INTERNATIONAL MOUNTAIN CONFERENCE
SEPTEMBER 11 – 15 2022

>> SYNTHESIZE MOUNTAINS OF KNOWLEDGE <<

Focus Session 52
Pathways towards nature-based adaptation and transformation in mountains

Characterising non-stationarity in predictive models of land use in Swiss mountain parks to inform scenarios for deliberative transformation.

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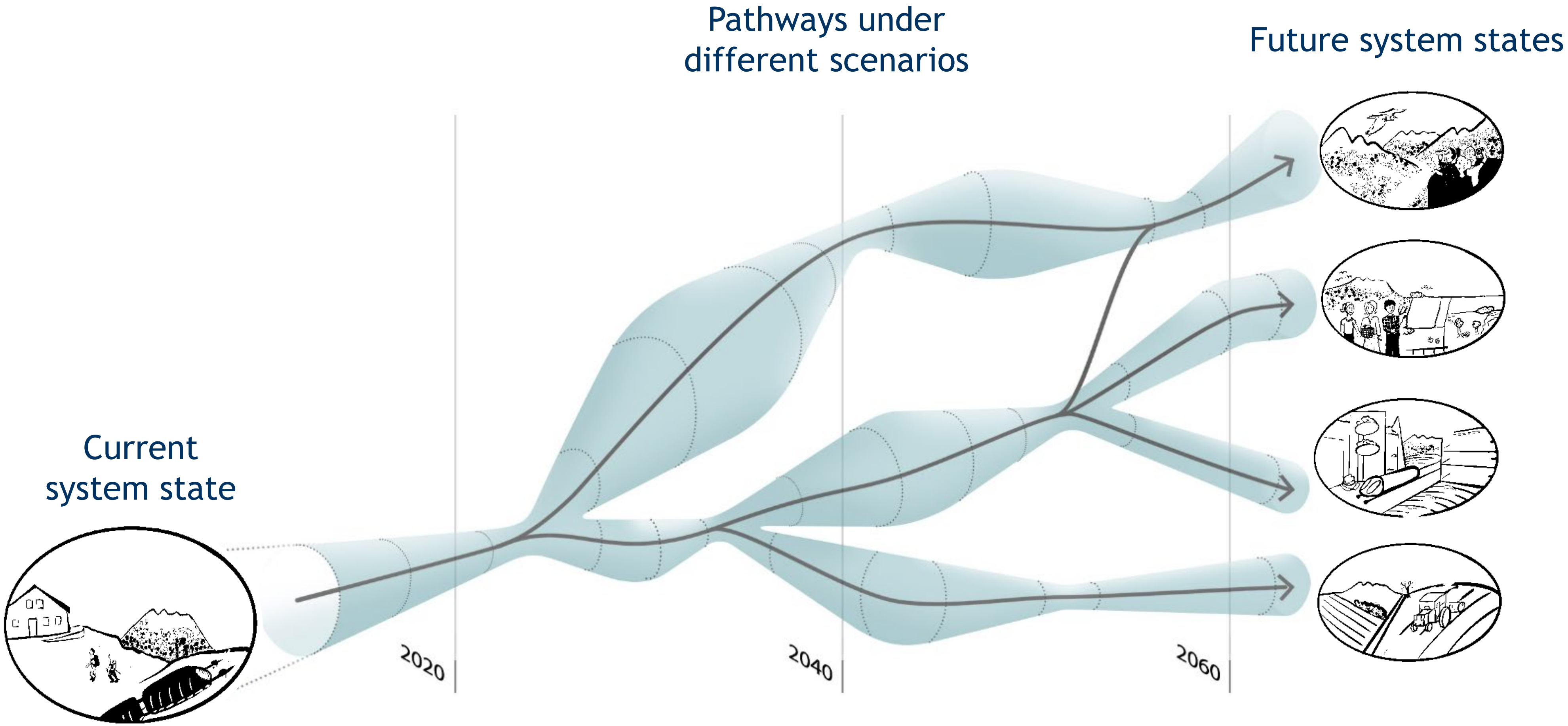
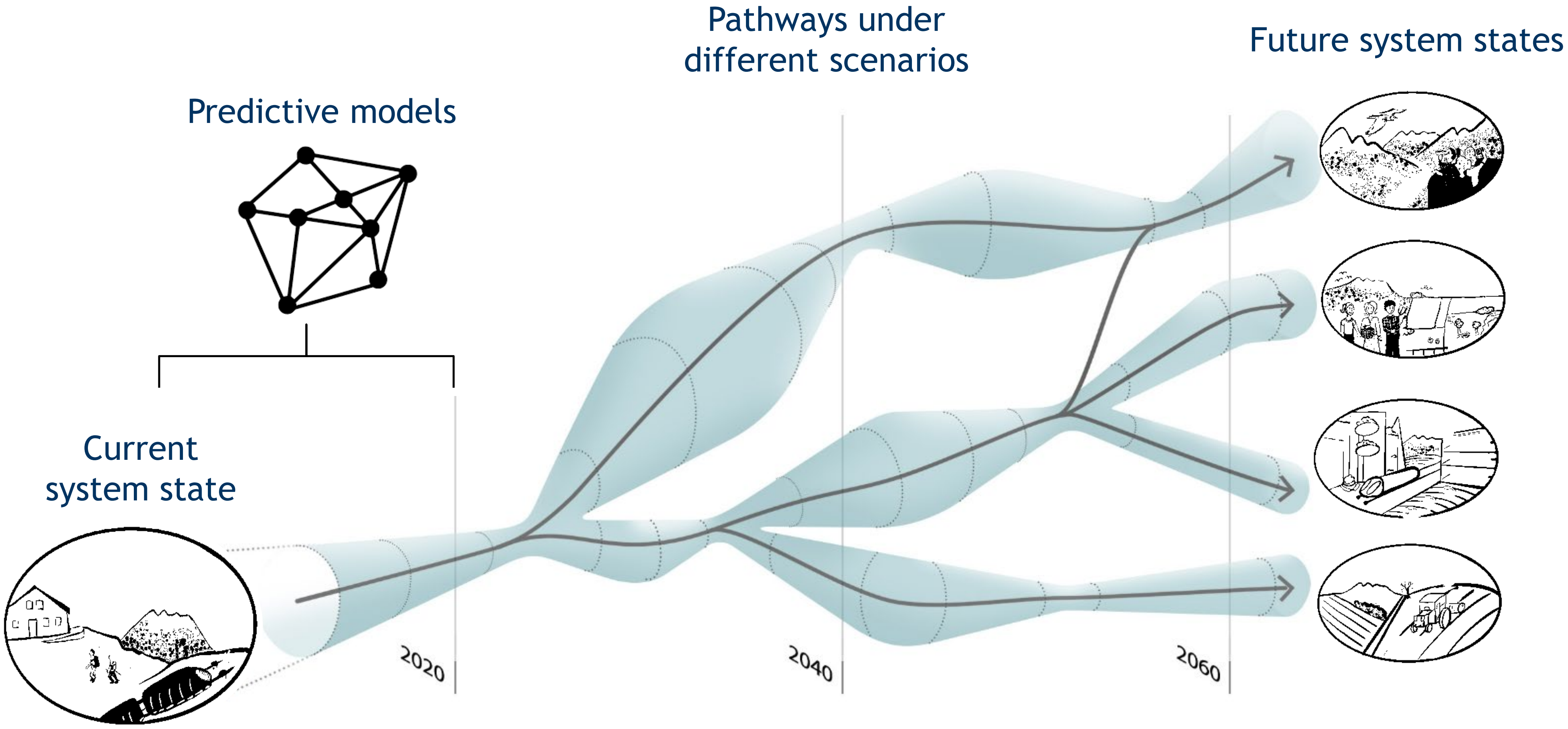
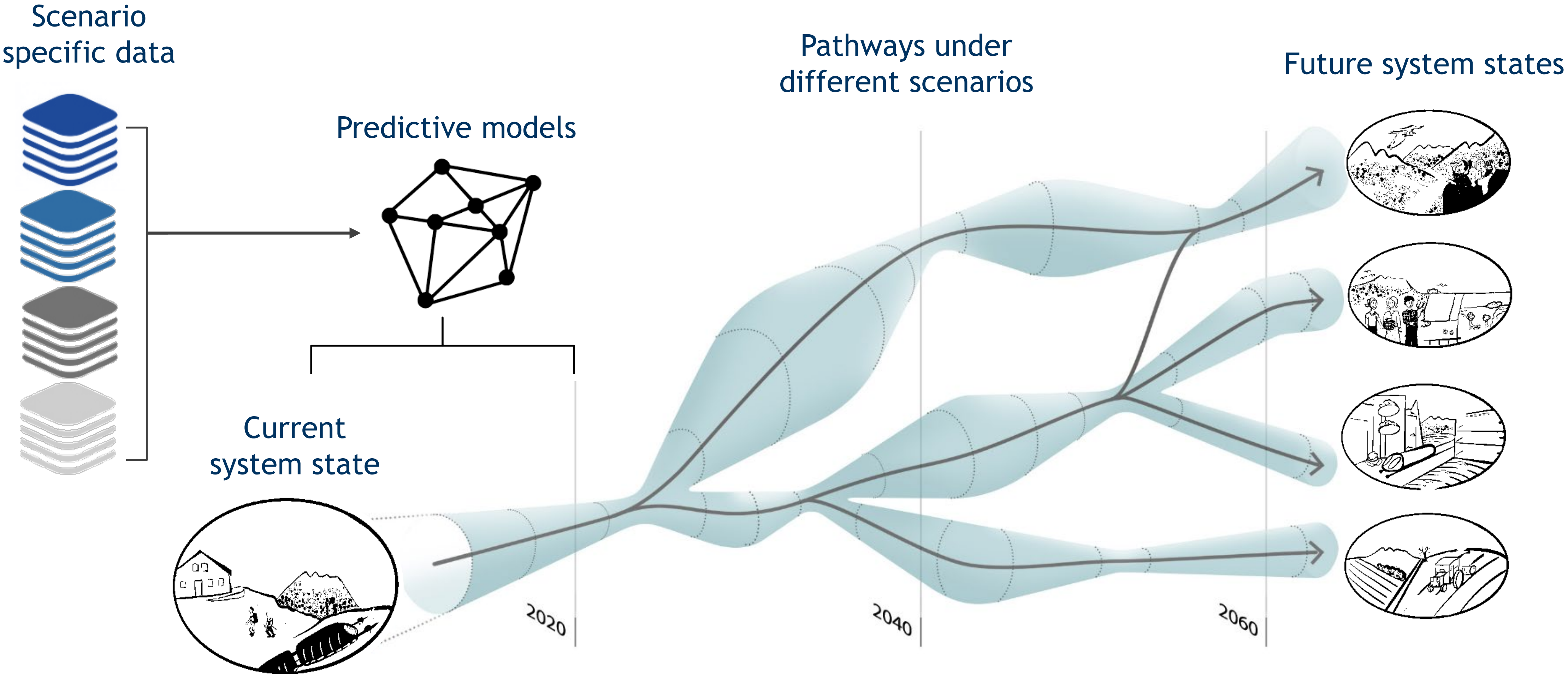
Scenario modelling of Socio-Ecological systems



