Leveraging Deep Learning and Natural Language Processing for hydrogeological insights from borehole logs

Previati et al. (2025) – Read the publication here: https://doi.org/10.1016/j.ejrh.2024.102157

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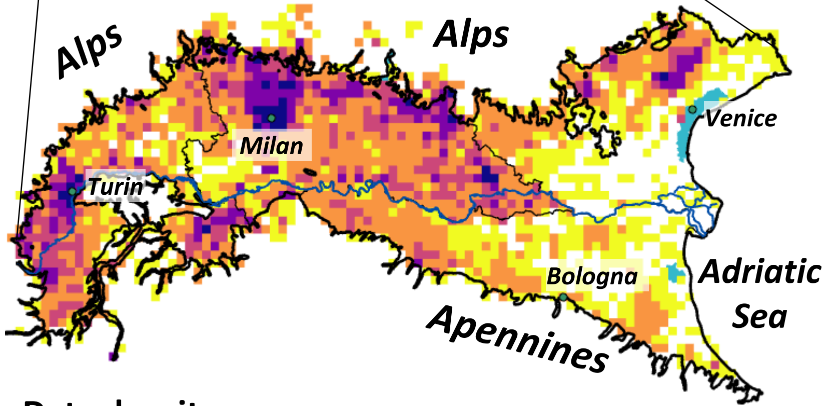
Study area

Po River Alluvial Plain

45’700 km^2



Data density (bh/km^2)

- ☐ No Data
- 🟨 < 0.2
- 🟧 < 1.0
- 🟥 < 2.0
- 🟪 < 5.0
- 🟦 < 20

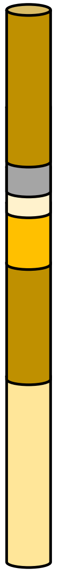
LSTM Classification Net

86,611 lithological descriptions

(70% training - 30% validation)

→ **39,265 boreholes**
387,297 descriptive intervals

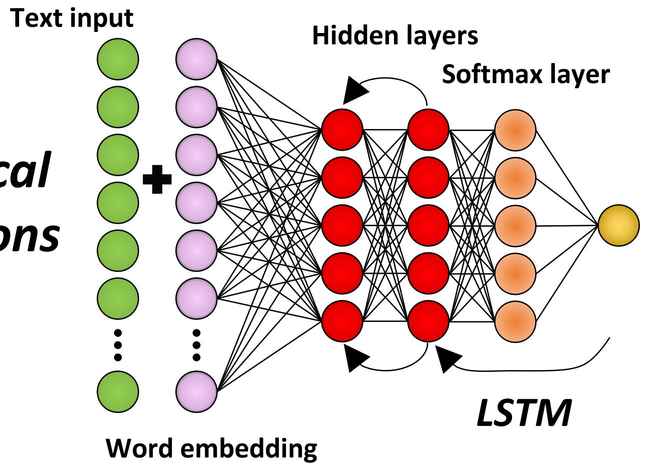
Borehole logs

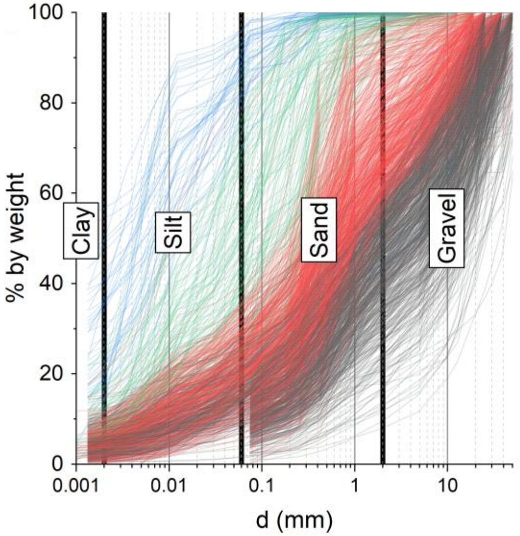


Lithological descriptions

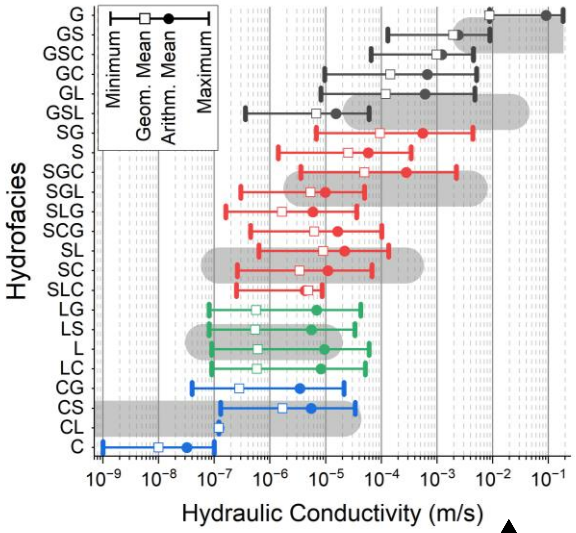
Grain size analysis

Deep learning classification





Classification



Parametrization

Empirical equations from grain size distributions

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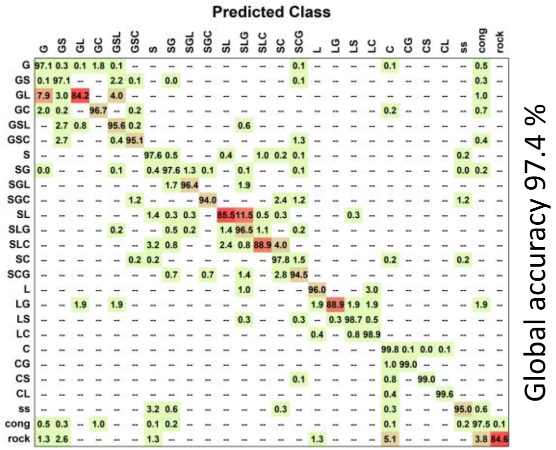
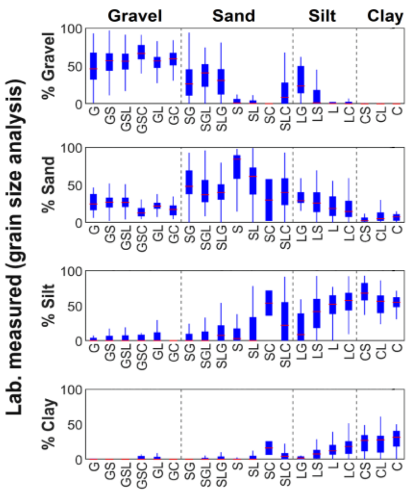
Confusion matrix



