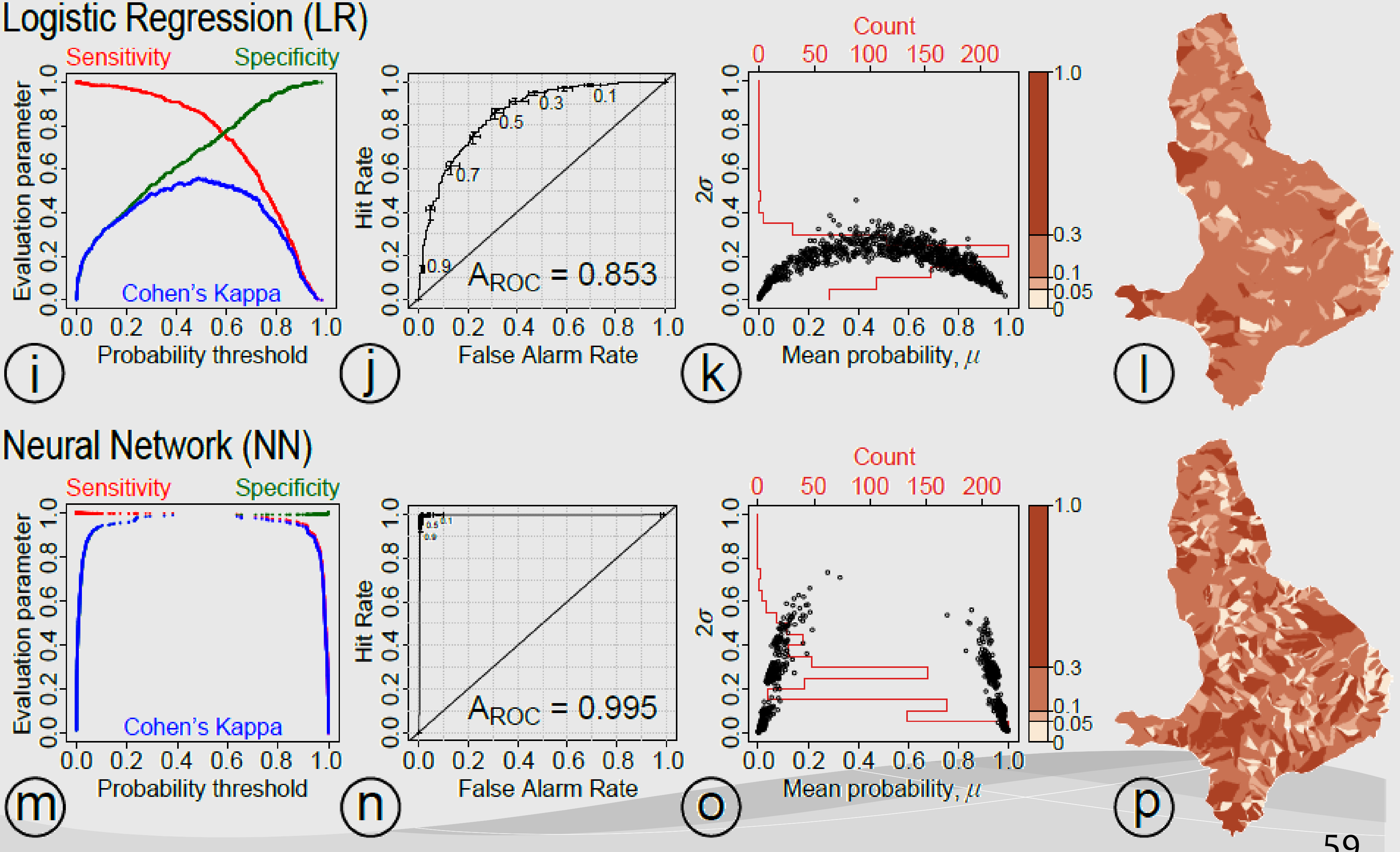
Quadratic Discriminant Analysis (QDA)