Scenario modelling of Socio-Ecological systems

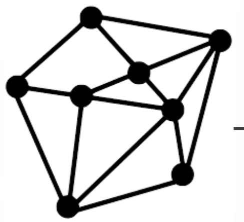


Scenario modelling of Socio-Ecological systems



Scenario modelling of Socio-Ecological systems

Predictive models



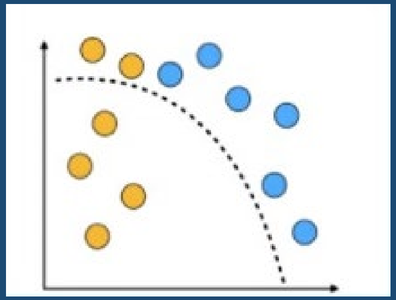
- Models are trained on historic data
- **Assumption:** Relationships remain stationary in time
- **BUT:** With multiple historical periods we can quantitatively demonstrate non-stationarity
- **Problem:** Non-stationarity will led to decreased model performance + increased uncertainty of predictions
- **No solution only mitigation:** Characterize non-stationarity and address in modelling/scenarios

Characterizing Non-stationarity

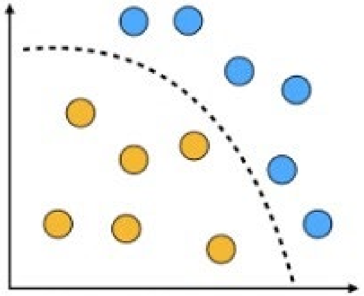
Label drift
- Output data shifts
- P(Y) changes

Feature drift
- Input data shifts
- P(X) changes

Data drift



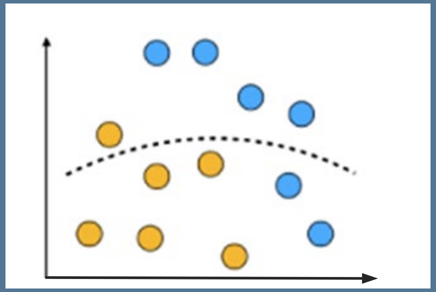
- Data changes
- Fundamental relationships do not change



