Participatory Socio-Environmental Systems Modeling over Knowledge Graphs

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Anastasios Zafeiropoulos
National Technical University of Athens

Eleni Fotopoulou
National Technical University of Athens

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Anastasios Zafeiropoulos
Institute of Communication and Computer Systems
National Technical University of Athens
Athens, Greece
tzafeir@cn.ntua.gr

Eleni Fotopoulou
Institute of Communication and Computer Systems
National Technical University of Athens
Athens, Greece
efotopoulou@netmode.ntua.gr

Symeon Papavassiliou
Institute of Communication and Computer Systems
National Technical University of Athens
Athens, Greece
papavass@mail.ntua.gr

***Abstract*—By considering the dynamicity and complexity that is present in modern Socio-Environmental Systems along with the misalignment in the usage of terms that are used by scientists in different disciplines, there is a need to support new ways of modelling and analysis based on the establishment of synergies and the collaboration among scientists. To address this challenge, we present a novel paradigm for modeling of Socio-Environmental Systems that aims to enable interdisciplinary scientists to realise participatory, reproducible and easily extensible modelling and analysis, across different temporal and spatial scales. To conceptualize the overall paradigm, emerging technologies for knowledge management and analysis are exploited, such as Knowledge Graphs and Machine Learning techniques. Knowledge Graphs are used as a variant of a semantic network, where constraints, structural elements and characteristics of nodes and links are continuously evolving. Machine Learning techniques are used for populating the Knowledge Graph with different types of data, as well as supporting analysis and inference processes over the produced knowledge. A proof of concept scenario has been implemented, focusing on the tracking of indicators specified in the Sustainable Development Goals.**

***Keywords*—knowledge graph, participatory modeling, socio-environmental system, machine learning, sustainable development goals**

I. Introduction

Nowadays, we have reached a critical point where human communities are having a drastic impact on natural environments, and vice-versa, the natural phenomena affect our societies in an unprecedented manner. The fundamental and unavoidable interplay between natural and societal systems needs to be jointly modelled and analysed to understand the basic underlying factors that will enable us to gain different capacities of control over it in the future, while ensuring a more virtuous cycle between human communities and natural environments.

Participatory Socio-Environmental Systems (SES) modeling is emerging, as an approach to characterize and explore complex societal and environmental issues in systematic and collaborative ways. Participatory SES modeling has an interdisciplinary perspective, integrating knowledge from various disciplines into conceptual and computational tools that can help to investigate complex problems among human and natural systems [1]. It can be applied over modern SES, that in many cases can be viewed as Socio-Cyber-Physical Systems (SCPS) [2], and as such present several of the characteristics and challenges of the dynamic, evolving, complex systems.

To support participatory SES modeling, a set of challenges have to be tackled, as detailed at [1]. Due to the interdisciplinary nature of SES modeling, it is important to bridge concepts coming from the epistemological pluralism across disciplines. Continuously evolving, interdisciplinary and semantically-expressive data representation schemas have to be developed and maintained, considering concepts related to environmental resources management (e.g., conceptual representation of pollutants, water/air quality indicators, pollution levels), cognitive, behavioural and group dynamics (e.g., cohesion levels, behavioural change, environmental friendly lifestyle), environmental economics and policies formulation.

Even by harmonizing terms among the various disciplines, the dynamicity of the considered systems and models makes challenging the mapping of the available data to well-defined concepts. There is a need for representation and analysis of rather diverse data in terms of volume, structure, spatial and temporal granularity and above all, source of origin. Representation and validation of concepts is a dynamic process, where data and models should be managed and interlinked as they change, while missing attributes, real causal links and relationships may be identified and assessed on-the-go. In this direction, novel techniques of treating and accounting for heterogeneous and diverse in nature and volume data, along with the emerging advances in computational power capabilities, are fundamental enablers in offering a new paradigm shift towards embedding intelligence in traditional environmental modeling.