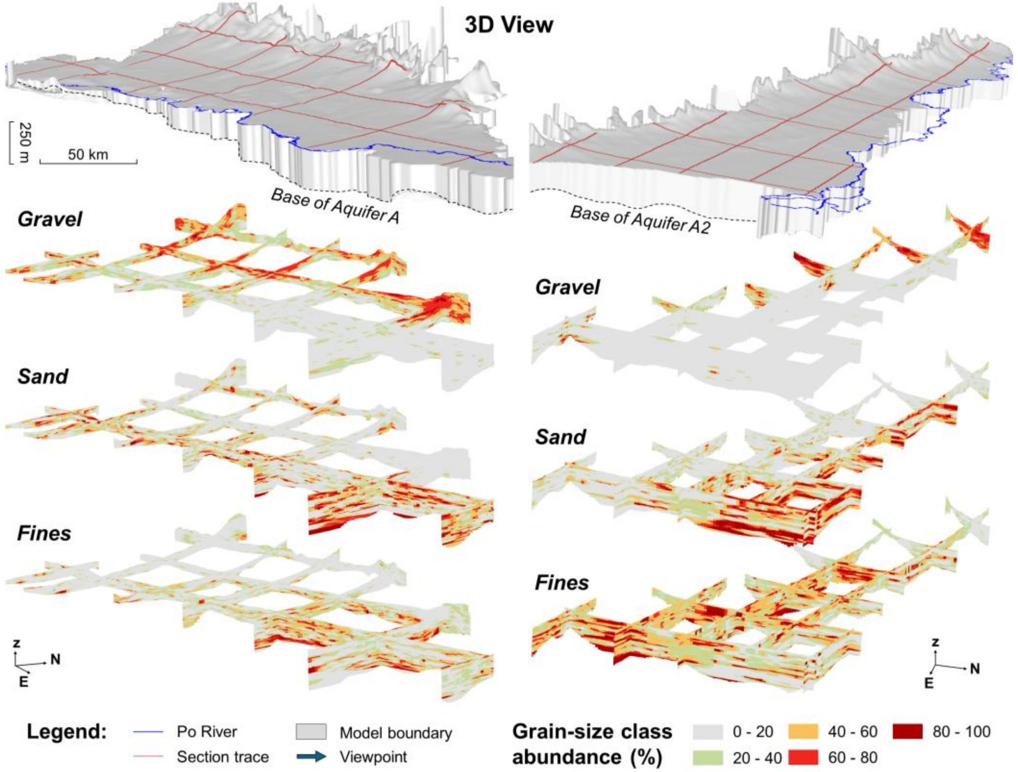
	G	GS	GL	GC	GSL	GSC	S	SG	SGL	SGC	SL	SLG	SLC	SC	SCG	L	LG	LS	LC	C	CG	CS	CL	ss	cong	rock
G	97.1	0.3	0.1	1.8	0.1	--	--	--	--	--	--	--	--	--	0.1	--	--	--	--	0.1	--	--	--	--	0.5	--
GS	0.1	97.1	--	--	2.2	0.1	--	0.0	--	--	--	--	--	--	0.1	--	--	--	--	--	--	--	--	--	0.3	--
GL	7.9	3.0	84.2	--	4.0	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	1.0	--
GC	2.0	0.2	--	96.7	--	0.2	--	--	--	--	--	--	--	--	--	--	--	--	--	0.2	--	--	--	--	0.7	--
GSL	--	2.7	0.8	--	95.6	0.2	--	--	--	--	--	0.6	--	--	--	--	--	--	--	--	--	--	--	--	--	--
GSC	--	2.7	--	--	0.4	95.1	--	--	--	--	--	--	--	--	1.3	--	--	--	--	--	--	--	--	--	0.4	--
S	--	--	--	--	--	--	97.6	0.5	--	--	0.4	--	1.0	0.2	0.1	--	--	--	--	--	--	--	--	0.2	--	--
SG	0.0	--	--	--	0.1	--	0.4	97.6	1.3	0.1	--	0.1	--	--	0.1	--	--	--	--	--	--	--	--	0.0	0.2	--
SGL	--	--	--	--	--	--	--	1.7	96.4	--	--	1.9	--	--	--	--	--	--	--	--	--	--	--	--	--	--
SGC	--	--	--	--	--	1.2	--	--	--	94.0	--	--	--	2.4	1.2	--	--	--	--	--	--	--	--	1.2	--	--
SL	--	--	--	--	--	--	1.4	0.3	0.3	--	85.5	11.5	0.5	0.3	--	--	--	0.3	--	--	--	--	--	--	--	--
SLG	--	--	--	--	0.2	--	--	0.5	0.2	--	1.4	96.5	1.1	--	0.2	--	--	--	--	--	--	--	--	--	--	--
SLC	--	--	--	--	--	--	3.2	0.8	--	--	2.4	0.8	88.9	4.0	--	--	--	--	--	--	--	--	--	--	--	--
SC	--	--	--	--	--	0.2	0.2	--	--	--	--	--	--	97.8	1.5	--	--	--	--	0.2	--	--	--	0.2	--	--
SCG	--	--	--	--	--	--	--	0.7	--	0.7	--	1.4	--	2.8	94.5	--	--	--	--	--	--	--	--	--	--	--
L	--	--	--	--	--	--	--	--	--	--	--	1.0	--	--	--	96.0	--	--	3.0	--	--	--	--	--	--	--
LG	--	--	1.9	--	1.9	--	--	--	--	--	--	--	--	--	--	1.9	88.9	1.9	1.9	--	--	--	--	--	1.9	--
LS	--	--	--	--	--	--	--	--	--	--	--	0.3	--	--	0.3	--	0.3	98.7	0.5	--	--	--	--	--	--	--
LC	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	0.4	--	0.8	98.9	--	--	--	--	--	--	--
C	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	99.8	0.1	0.0	0.1	--	--	--
CG	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	1.0	99.0	--	--	--	--	--
CS	--	--	--	--	--	--	--	--	--	--	--	--	--	--	0.1	--	--	--	--	0.8	--	99.0	--	--	--	--
CL	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	0.4	--	--	99.6	--	--	--
ss	--	--	--	--	--	--	3.2	0.6	--	--	--	--	--	0.3	--	--	--	--	--	0.3	--	--	--	95.0	0.6	--
cong	0.5	0.3	--	1.0	--	--	0.1	0.2	--	--	--	--	--	--	--	--	--	--	--	0.1	--	--	--	0.2	97.5	0.1
rock	1.3	2.6	--	--	--	--	1.3	--	--	--	--	--	--	--	--	1.3	--	--	--	5.1	--	--	--	--	3.8	84.6

Predicted grain size



Spatialization

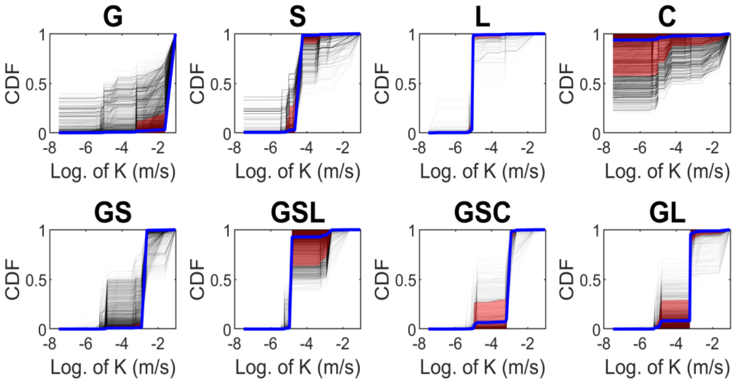
3D interpolation of grain size and permeability values attributed to borehole logs