Training data with decision boundary

P(Y|X)
Probability of y output given x input

Concept drift



- Reality/behavioral change
- Relationships (i.e. P(Y|X)) change not the input

Figure adapted from Hodler 2022

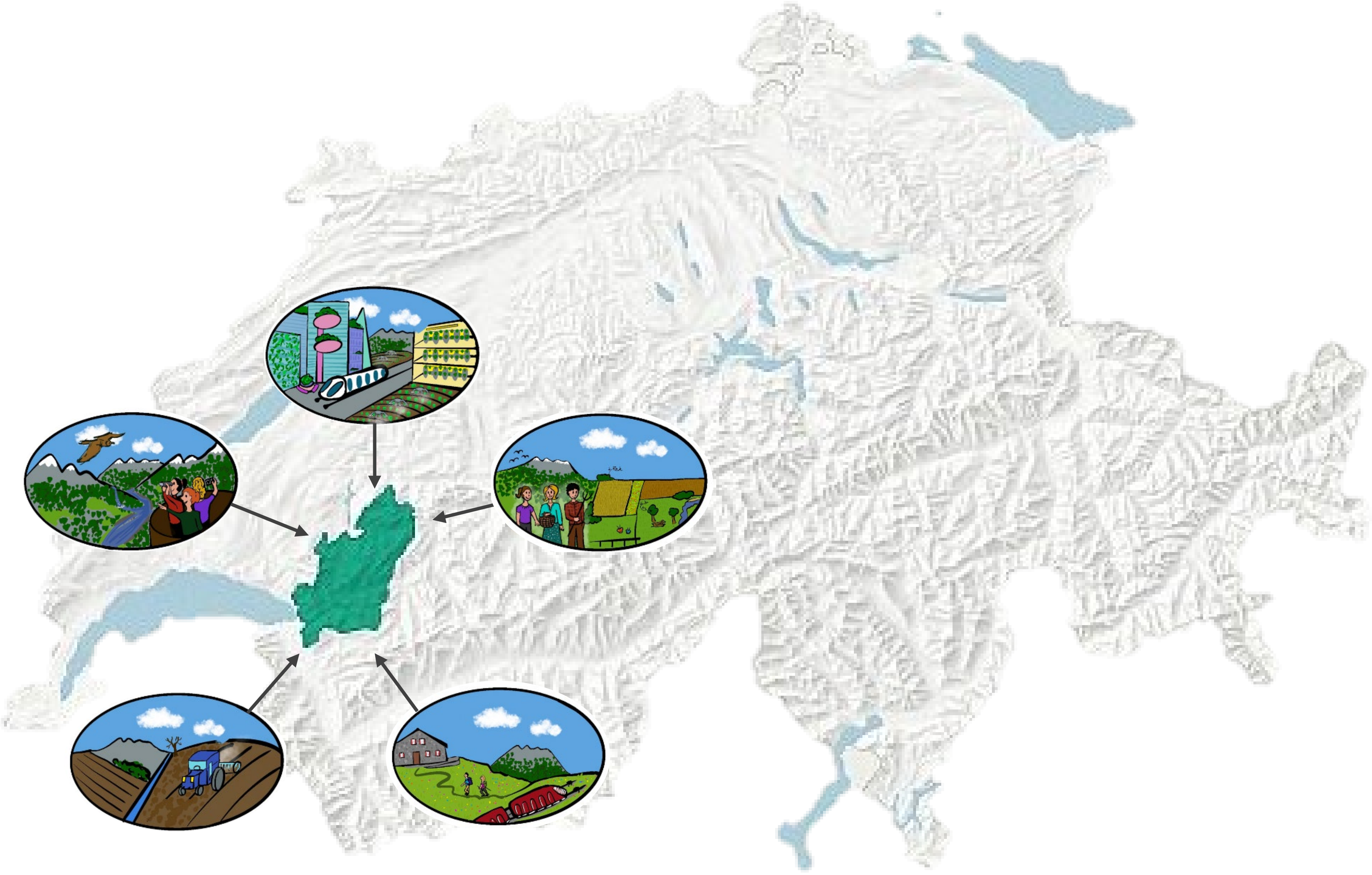
Case study

Parc
Gruyère
Pays-d'Enhaut

ValPar.CH

Case study

Parc
Gruyère
Pays-d'Enhaut



Scenarios:

- Biodiversity-promoting Switzerland
- Switzerland with diverging rural and urban areas
- Switzerland with conditions for a desired future of Ecological Infrastructure

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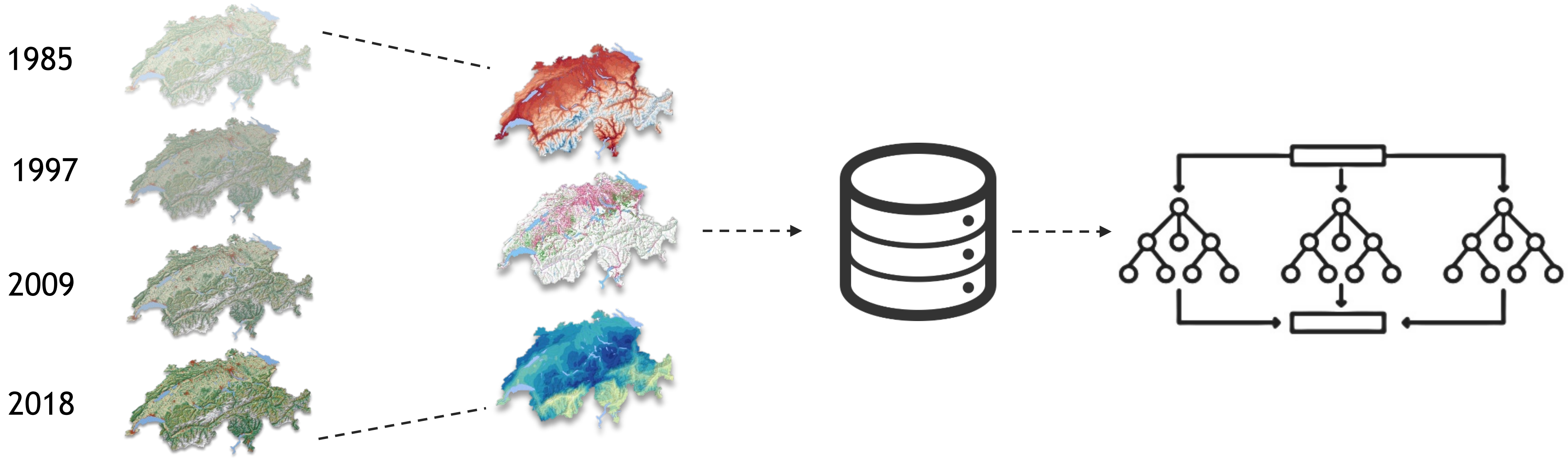
Land use land cover (LULC) modelling