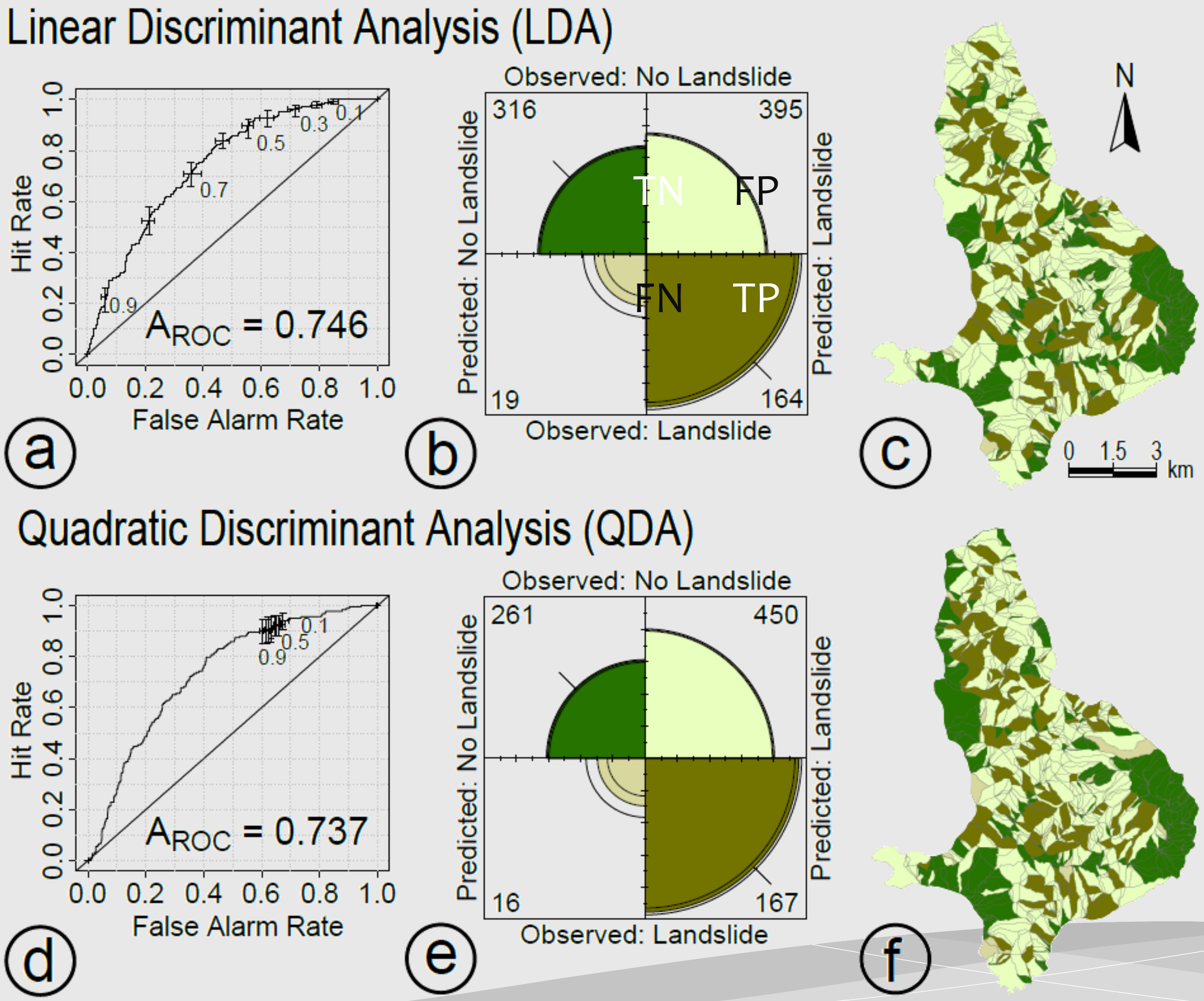
Single Models Training Evaluations

Logistic Regression (LR)