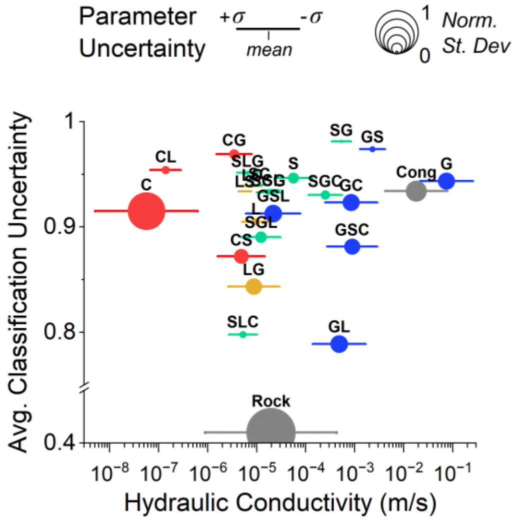


Increased data density for modeling from 0.3 to 8.7 data/km^2

Classification uncertainty

Probabilistic parametrization from the DL classification uncertainty





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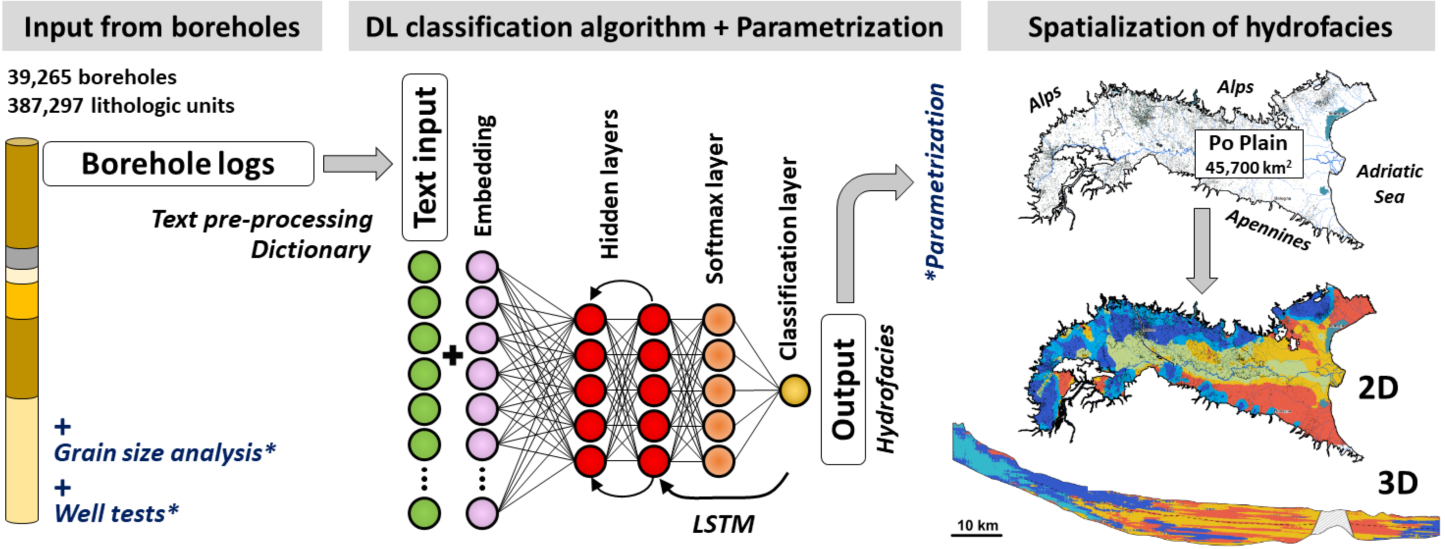

- Deep learning text classification of borehole geological/stratigraphic descriptions
- Recurrent neural network (RNN) with long short-term memory (LSTM) and word embedding

- Hydrofacies classification of litho-textural logs for the Po River alluvial plain
- Hydraulic conductivity associated to hydrofacies classes from the sediment grain size

- Hydrofacies models generated from new semi-quantitative hydrogeological data

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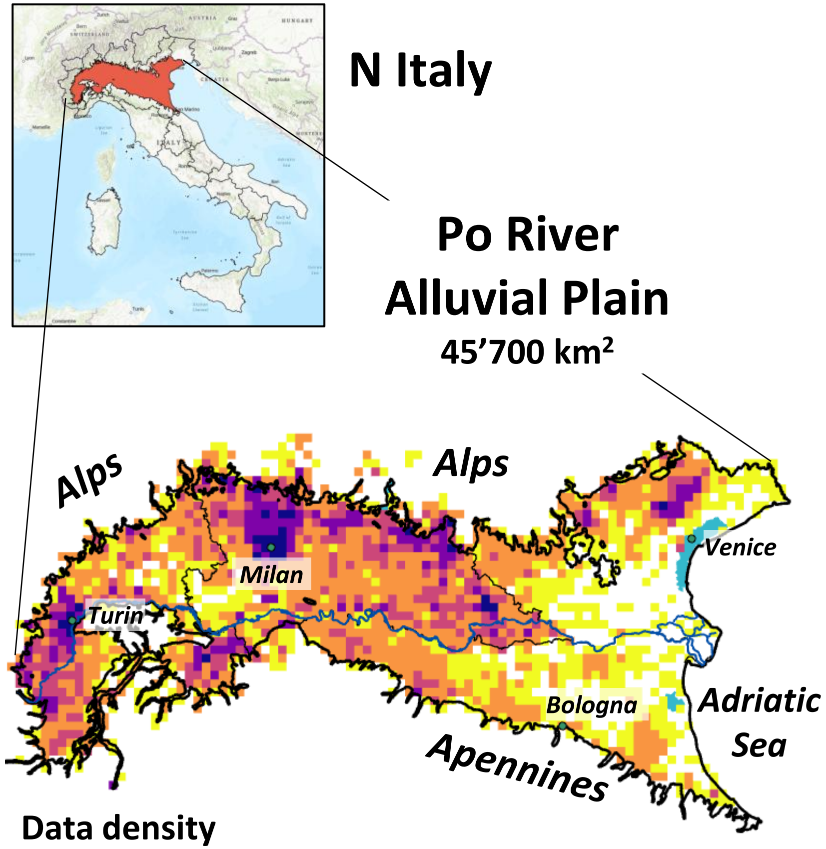

N Italy

Po River Alluvial Plain
45'700 km^2

Data density (bh/km^2)

- ☐ No Data
- 🟨 < 0.2
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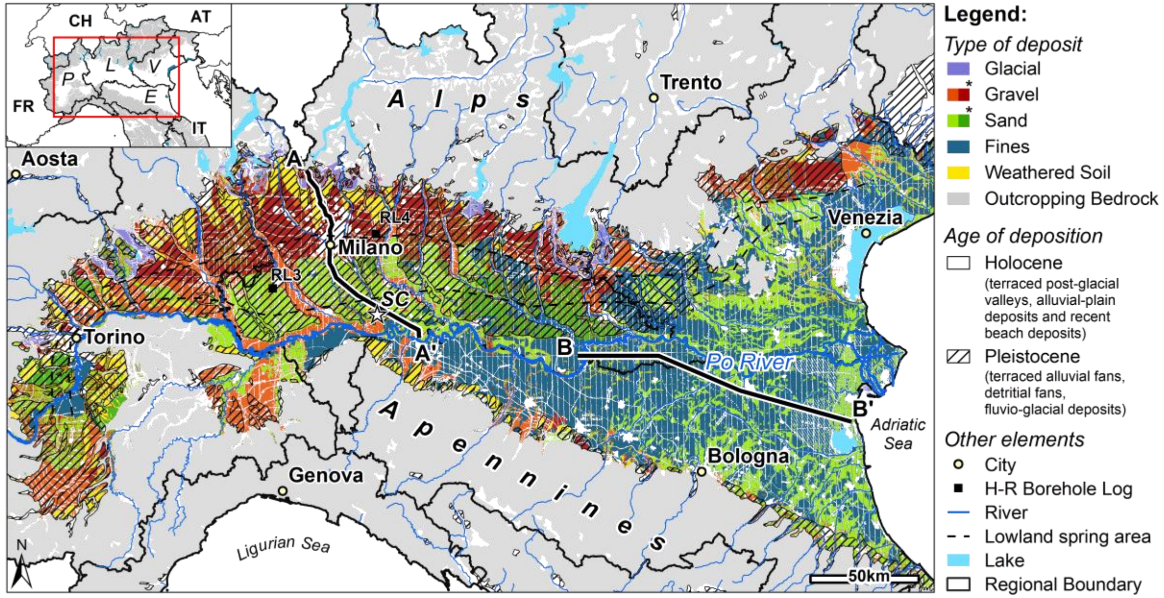
39,265 boreholes
387,297 descriptive intervals
(70% training - 30% validation)

Geological setting



Neogenic-Quaternary siliciclastic sequence that blankets the external fronts of mountain chains, composed of syntectonic and recent alluvial sediments from the Po River