100m raster data for 4 time points, aggregated to 10 LULC classes

Socio-economic/ biophysical/ LULC focal predictors

LULC suitability datasets for each time period (40)

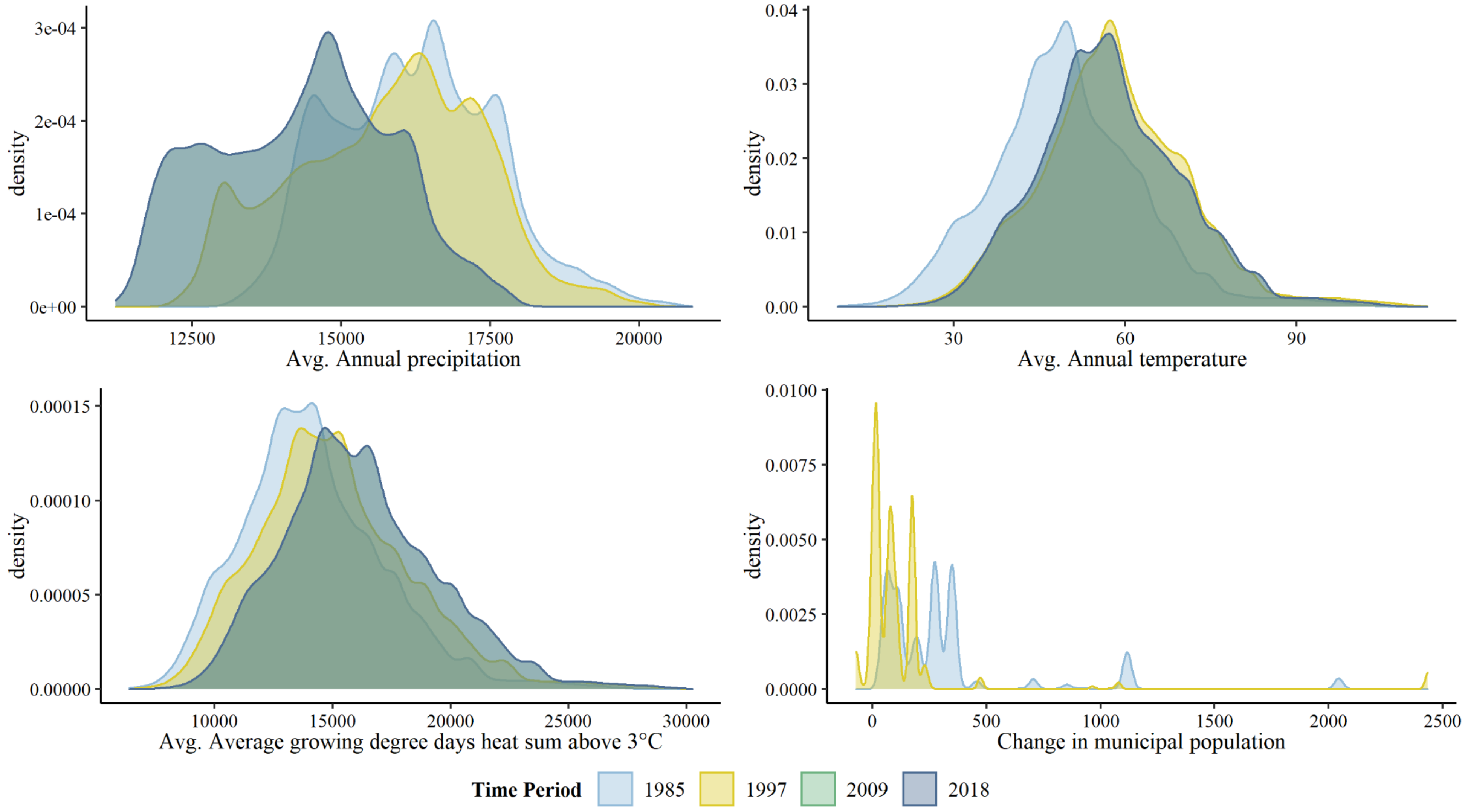
Random Forest supervised classification model for each dataset

Label drift

Coverage of LULC classes as % of total area of park Gruyère Pays-d'Enhaut

LULC class	1985	1997	2009	2018	Avg. % difference
Urban	1.16	1.38	1.5	1.63	0.157
Static	7.23	7.19	6.91	6.77	0.153
Open Forest	6.67	6.77	8.53	7.97	0.433
Closed Forest	31.48	33.01	31.91	32.87	0.463
Shrubland	8.32	7.91	7.76	7.78	0.180
Intensive Agriculture	0.26	0.27	0.12	0.11	0.050
Alpine Pasture	35.1	34.13	33.88	33.6	0.500
Grassland	9.7	9.28	9.35	9.23	0.157
Permanent crops	0.08	0.06	0.04	0.03	0.017