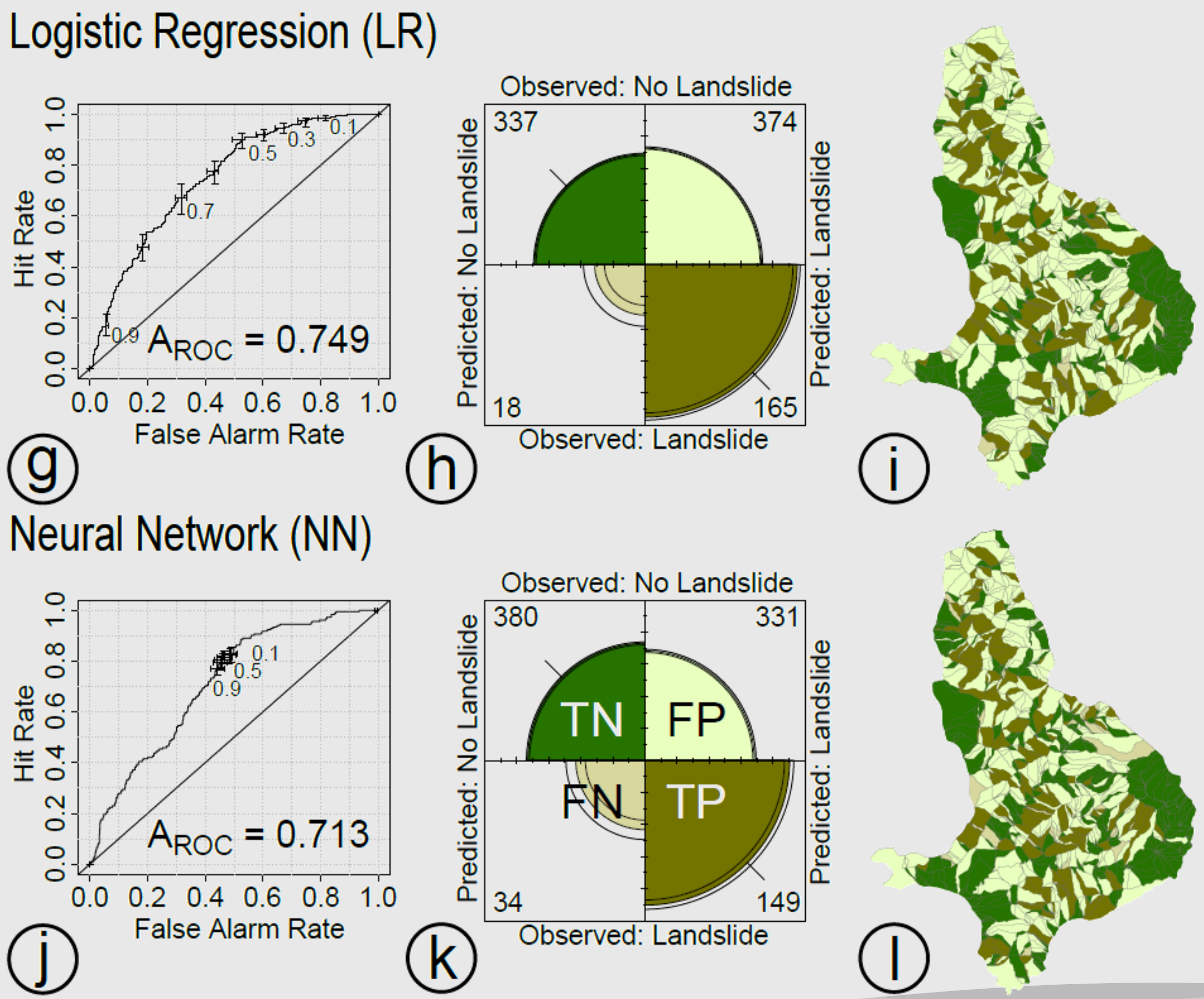
Neural Network (NN)