Hydrostratigraphic units forming regional-scale aquifer groups

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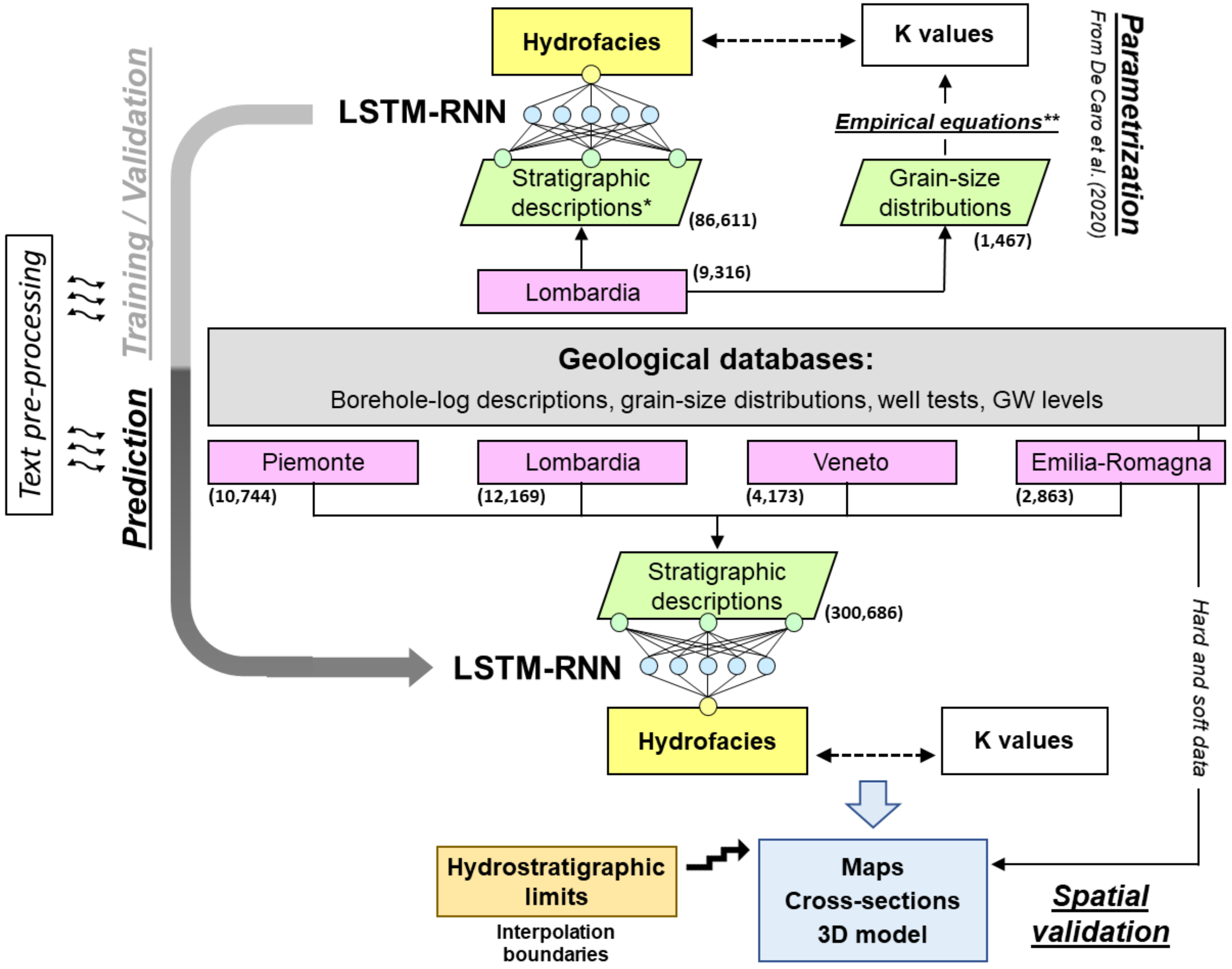
WORKFLOW



Hydrofacies ← - - → K values

LSTM-RNN

Empirical equations**

Stratigraphic descriptions* (86,611)

Grain-size distributions (1,467)

Lombardia (9,316)

Parametrization

From De Caro et al. (2020)

Text pre-processing

Training / Validation

Prediction

Geological databases:

Borehole-log descriptions, grain-size distributions, well tests, GW levels

Piemonte (10,744)

Lombardia (12,169)

Veneto (4,173)

Emilia-Romagna (2,863)

Stratigraphic descriptions (300,686)

LSTM-RNN

Hydrofacies ← - - → K values

Hard and soft data

Hydrostratigraphic limits

Interpolation boundaries

Maps
Cross-sections
3D model

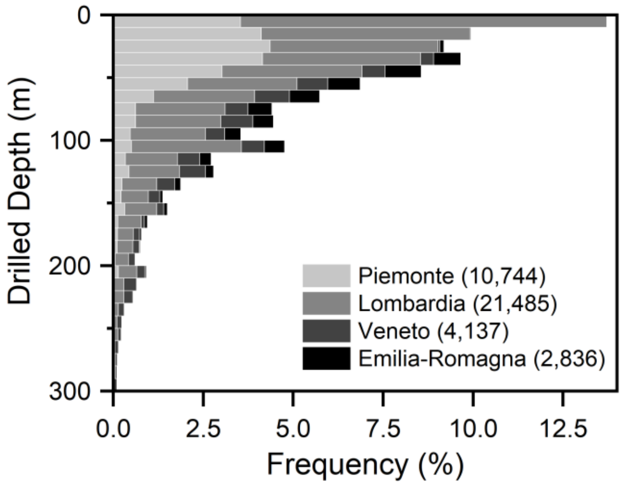
Spatial validation

LSTM Classification Net

86,611 lithological descriptions

(70% training - 30% validation)

Borehole length



39,265 boreholes

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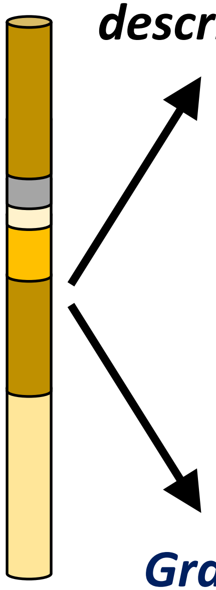
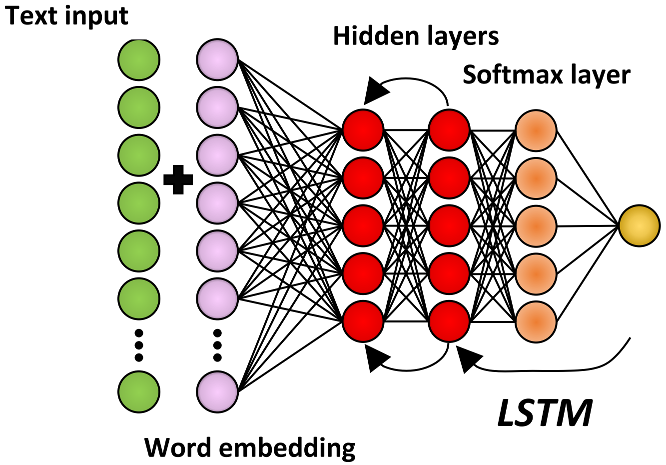
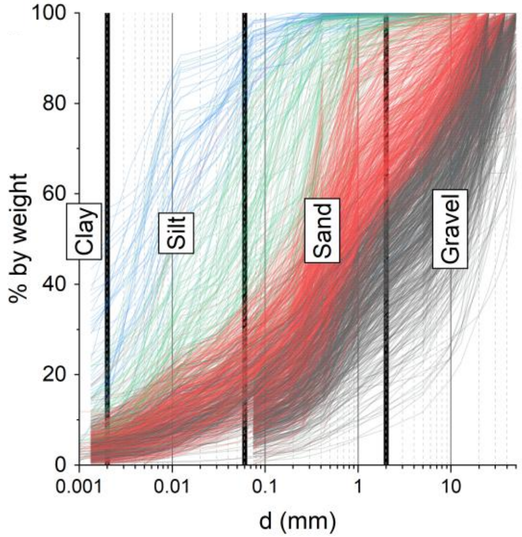


Lithological descriptions

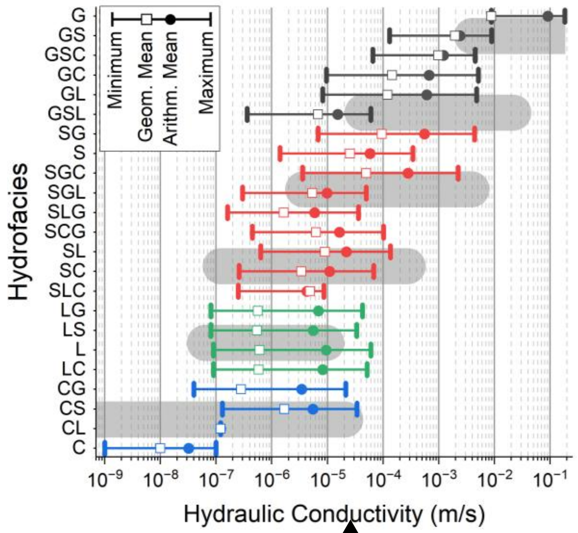
Grain size analysis

Deep learning classification





Classification



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Empirical equations from grain size distributions