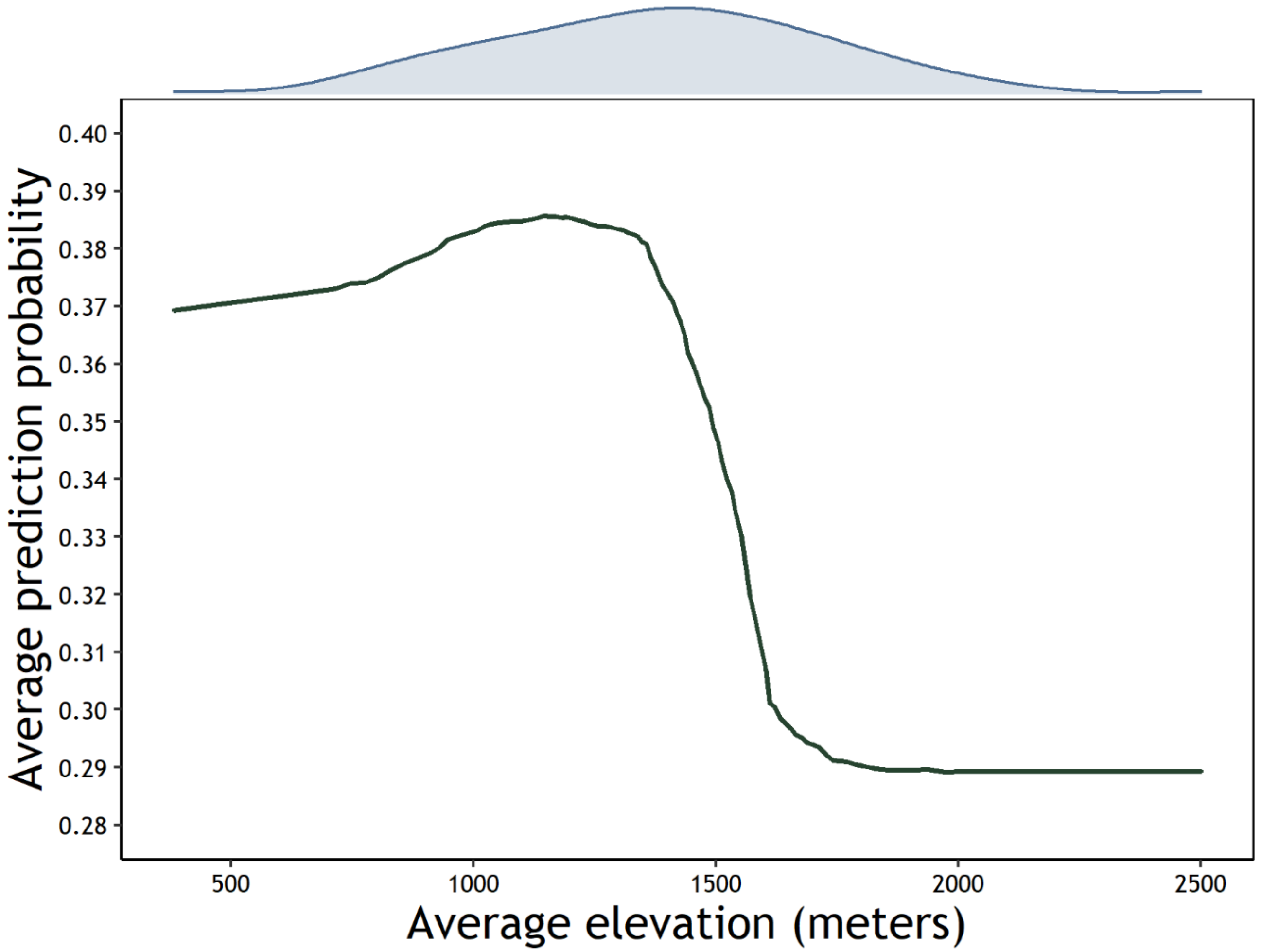
Feature drift



Concept drift

How can we quantify?: Partial dependence plots (PDPs)

- Change in average prediction probability of dependent variable across the values of a single predictor
- Marginalized over all predictors i.e aggregation of all instances



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Concept drift

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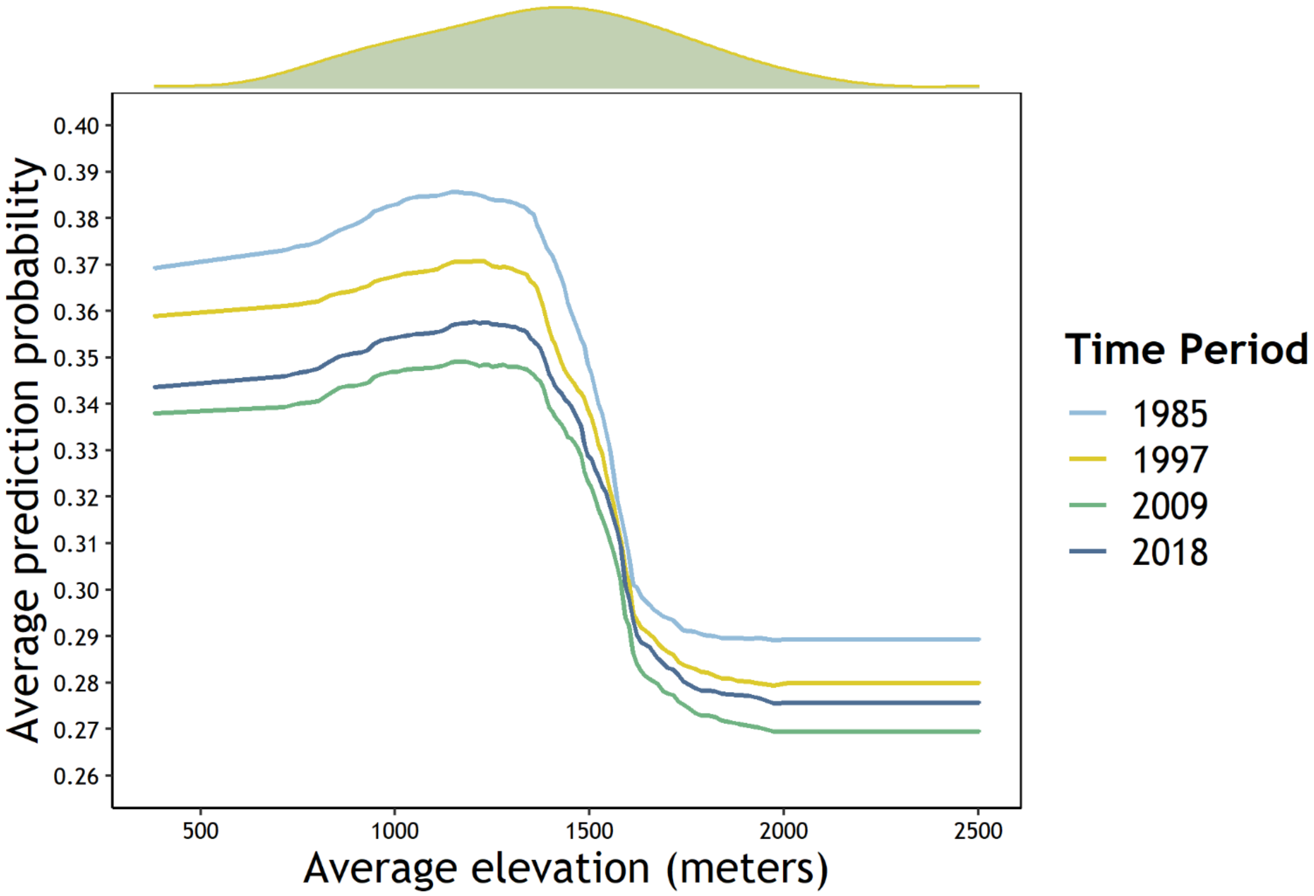
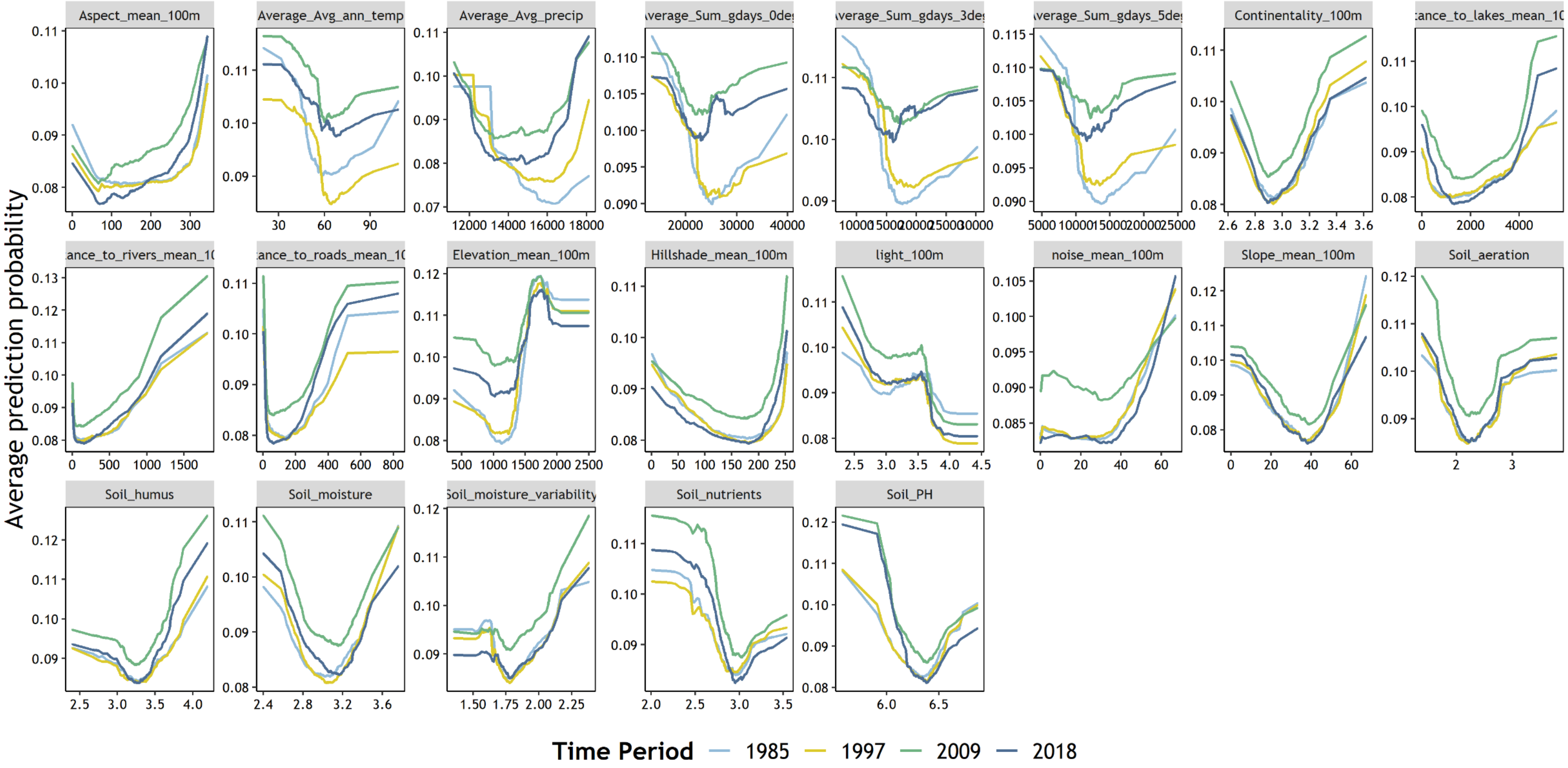