To improve prediction of SES evolution in terms of accuracy and depth, considering their dynamic nature, novel analysis methodologies are required taking advantage of graph networks analysis and machine learning (ML) techniques. Identification of sources of uncertainty is critical, whether this is due to the model structure or the collected data. Uncertainty types and sources have to be identified, prioritized and managed throughout the whole modeling process [1]. Environmental impact assessment has to be realized and translated into quantifiable effects for the environmental problem in question. Furthermore, there is a need to track and improve the interaction between humans and the environment, considering continuous feedback loops through observing systemic changes, as well as changes in perceptions and attitudes.

A. Contribution and Outline

The aforementioned challenges create the need to introduce new ways for managing the plethora of data collected by smart environmental sensing systems and national or international observatories. A fundamental modeling transformation has to be introduced at the data provision level, where we move from the traditional data world perspective towards a knowledge world perspective. Towards this direction, in the current work, we detail a novel participatory modelling paradigm, aiming to enable interdisciplinary scientists to realise participatory, reproducible and easily extensible SES modelling and analysis, across different temporal and spatial scales.

To achieve so, we take advantage of emerging technologies, namely Knowledge Graphs (KGs) [3] and Machine Learning (ML) techniques. A KG is considered as a variant of a semantic network, where constraints, structural elements and characteristics of nodes and links are continuously evolving based on the processing of the collected data. KGs are essential for organizing available data, discovering and representing relationships, and enabling inference and knowledge extraction in a comprehensive manner and in its full capacity. Semantic consistency is introduced, considering the ontological differences across disciplines. ML techniques are used to support data fusion mechanisms for mapping data to knowledge in the KG, as well as for analysis purposes for extracting insights based on the data made available in the KG.

Following, upon a short overview of the concept of KGs, the overall approach for enabling participatory SES modelling over KGs is presented. The approach is accompanied with the development of a proof of concept scenario, targeted to the monitoring of indicators and public interest related to concepts specified by United Nations (UN) as the Sustainable Development Goals (SDGs).

II. Background Knowledge on Knowledge Graphs

The main idea under the concept of a Knowledge Graph (KG) is the usage of graphs to represent data, often enhanced with some way to explicitly represent knowledge [3], [4]. Graphs provide an abstraction of the knowledge for a wide range of application domains, where the edges of the graph represent relationships between the nodes that may evolve across time. They allow the maintainers to postpone the definition of a schema, allowing the data to evolve in a more flexible manner, characteristic that is considered very helpful in cases where someone has to represent incomplete knowledge [3], [5].

Under this perspective, data modelling and conceptual representation in the form of a Knowledge Graph (KG) is a promising technology. Through KGs, enabled by advanced data fusion techniques, we can achieve extraction and representation of knowledge from unstructured/structured data sources, manage data and models as they change, discover missing links across the KGs and complement pure statistical approaches with knowledge representations and reasoning. KGs are considered important for improving accuracy, explainability and trustworthiness of machine learning models [6].

A KG can complement the functionalities provided by data repositories by mining data from them and enriching them semantically [7] or by discovering new datasets on the web via semantic crawling mechanisms [8]. Furthermore, by exploiting statistical relational learning techniques, prediction of missing edges, prediction of properties of nodes, and clustering of nodes based on their connectivity patterns can be realised [6].

Various approaches have been made available the last years for developing KGs and associated applications for tackling social good aspects. Such KGs are mainly targeted to environmental and health domains. For instance, in [9], it is proposed the development of a global Climate Action KG to enable the rapid discovery of new insights and knowledge and the efficient exploration of important connections between domains (e.g., water, energy) and/or stakeholders.

III. Participatory Socio-Environmental Systems Modeling Approach

The proposed approach for supporting participatory SES modeling is depicted at Figure 1. The approach is separated in three conceptual parts. The first part regards the conceptualization and continuous population of the KG, fusing data coming from a variety of data sources. The second part regards the support of participatory SES modeling to capture systemic changes, taking advantage of the knowledge in the KG and the existence of mature modeling techniques. The third part regards the support of a set of analysis processes that can be used to assess the impact of various scenarios, based on the outcomes of the modeling process in the second part.