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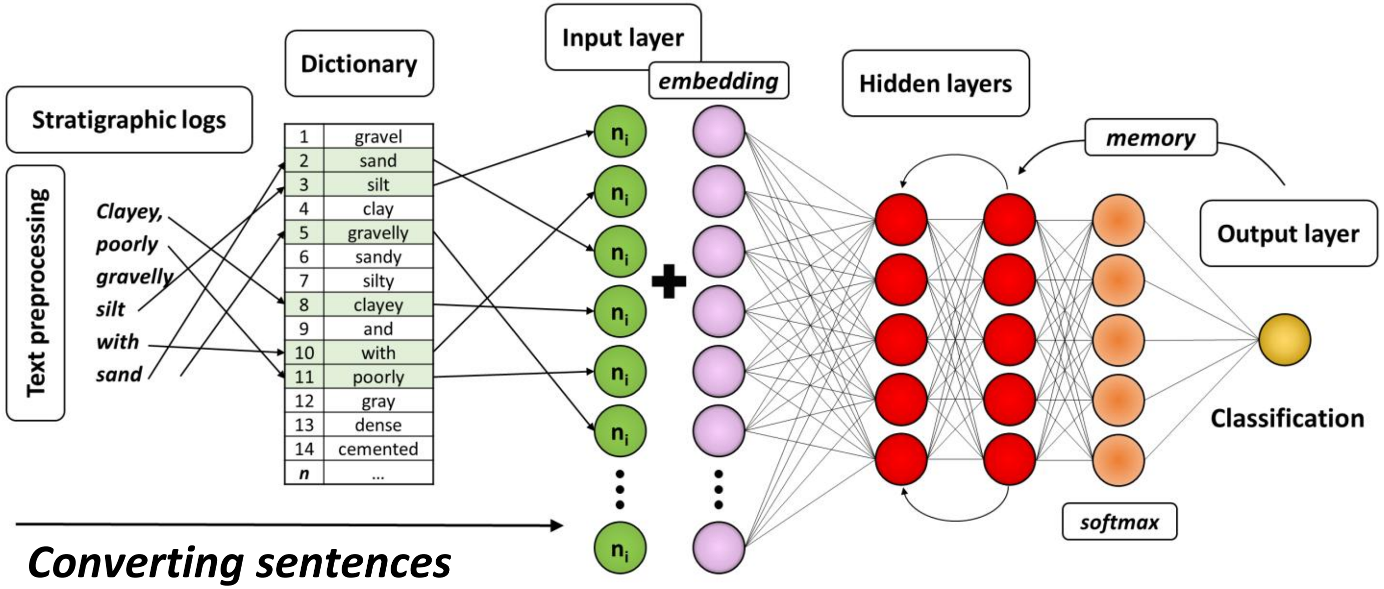
Text pre-processing

- *Remove punctuation*
- *Remove uppercase*
- *Mistakes identification*

Dictionary
(In Italian)

≈ 3000 terms

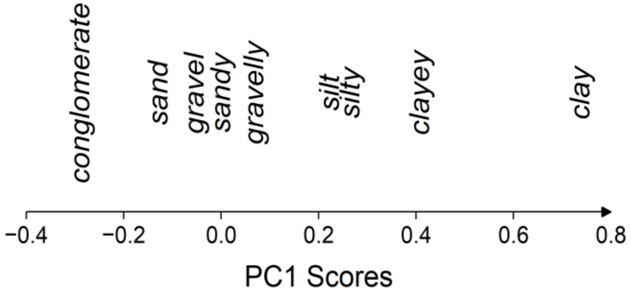
Features of the geological text deep learning classification algorithm



1	gravel
2	sand
3	silt
4	clay
5	gravelly
6	sandy
7	silty
8	clayey
9	and
10	with
11	poorly
12	gray
13	dense
14	cemented
n	...

Converting sentences into numerical sequences

Classification learning process RNN + LSTM



The word embedding vectors for the most frequent litho-textural terms!

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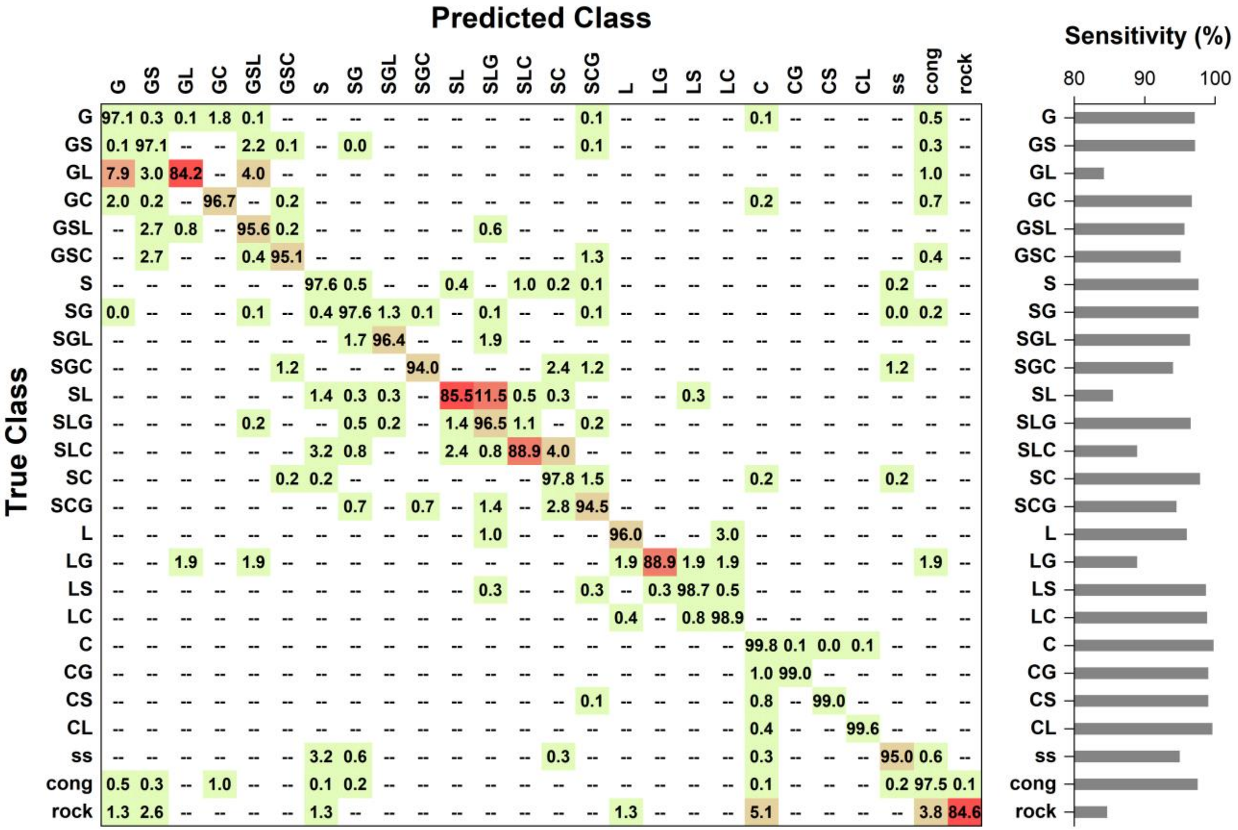
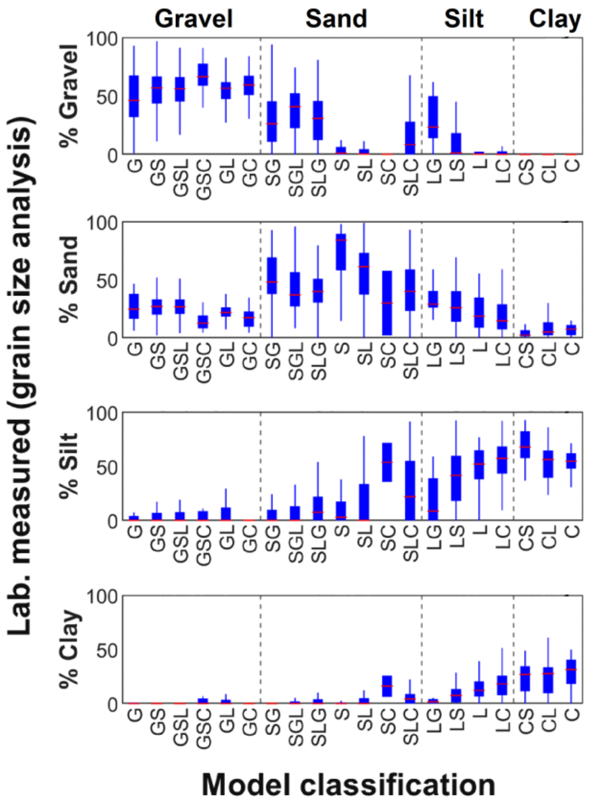
Classification confusion matrix

global validation accuracy (97.4%)