Concept drift

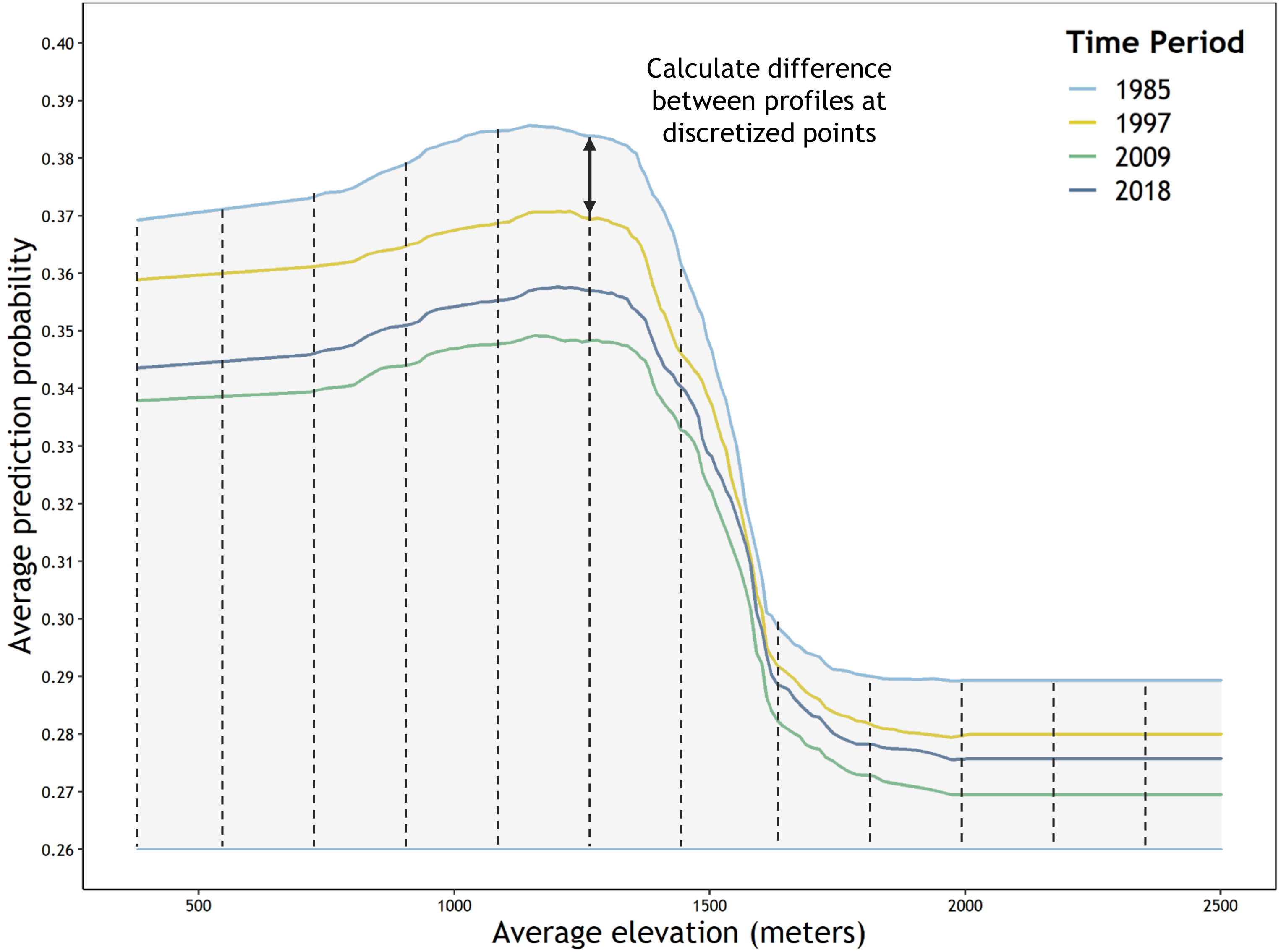


Concept drift

Model drift = Square root of the mean square difference(RMSD) between the PD profiles