Single Models Validation

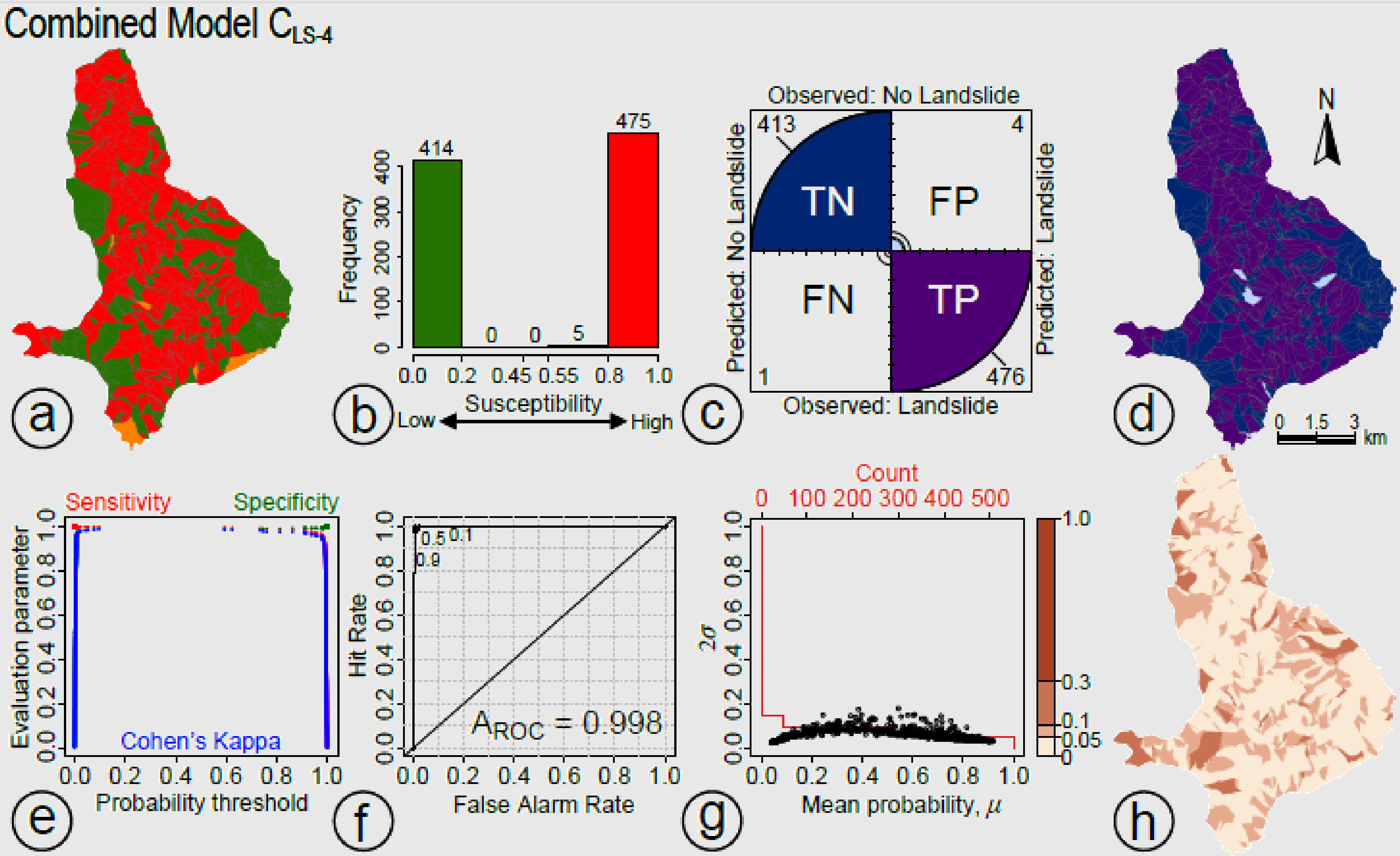


Single Models Validation



Combined Model Results

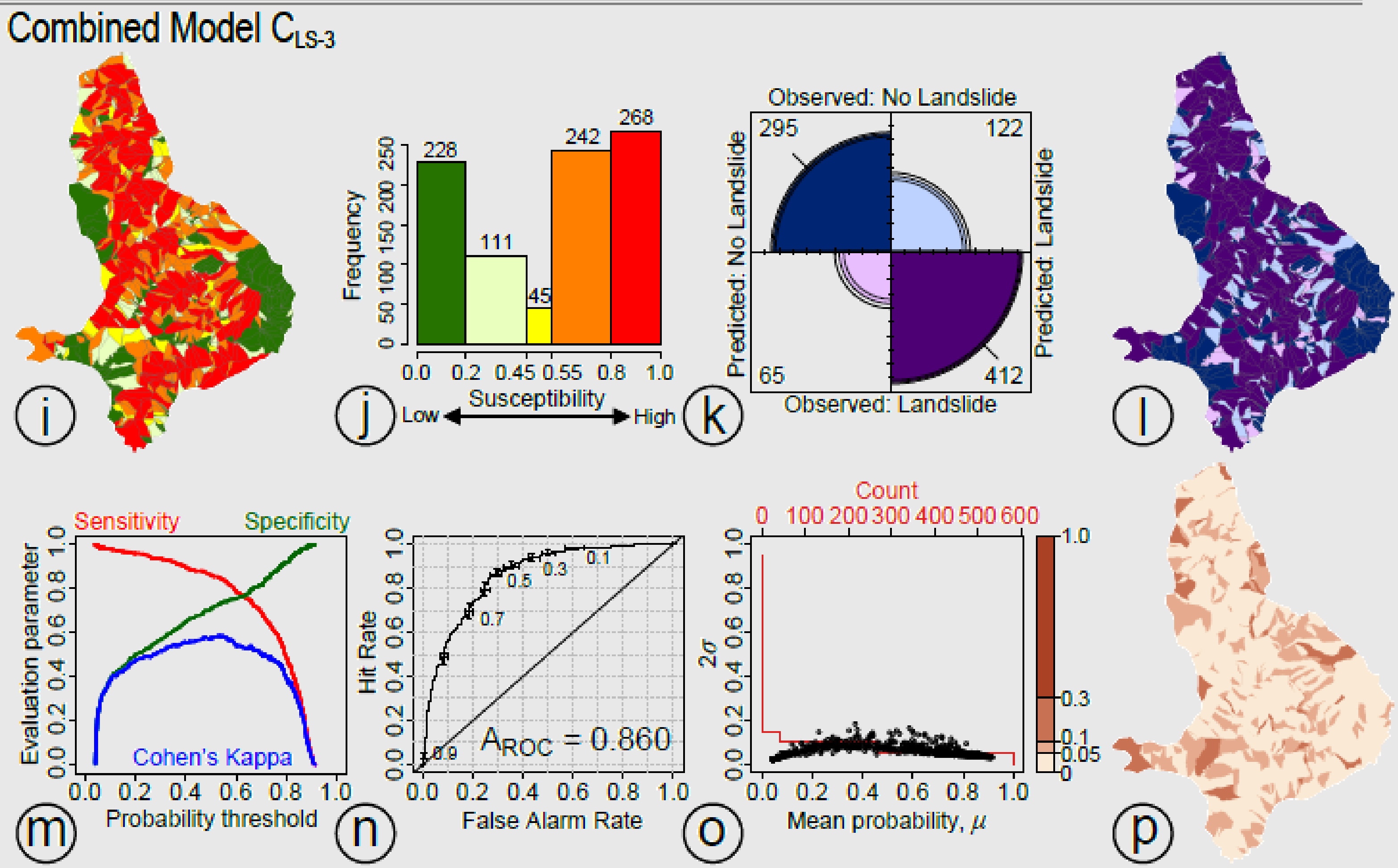
COMBINATION MODEL
LDA, QDA, LR, NN



Higher significance level ⇨ **NNM** model

Combined Model Results

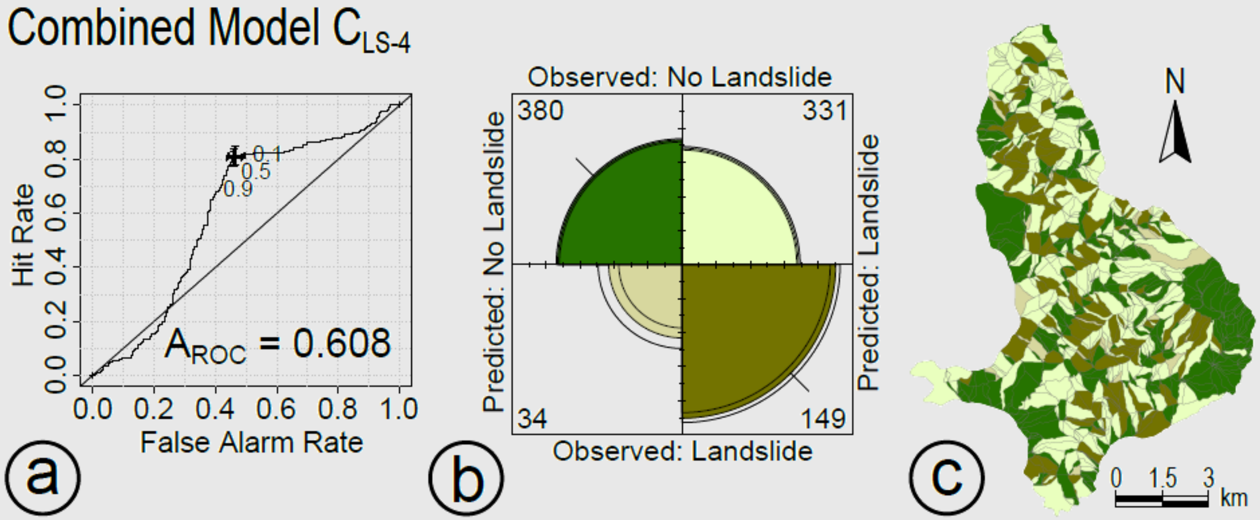
COMBINATION MODEL
LDA, QDA, LR



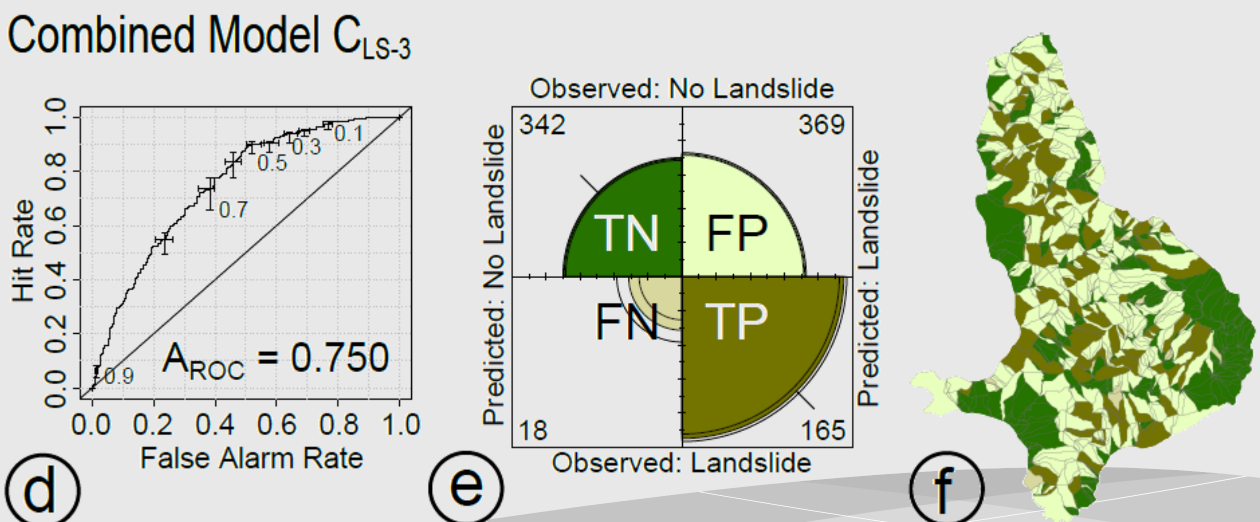
Higher significance level ⇨ **QDA, LRM** model

Combined Model Validation

LOGISTIC REGRESSION
COMBINATION MODEL
LDA, QDA, LR, NN



LOGISTIC REGRESSION
COMBINATION MODEL
LDA, QDA, LR



LAND-SIP

LAND-SIP

LANDslide - **S**usceptibility **I**nput **P**reparation

LAND-SIP

LAND-SIP (**LAND**slide - **S**usceptibility **I**nput **P**reparation) is **designed** for the **preparation** of the **input** for **LAND-SE**.

In the **standard mode, LAND-SE requires two input files** (training.txt and validation.txt) in **tab separated** .txt **format, storing data in a tabular structure.** In the **geographical mode** the **tools provide** directly **geographical outputs, but require two shapefile** (training.shp and validation.shp) **reporting coordinates of** the **mapping unit**.

Input tabular format

The two **.txt files** are organized in **columns with** the **following information**:

- the **1st column** contains the **univocal code** of the **mapping unit** identification;
- the **2nd column** contains the **value** of the **grouping variable**, which is the absence/presence (respectively 0 and 1) of landslides in the mapping unit;
- the **3rd to the *n*-th columns** contain **values of** the ***n*** **explanatory variables** (i.e. independent variables).