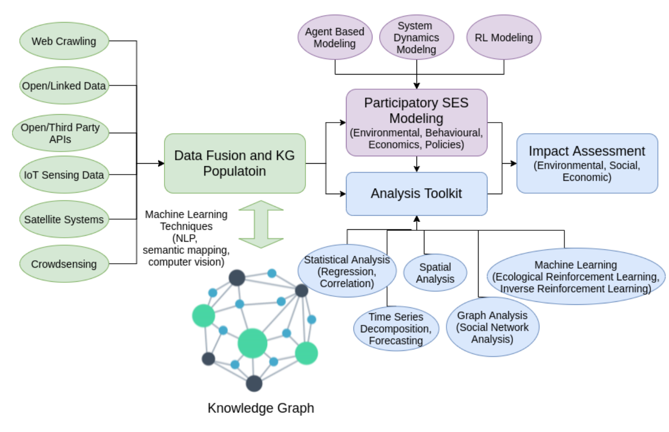

Fig. 1. Participatory SES Modeling Approach.

A. Data Fusion and Knowledge Graph Population

A KG is a graph that contains explicit knowledge and facts. With the term explicit knowledge, we refer to the conceptualization of the entities of the KG and the relationships among them. The definition of explicit knowledge is usually the first step towards the creation of a KG. Existing knowledge from ontologies, information models and taxonomies is used for this purpose. The represented explicit knowledge is not static, since entities can be added or removed on the go, while relationships can be also created or updated. This is a live process that runs in parallel with the population of the KG with instance data.

The latter is known as facts and can be imported by any type of structured, semi-structured or unstructured data source. Such data regard open data and linked data in open data repositories (e.g., time-series data, documents, directives, policies in textual format), data that can be consumed through open or third-party Application Programming Interfaces (APIs), data provided by environmental sensing systems (e.g., time-series data from IoT nodes), data collected from existing organizations and citizens' observatories, data coming from satellite systems (e.g., images) and data retrieved through semantic crawling of web resources. Such data can be processed in real time or stored in centralized repositories prior to their processing.

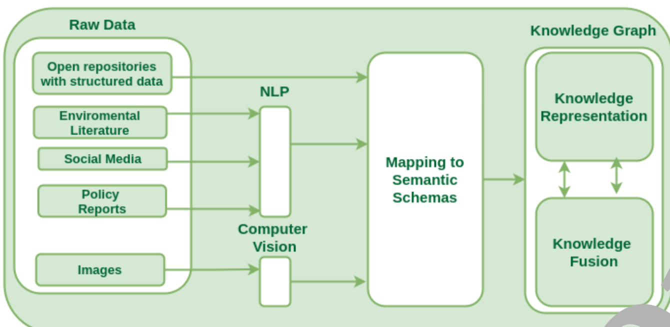

Fig. 2. Data Fusion Mechanisms.

In addition to the heterogeneity of the origin of the sources of these data, they also differ in terms of structure, volume and spatial and temporal granularity. To be able to process them in a unified way and populate the KG, a set of data fusion and homogenization mechanisms are applied as depicted at Figure 2. Data fusion is based on processing techniques that increase the quality of the aggregated data (e.g., outliers' removal, data aggregation in temporal or spatial scale) as well as techniques able to extract knowledge over the data. In the latter case, various ML techniques can be applied for identifying hidden relationships, supporting link prediction and continuous links and relationships validity and strength evaluation. In case of data in textual format, entities recognition can take place through Natural Language Processing (NLP) techniques, while computer vision techniques can be applied for knowledge extraction over images.

B. Participatory SES Modeling

Following, participatory SES modeling can take place, taking advantage of the homogeneous and expressive representation of the collected data in the KG. Participatory SES modelling involves developing models to investigate complex problems arising from interactions among human and natural systems [1]. Scientists have access to a dynamically updated repository of knowledge, where the denoted concepts and relationships are semantically aligned, considering their representation across different disciplines.

Various modeling techniques can be used for participatory SES modeling. These include agent-based modelling, system dynamics modeling and the development of reinforcement learning environments that simulate SES. The produced models may examine environmental, economics, behavioural and policy-making aspects or a combination of them.