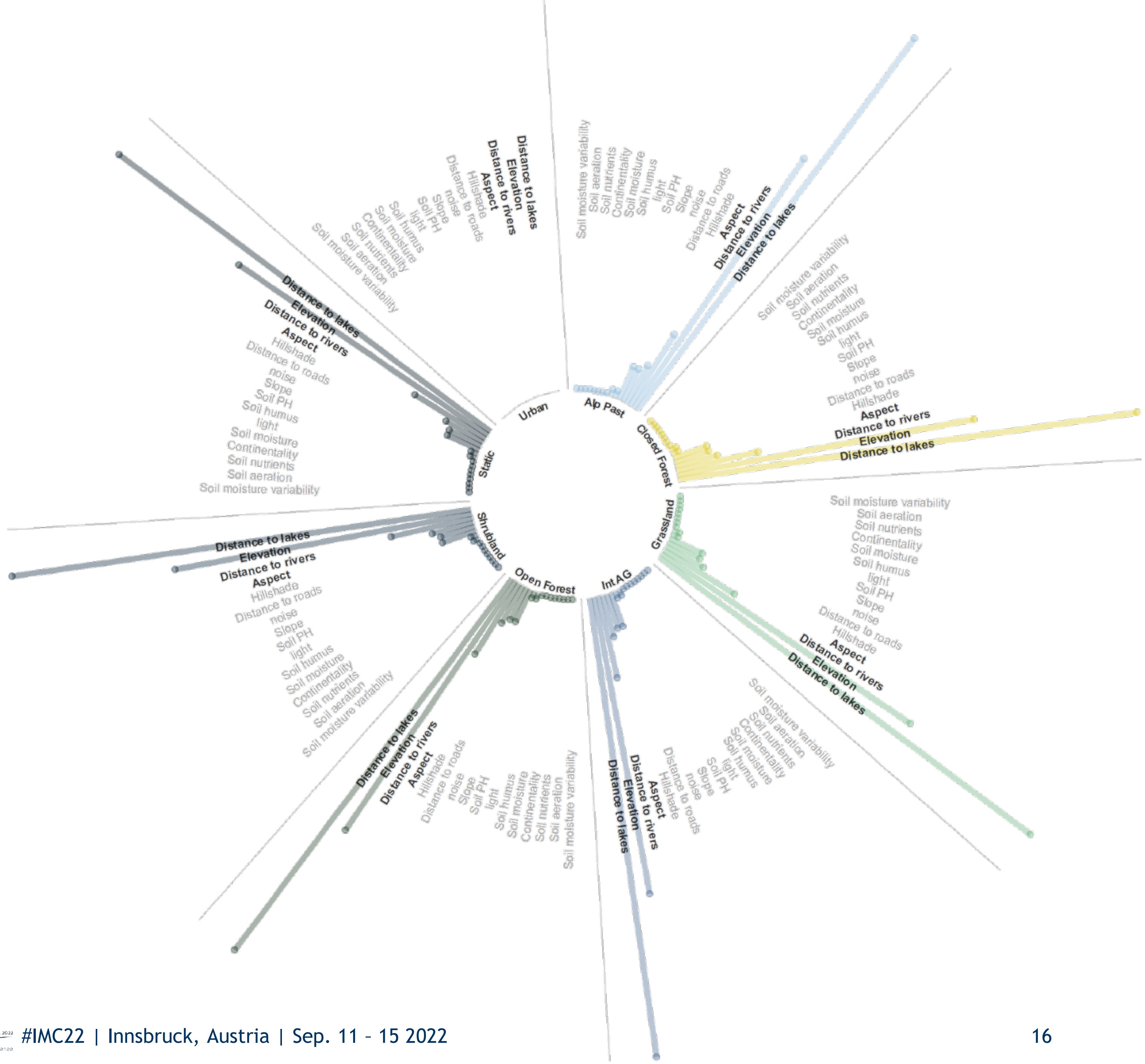
- Requires profiles to be discretized
- Unitless
- Minimum value of RMSD = 0 (perfectly overlapping profiles)

Biecek and Pękala 2022



Concept drift

- Average drift across time periods as compared to final period (2009-2018)
- Large range of drift values between predictors
- Consistency in highest drift predictors across LULC classes



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Implications for scenarios

- Scenarios for deliberative transformation simulated top-down (i.e. planned changes to specific aspects in the system)
- Proscribing changes often based on historically characterized relationships
- Ignoring change in these relationships (exemplified by concept drift) increases uncertainty of results = flawed recommendations.

+1.4°C RCP 2.6	+2.3°C RCP 4.5	+3.1°C RCP 8.5	+2.3°C RCP 4.5	+1.4°C RCP 2.6
Low 9.5M	Reference 10.5M	High 11.5M	Reference 10.5M	Reference 10.5M
22% (2030) 30% (2060)	17% (2030) 22% (2060)	15% (2030) 0% (2060)	15% (2030) 20% (2060)	17% (2030) 25% (2060)

Implications for modellers

- During calibration, detect drift and adapt predictive models to mitigate
- Temporal drift: Numerous adaptations to popular ML algorithms: Streaming Random Forests (Abdulsalam et al. 2011)
- Spatial drift: regionalized modelling
- Further research needed