	G	GS	GL	GC	GSL	GSC	S	SG	SGL	SGC	SL	SLG	SLC	SC	SCG	L	LG	LS	LC	C	CG	CS	CL	ss	cong	rock
G	97.1	0.3	0.1	1.8	0.1	--	--	--	--	--	--	--	--	--	0.1	--	--	--	--	0.1	--	--	--	--	0.5	--
GS	0.1	97.1	--	--	2.2	0.1	--	0.0	--	--	--	--	--	--	0.1	--	--	--	--	--	--	--	--	--	0.3	--
GL	7.9	3.0	84.2	--	4.0	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	1.0	--
GC	2.0	0.2	--	96.7	--	0.2	--	--	--	--	--	--	--	--	--	--	--	--	--	0.2	--	--	--	--	0.7	--
GSL	--	2.7	0.8	--	95.6	0.2	--	--	--	--	--	0.6	--	--	--	--	--	--	--	--	--	--	--	--	--	--
GSC	--	2.7	--	--	0.4	95.1	--	--	--	--	--	--	--	--	1.3	--	--	--	--	--	--	--	--	--	0.4	--
S	--	--	--	--	--	--	97.6	0.5	--	--	0.4	--	1.0	0.2	0.1	--	--	--	--	--	--	--	--	0.2	--	--
SG	0.0	--	--	--	0.1	--	0.4	97.6	1.3	0.1	--	0.1	--	--	0.1	--	--	--	--	--	--	--	--	0.0	0.2	--
SGL	--	--	--	--	--	--	--	1.7	96.4	--	--	1.9	--	--	--	--	--	--	--	--	--	--	--	--	--	--
SGC	--	--	--	--	--	1.2	--	--	--	94.0	--	--	--	2.4	1.2	--	--	--	--	--	--	--	--	1.2	--	--
SL	--	--	--	--	--	--	1.4	0.3	0.3	--	85.5	11.5	0.5	0.3	--	--	--	0.3	--	--	--	--	--	--	--	--
SLG	--	--	--	--	0.2	--	--	0.5	0.2	--	1.4	96.5	1.1	--	0.2	--	--	--	--	--	--	--	--	--	--	--
SLC	--	--	--	--	--	--	3.2	0.8	--	--	2.4	0.8	88.9	4.0	--	--	--	--	--	--	--	--	--	--	--	--
SC	--	--	--	--	--	0.2	0.2	--	--	--	--	--	--	97.8	1.5	--	--	--	--	0.2	--	--	--	0.2	--	--
SCG	--	--	--	--	--	--	--	0.7	--	0.7	--	1.4	--	2.8	94.5	--	--	--	--	--	--	--	--	--	--	--
L	--	--	--	--	--	--	--	--	--	--	--	1.0	--	--	--	96.0	--	--	3.0	--	--	--	--	--	--	--
LG	--	--	1.9	--	1.9	--	--	--	--	--	--	--	--	--	--	1.9	88.9	1.9	1.9	--	--	--	--	--	1.9	--
LS	--	--	--	--	--	--	--	--	--	--	--	0.3	--	--	0.3	--	0.3	98.7	0.5	--	--	--	--	--	--	--
LC	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	0.4	--	0.8	98.9	--	--	--	--	--	--	--
C	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	99.8	0.1	0.0	0.1	--	--	--
CG	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	1.0	99.0	--	--	--	--	--
CS	--	--	--	--	--	--	--	--	--	--	--	--	--	--	0.1	--	--	--	--	0.8	--	99.0	--	--	--	--
CL	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	0.4	--	--	99.6	--	--	--
ss	--	--	--	--	--	--	3.2	0.6	--	--	--	--	--	0.3	--	--	--	--	--	0.3	--	--	--	95.0	0.6	--
cong	0.5	0.3	--	1.0	--	--	0.1	0.2	--	--	--	--	--	--	--	--	--	--	--	0.1	--	--	--	0.2	97.5	0.1
rock	1.3	2.6	--	--	--	--	1.3	--	--	--	--	--	--	--	--	1.3	--	--	--	5.1	--	--	--	--	3.8	84.6

Predicted vs measured grain size



G = gravel, S = sand, L = silt, C = clay, ss = sandstone, cong = conglomerate, and rock = generic rock type.

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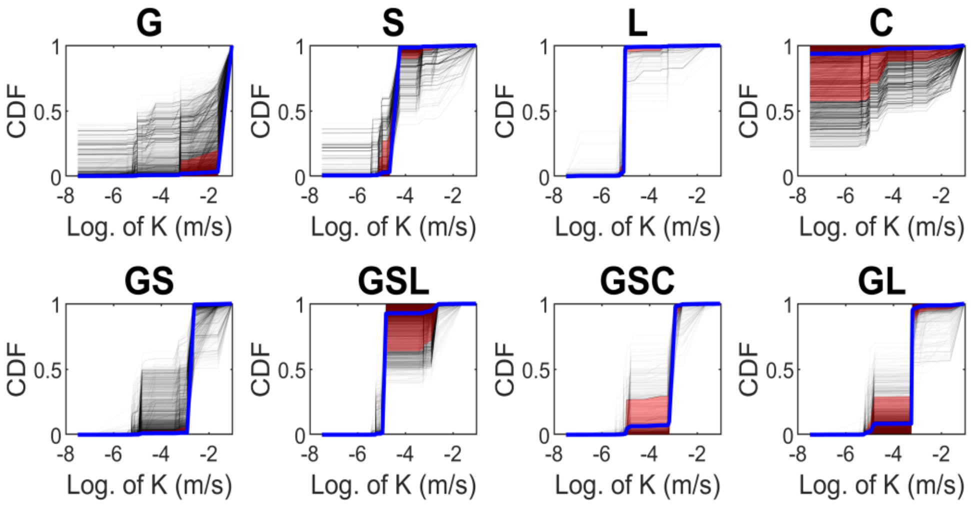
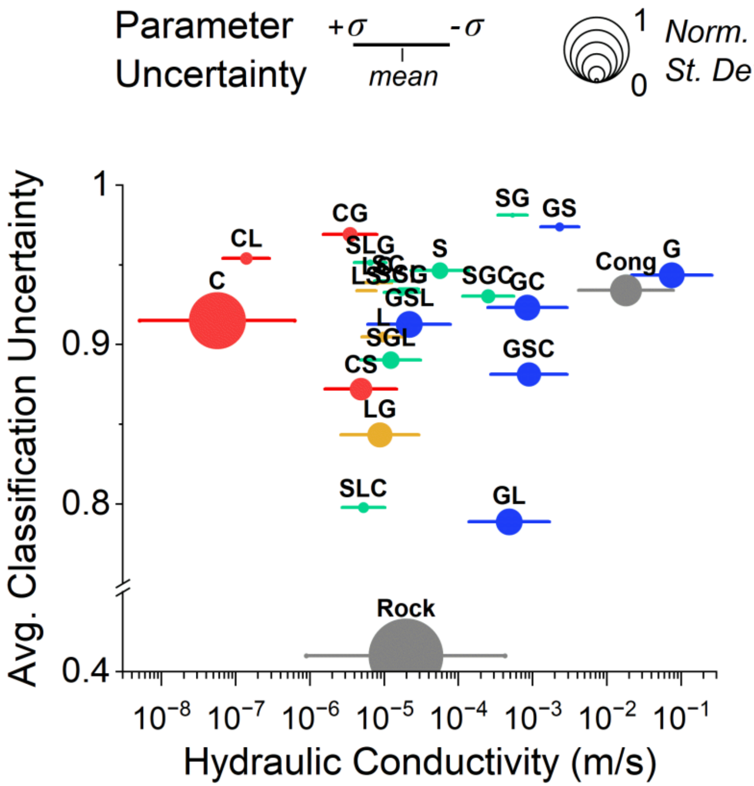
Classification uncertainty

Probabilistic parametrization from the DL classification uncertainty (***softmax*** **layer**)





The resulting uncertainty in the associated parameter (K) can vary significantly, depending on the classifier's confidence in assigning alternative classes.