Agent-based models (ABM) are key to SES modelling, since they simulate the actions and interactions of autonomous agents (both individual or collective entities) and can explicitly represent the decision-making of human actors [10]. Agent-based modelling is considered a valuable tool for SES materialization enabling the exploration of the impact of human interactions on a broad range of social and ecological patterns [11]. System dynamics is a methodology and mathematical modeling technique to frame, understand, and discuss complex issues and problems. While agent-based models are used to describe disaggregated parts of a system, system dynamics models represent the aggregated system in the form of stocks and flows [12].

SES participatory modeling can be also assisted by emerging Machine Learning (ML) techniques. For instance, someone can blend the reinforcement learning (RL) approach with ABM so as to better capture the probabilistic nature of the ecological footprint that may have a group action towards environmental sustainability. As stated before, ABM modeling is based in the definition of some rules that are defined by domain experts. This means that modeling rules affecting an agent's states and actions are known beforehand. Integration of RL agents at ABM modeling can better represent real life phenomenons where environmental variables may evolve over time and are not always known in depth. Discovering these rules is often challenging and requires deep insight about an agent's behaviours. Inverse reinforcement learning (IRL) can complement ABM by providing a systematic way to find behavioural rules from data [13]. At this approach, rules are extracted from the same data and get dynamically shaped during the learning process. IRL frames learning behavioural rules as a problem of recovering motivations from observed behaviour and generating rules consistent with these motivations.

C. Analysis Toolkit and Impact Assessment

The produced participatory SES models will be available to scientists for their analysis, taking advantage of both the models and the up-to-date data in the KG. A set of analysis techniques can be applied for extraction of insights. Such techniques may include pure statistical analysis, spatial analysis, graph analysis, time series analysis or application of specific supervised or unsupervised ML techniques.

Pure statistical analysis may be applied in small and medium size data and proceed -among other- with detection of data clusters, classification in high level categories or identification of hidden correlations among data. Spatial analysis is applicable in many cases, since most environmental problems have a clear spatial dimension [14]. Tracking of evolution of environmental phenomena, identification of specific locations for objects or events given certain well-defined socio-environmental criteria, survey for protected areas that are close to industrial sites are examples of types of spatial analysis that can be applied. Graph analysis offers a large set of potential techniques such as Social Network Analysis (SNA), where social structures are observed through the use of networks and graph theory. For instance, SNA can help to explain natural resources governance in diverse settings, to examine how decision makers adapt to a changing social and ecological context and to understand the transmission of local ecological knowledge [15]. Time series decomposition permits the detection of patterns that are repeated in time and can be useful for forecasting the future evolution of SES phenomena.

Various ML techniques can be applied for analysis of the collected data, in accordance with the developed SES models. ML can be applied in various settings, especially in cases where traditional techniques fail to capture the relationships between variables. Based on data exploration, new knowledge can be produced, while ecological patterns recognition and prediction in space and time may take place. For instance, in Section III-B, we refer to the integration of RL agents at ABM modeling to better represent real life phenomena.

Moving one step further, by taking advantage of the developed SES models and analysis mechanisms impact assessment processes may take place. Impact assessment may regard environmental, social, economic aspects or a combination of them. Examination of the impact of different scenarios can be facilitated through the production of easy to grasp visualisations related to Key Performance Indicators (KPIs) monitoring.

IV. Proof of Concept Implementation

A proof of concept implementation of the proposed approach has taken place and is made openly available at [16]. The implementation focuses on the development of a KG that represents concepts related to the SDGs. Information related to specific series, targers, indicators and goals per country is enriched with published articles in the media and associated metadata. The objective is to track the status of country-specific KPIs, as they have been defined in the 2030 Agenda for Sustainable Development, while examining the overall interest of the public in the area of each SDG based on the identification of relevant news items. In this way, scientists from various disciplines can proceed to SES participatory modeling and prepare different impact assessment reports. In the proof of concept, an existing model has been adopted and examined, related to the impact of CO_2 emissions into the increase of the temperature. The overall workflow followed in the developed scenario is depicted at Figure 3.