Txt input example

ID

Dependent Variable (grouping)

Independent variables (thematic information)

SU_ID	FRAX	SUOLO1	SUOLO2	SUOLO3	SUOLO4	SUOLO5	DEM_AVG	DEM_STD	SLP_MEAN	SLP_STD
6	1	53.82	35.94	6.29	3.96	0	316.62	44.54	28.43	11.31
7	1	27.31	28.3	41.68	2.72	0	250.78	17.58	28.08	11.05
10	1	40.46	32.96	23.22	3.36	0	249.62	24.71	29.78	12.25
41	0	54.54	33.5	7.95	4.02	0	188.26	51.04	23.43	11.33
44	1	16.45	47.24	24.45	11.85	0	189.18	24.47	36.95	12.48
45	1	9.45	58.19	17.51	4.12	9.85	254.83	49.18	34.3	11.89
61	1	18.35	65.35	13.2	2.1	0	237.16	39.34	35.17	11.12
62	1	56.61	29.64	5.55	8.2	0	186.18	12.33	36.78	11.98
63	1	34.77	33.12	17.02	12.04	3.05	146.41	30.28	25.36	14.09
85	0	64.56	22.73	7.61	5.11	0	173.7	34.13	31.25	12.37
86	0	72.7	23.58	0.73	3	0	175.13	21.41	29.29	11.51
92	0	12.37	72.67	7.01	7.95	0	207.11	23.23	35.31	9.22
100	0	29.38	33.78	33.94	2.9	0	262.76	31.42	27.09	10.74

shp input example

Information for success/prediction rate curve estimations

Only for polygon-like mapping unit

SU_ID	LANDSLIDE_AREA	MAPPING_UNIT_AREA
6	53	1200
7	27	3000
10	40	2200
41	0	3000
44	16	1300
45	9	5000
61	18	400
62	56	2000
63	34	1400
85	0	2000
86	0	10000
92	0	12300
100	0	10000

Dataset partition

LAND-SIP is able to perform **different training** and **validation dataset partition**:

- **balanced** (i.e. same number of mapping units with grouping value equal to 0 and 1) **or unbalanced** (i.e. different number) datasets partition through random sampling;
- **reduced** datasets partition (i.e. size of the original dataset is reduced) useful in case of large datasets;
- **spatial** dataset partition (training and validation datasets area in different stud areas).

Input format & Functionalities

LAND-SIP is **able to work** with **raster** (.asc or GRASS raster layers) and **polygons** (GRASS vector layers).

LAND-SIP is **able to use** a **mask to extract data.**

Data provided as **.asc files in a folder**, or **as layers** in a **GRASS location** **are read**, **elaborated** and properly **formatted and stored** **in** a **.Rdata file ready** for **LAND-SVA** and **LAND-SE**.

LAND-SIP is **able to execute in cascading** **LAND-SVA** and **LAND-SE**.

LAND-SVA

LAND-SVA

LANDslide - **S**usceptibility **V**ariable **A**nalysis

LAND-SVA

LAND-SVA (**LAND**slide - **S**usceptibility **V**ariable **A**nalysis) is **designed for** the **explorative analysis** of the **LAND-SE training** and **validation input datasets.**

LAND-SVA helps in selecting the **optimal explanatory variable set to be used in the analysis.**

LAND-SVA functionalities

LAND-SVA performs:

- **conditional density analysis** of the input variables;
- **pair-wised correlation analysis** of the input variables;
- **multi-collinearity test** of the input variables.

LAND-SVA is able to exclude correlated variables from the **LAND-SE training** and **validation** input **datasets.**

LAND-SUITE applications

The **software was applied**:

- at **different scale** and with **different** data **resolution** in test sites in Italy and elsewhere
- using **different mapping units** types (pixel, slope units, administrative units)
- to perform **different validation tests** (temporal, spatial, cross validation)
- to predict **different type** of processes (landslides, floods, forest fires, rock falls source areas, …)

LAND-SE Description/Dowload

Geosci. Model Dev., 9, 3533-3543, 2016
https://doi.org/10.5194/gmd-9-3533-2016

Volume 9, issue 10

Article | Assets | Peer review | Metrics | Related articles

Model description paper

04 Oct 2016

LAND-SE: a software for statistically based landslide susceptibility zonation, version 1.0

Mauro Rossi and Paola Reichenbach
CNR IRPI, via Madonna Alta 126, 06128 Perugia, Italy