- Some classes are confidently classified and have a low parameter uncertainty because the few indecisions involve classes with similar values
- For other classes, despite being relatively confident, the parameter uncertainty is higher due to the markedly different K values of potential alternative classifications

Leveraging Deep Learning and Natural Language Processing for hydrogeological insights from borehole logs

Previati et al. (2025) – Read the publication here: https://doi.org/10.1016/j.ejrh.2024.102157

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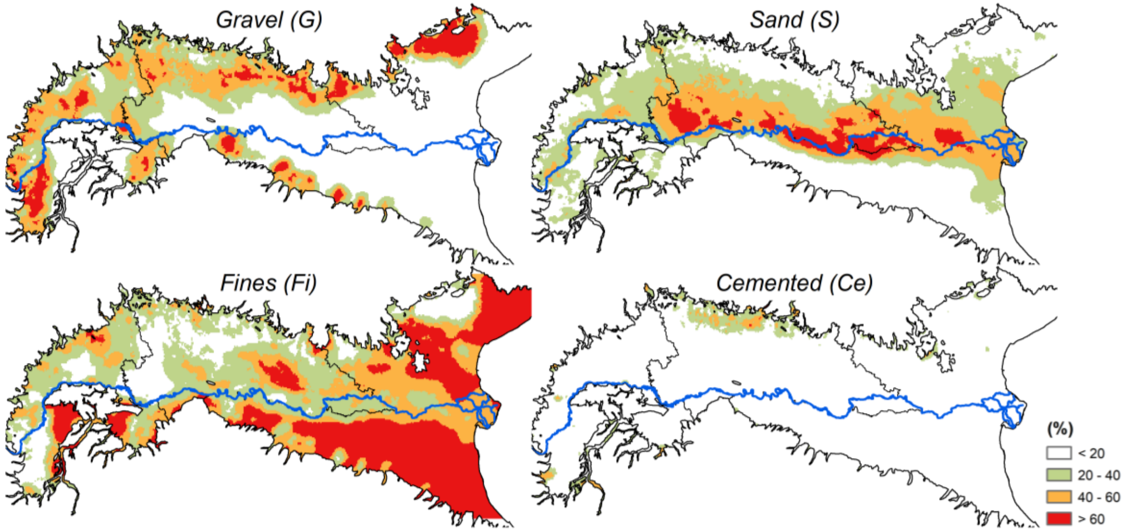
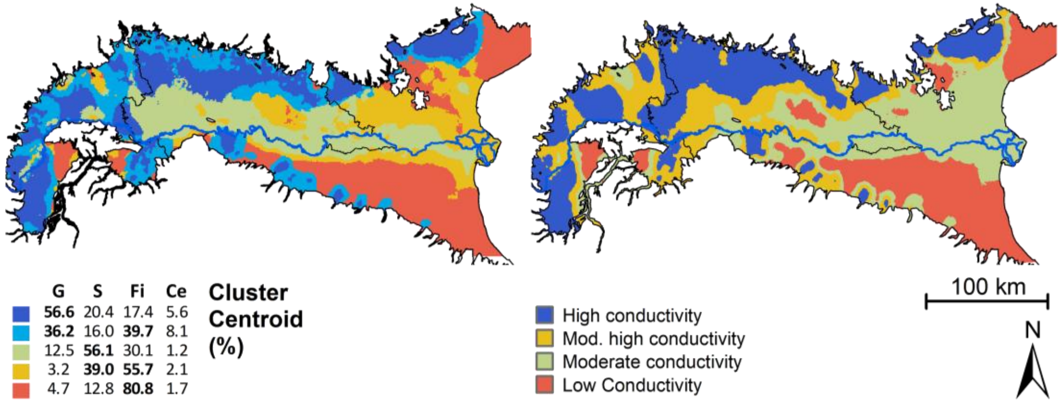
Grain size maps (50m depth)



Hydrogeological maps (50m depth)

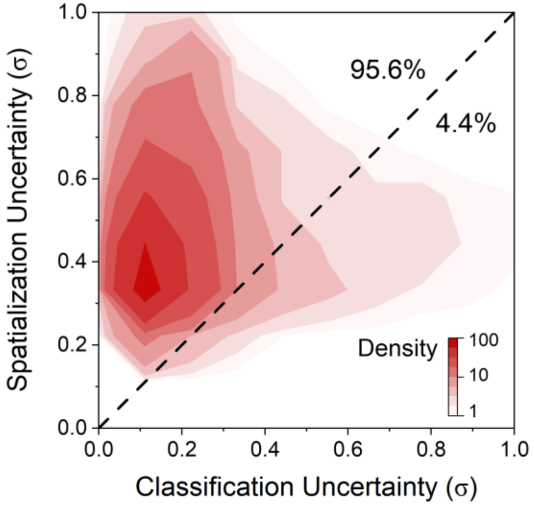


	G	S	Fi	Ce
🟦	**56.6**	20.4	17.4	5.6
🟦	**36.2**	16.0	**39.7**	8.1
🟩	12.5	**56.1**	30.1	1.2
🟨	3.2	**39.0**	**55.7**	2.1
🟥	4.7	12.8	**80.8**	1.7

Cluster Centroid (%)

🟦 High conductivity
🟨 Mod. high conductivity
🟩 Moderate conductivity
🟥 Low Conductivity