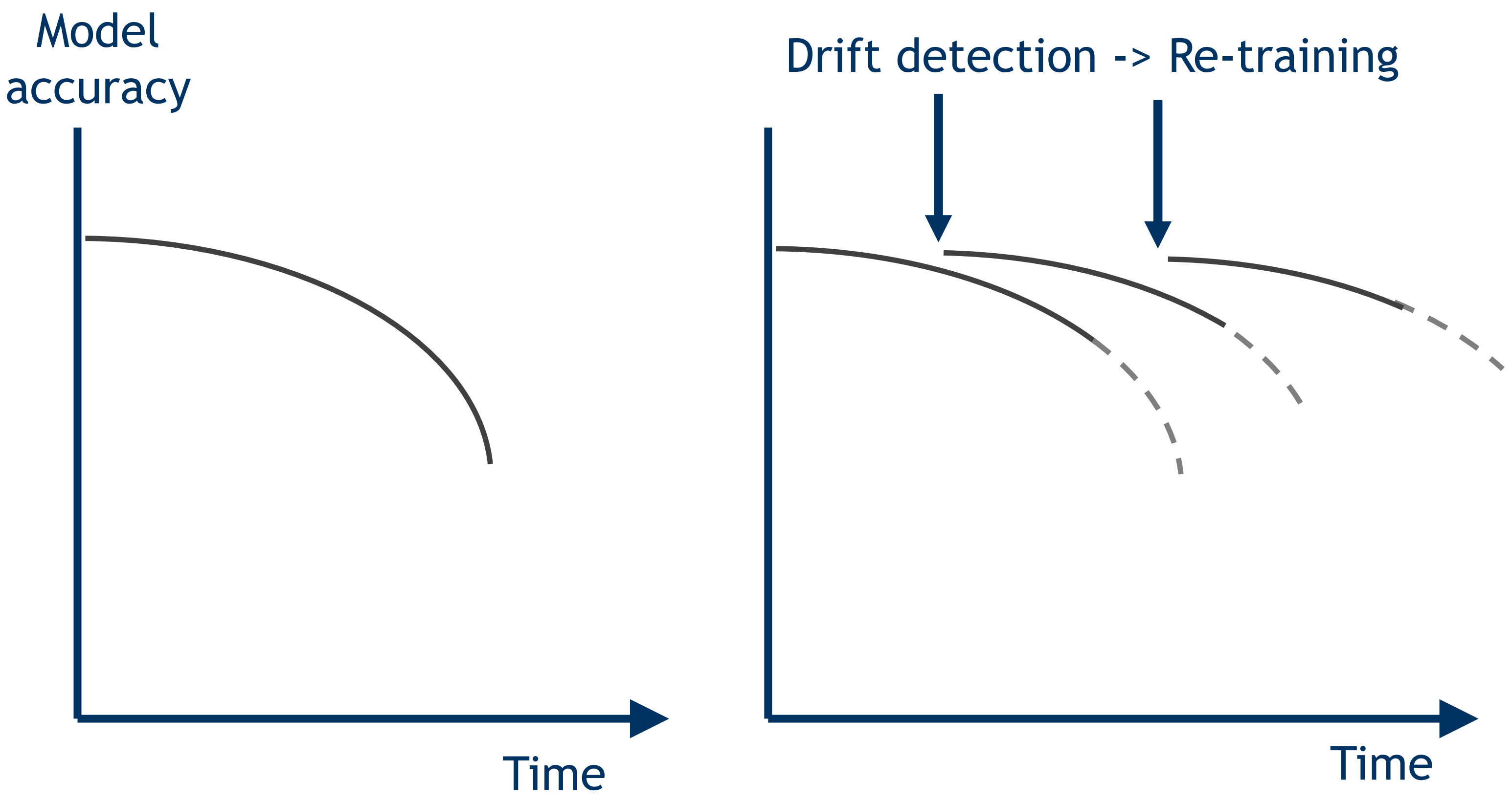
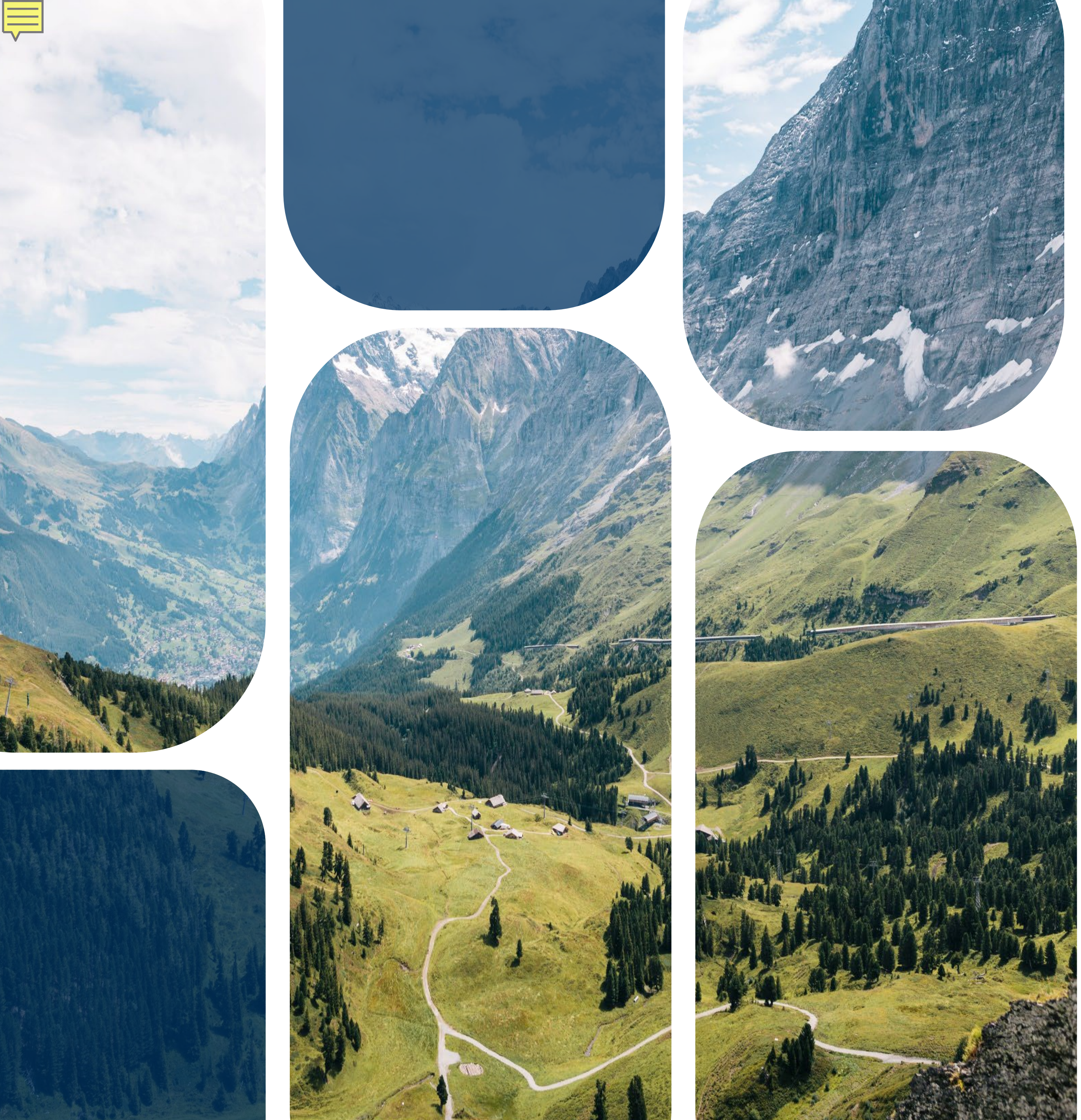


Figure adapted from Dral and Samuylova 2020



Thank you for listening

I will now take any questions.

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ValPar.CH https://valpar.ch/index_de.php

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@Blen_Back

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