Received: 15 Mar 2016 – Discussion started: 29 Apr 2016 – Revised: 10 Aug 2016 – Accepted: 02 Sep 2016 – Published: 04 Oct 2016

https://www.geosci-model-dev.net/9/3533/2016/

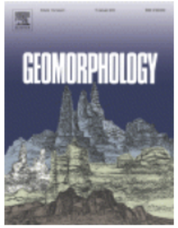
https://www.geosci-model-dev.net/9/3533/2016/gmd-9-3533-2016-supplement.zip

Optimal susceptibilty zonation

ELSEVIER

Geomorphology

Volume 114, Issue 3, 15 January 2010, Pages 129-142



Optimal landslide susceptibility zonation based on multiple forecasts

Mauro Rossi, Fausto Guzzetti, Paola Reichenbach, Alessandro Cesare Mondini, Silvia Peruccacci

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https://doi.org/10.1016/j.geomorph.2009.06.020

https://www.sciencedirect.com/science/article/pii/S0169555X0900258X

Review statistical susceptibilty models

ELSEVIER

Earth-Science Reviews
Volume 180, May 2018, Pages 60-91

A review of statistically-based landslide susceptibility models

Paola Reichenbach [a], Mauro Rossi [a], Bruce D. Malamud [b], Monika Mihir [b, c], Fausto Guzzetti [a]

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https://doi.org/10.1016/j.earscirev.2018.03.001

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https://www.sciencedirect.com/science/article/pii/S0012825217305652

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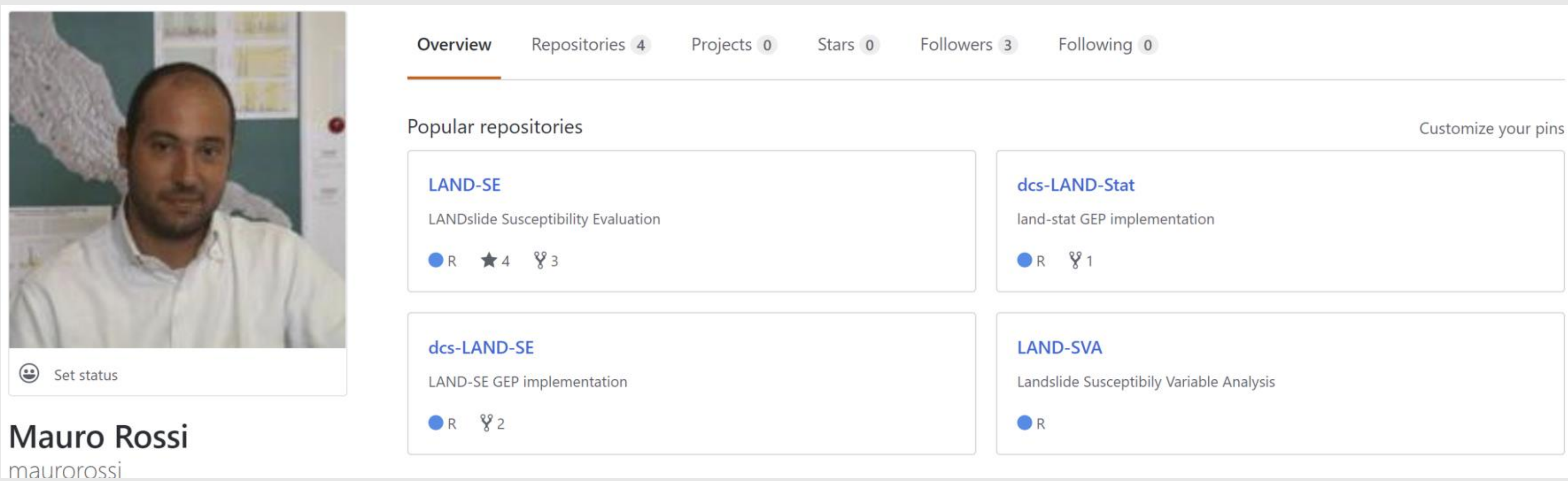
LAMPRE

LAndslide Modelling and tools for vulnerability assessment Preparedness and REcovery management

http://www.lampre-project.eu/index.php?option=com_phocadownload&view=category&id=7:wp6-preparedeness-prevention-recovery-reconstruction&Itemid=203

Other links …

GitHub



https://github.com/maurorossi

Other links …

mauro.rossi@irpi.cnr.it

Index

- Introduction to LAND-SUITE
- **Hands on using a basic example**