Spatialization vs Classification Uncertainty



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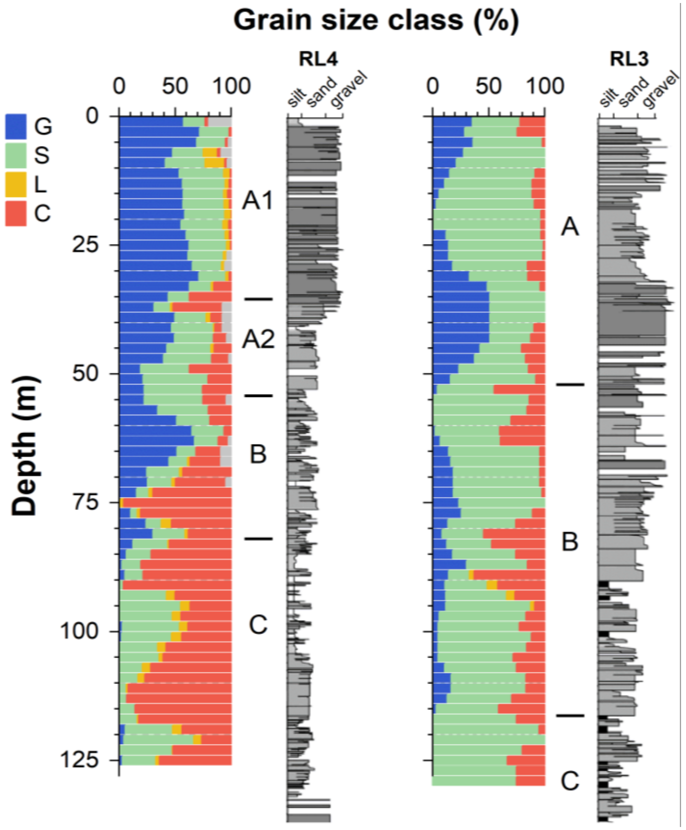
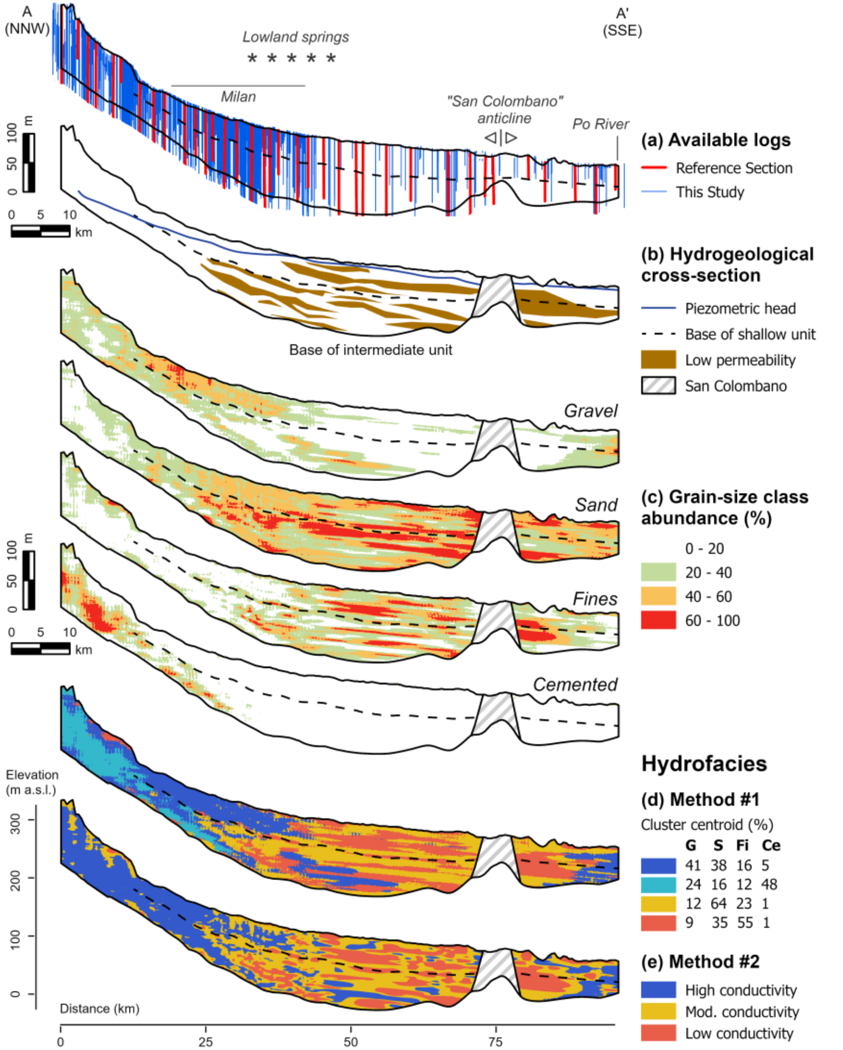
1D comparison of grain size logs:

- Identification of main aquifers



Creation of hydrogeological cross-sections



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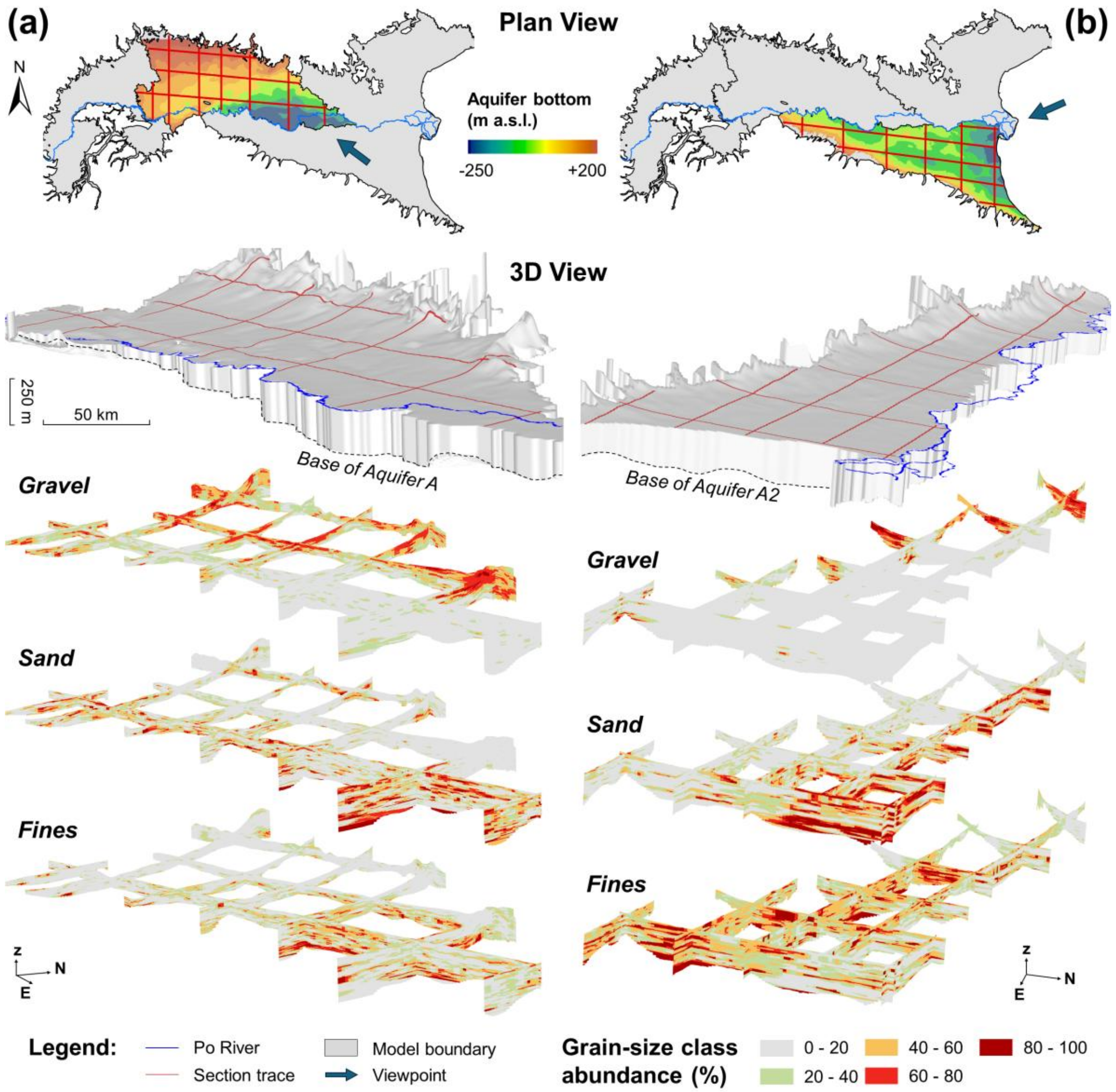

3D hydrogeological model

3D interpolation (ordinary kriging) of grain size and permeability values attributed to borehole logs

- Constrained by hydrostratigraphic surfaces (aquifer boundaries)

Increased data density for modeling from 0.3 to 8.7 data/km^2

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Conclusions

- ✓ **High Accuracy**: The deep learning LSTM-based algorithm achieved a 97.4% classification accuracy for hydrofacies recognition from borehole log texts.
- ✓ **Enhanced Data Density**: Spatial data density improved significantly—from 0.34 to 8.7 data/km²—by integrating borehole descriptions with grain size and aquifer test data.
- ✓ **Consistent Validation**: Results showed strong agreement with existing hydrogeological maps, cross-sections, and literature data.
- ✓ **Algorithm Strengths**: Key success factors included a large training dataset, use of word embeddings, and detailed grain size references in structured logs.
- ✓ **Replicability**: The method is transferable to other regions with adequate borehole data and pre-labeled training sets.

Limitations

- Relies heavily on grain size descriptions, lacking a stratigraphic perspective.
- Cannot fully substitute for quantitative subsurface modeling or define hydrostratigraphic boundaries alone.
- The method is effective for mapping hydrofacies proportions within units but not for delineating stratigraphic boundaries.

Future Potential

Combining text-based classification with additional well logs could support more advanced hydrostratigraphic modeling.