Work package number	2	Lead beneficiary	TARTU		
Work package title	Causal knowledge discovery				
Participant number	1	4	5	8	3
Short name of participant	EAWAG	TARTU	EPFL	URV	SCITE
Person month per participant	24	24	6	6	6
Start month	7				
End month	30				

Objectives

- To develop an evolutionary-diversification AI-inspired framework for causal discovery
- To derive functionality rules required for causality-based computation discovery
- To apply diversification rules to mimic the empirical patterns for the Oceans' sustainability case study

Description of work

Task T2.1: Develop EEDA algorithms (M7-M24) *Leader:* ***EAWAG****. Contributors: 1*

T2.1 provides process-based algorithms with diversifying traits and interactions for species, human groups and technologies to allow WP2 to implement this feature in causal knowledge discovery. Causal modeling is particularly relevant in Earth, Ecosystem and Sustainability science where rapid progress of AI in explainable technology [4, 16, 27, 28] will increase our ability to make stronger inferences about future sustainability challenges and solutions [29]. EEDA solutions will be required to explore a broad range of sustainability scenarios, particularly relevant to find diversification rates in species, technologies and human strategies that best represent the empirical observations for the sustainability of the Oceans data knowledge discovery generated in WP1.

Task T2.2: This task extends T2.1 into EEDA deep learning networks metrics for general principles of causal discovery (M7-M24) *Leader:* ***TARTU****. Contributors: 4*

Using as input the knowledge graphs extracted from WP1, the goal of this task is to use deep learning technology to infer sustainability paths. In particular, this task will train graph neural networks (specifically designed to handle network data) to predict the effects of the complex interactions between species, human groups and exploitation technology. Simulations and the Ocean case will be first studied and calibrated. Once the deep learning model is trained, causal perturbations on the inputs and biases towards sparse models will be implemented to give an explainable account for the key causal interactions. Finally, the model will be optimised with respect to human interventions to aim the ecological system under study towards plausible sustainability paths.

Task T2.3: Based on the framework developed in T2.1 and T2.2, URV will derive automation rules for causal discovery (M21-M27) *Leader:* ***URV****. Contributors: 8*

URV will complement T2.1 and T2.2 to obtain scenarios of EEDA that represent the causal knowledge discovery graphs that best represent the empirical patterns. URV will work together with T2.1 and T2.2 to address the fit-complexity trade-off and to obtain the posterior probabilities for the rules and expressions generated with the EEDA.

Task T2.4: Causal reproducible knowledge graphs (M15-M21) *Leader:* ***EPFL****. Contributors: 5*

In this task the EPFL will integrate the work done in T2.1 and T2.2 into reproducible and replicable causal knowledge graphs. T2.4 samples the causal graphs to obtain the robustness of the inference. Robustness will be analyzed working closely to the URV partner in T2.3.

Task T2.5: In this task SCITE will apply visualization algorithms to T2.1 and T2.2 (M21-M27) *Leader:* ***SCITE****. Contributors: 3*

Spatial and networks patterns will be represented in static (figures) and dynamic (animations) visualizations using cutting-edge graphic libraries like $D3.js$, $Vega.jl$, $NetworkD3.js$, Leaflets, and $ggplot2$. Animations will represent the EEDA and deep learning networks patterns. Storytelling techniques will be applied in order to effectively communicate those findings.

Task T2.6: All participants apply results from EEDA and deep learning networks into a fully automated, reproducible and animated Oceans' sustainability case study (M21-M30) *Leader:* ***EAWAG****. Contributors: 1,3,4,5,7,8*

EEDA and deep learning networks will generate the sustainability of the Oceans causal knowledge graph (Figure 2).

Deliverables

D2.1 Report on definition of EEDA rules for causal discovery **(M18)**

~~**D2.2** Report on definition of EEDA deep learning networks applied to causal computation discovery **(M18)**~~