The KG population starts with the integration of the SDG ontology (step 1) that has been developed to represent the United Nations (UN) SDGs [17]. The SDG ontology includes four main classes namely sdgo:Goal, sdgo:Target, sdgo:Indicator and sdgo:Series that represent the SDG hierarchy [17]. The KG has been implemented in the Neo4j graph database platform, where the neosemantics (n10s) plugin has been used to enable the use of RDF. After the integration of the SDG ontology, all the necessary RDF prefixes and namespaces are imported (step 2) to support the semantic alignment with future data comming from open third party APIs or web crawling sources. Following, the United Nations SDG API [18] has been used (step 3) to retrieve all available goals, targets, indicators and series instances. With the help of the APOC Neo4j's standard library, the retrieved instances were imported in the KG (step 3) and interlinked with a set of relations with the specific classes of the SDG ontology.

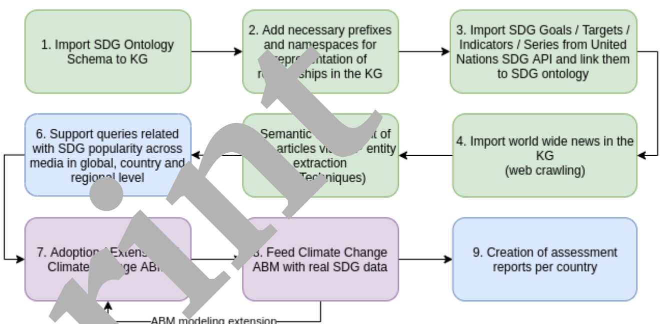

Fig. 3. Participatory SES modeling scenario workflow.

At this point the explicit knowledge of the KG is produced, making the KG ready to be populated with facts from other third part APIS. Such facts are retrieved on a daily basis within the News API [19] that locates articles and breaking news headlines from news sources and blogs across the web. Each news item is added as a new node in the KG (step 4) with specific fields (title, description, content, url). After the insertion of the new "article" nodes to the KG, it is necessary to proceed to the semantic enrichment of the news items via NLP techniques (step 5). This step is necessary since up to now KG explicit knowledge contains only classes and instances related with the SDG ontology and is not interlinked with the "article" facts retrieved from the web.

The nodes with the news articles are interlinked with relevant wikipages applying both the neo4j APOC NLP entity extraction library and the Google Cloud Platform Entity Extraction procedures. Furthermore, the LinkedSDG API [20] is used to automatically discover the semantic links between news items content with relevant SDG data series. Each one of the news items is interlinked with one or more geographic areas with some weight, where the bigger weights refers to larger identification of news articles for this area. Similarly, each news item is interlinked with one or more data series, which are already mapped to specific indicators, target and goals. The interlinking is characterized with a specific value that gives a hint regarding the semantic closeness of the news item with the concept measured in the data series. An indicative example for the relationships of a news item is depicted at Figure 4. This news item (orange node) is semantically close to approximately 20 SDG data series (grey nodes), while 6 geographic areas (brown nodes) are noticed.

Fig. 4. Identified relationships for a news item.

Upon the population of the KG, the modeling and analysis process may take place. In our case, we have focused on the specification and application of a set of queries to extract knowledge over the KG (step 6). The objective is to show the feasibility for interlinking information from various sources and making queries over it for jointly analysing the fused data. In Figure 5, we provide the results of an indicative query regarding the latest news items that are related with a specific SDG (end poverty in all its forms everywhere) represented as a green node. The metadata of the news items are also included in the query results. The orange nodes refer to indicative relevant news items to the specific goal, while each news item refers to specific geographic areas (brown nodes) and shows semantic proximity to specific wikipages (red nodes).

Similarly, a query is applied that depicts (Figure 6) recent news items (published one day ago) that are relevant to SDGs and refer to Europe. A small set of the identified articles are included in the figure to avoid its overloading. For each news item, there is information regarding its relationship with existing data series and the associated indicator, target and goal. Based on the outcomes of the query and the produced visualisation, the scientists are able to focus on articles that regard different levels of the SDG hierarchy and geographic areas. This may be useful for locating SDG issues of high interest on behalf of the media and try to use the relevant SDG data series to develop ABM models that can contribute towards the specification of socio-environmental policies.

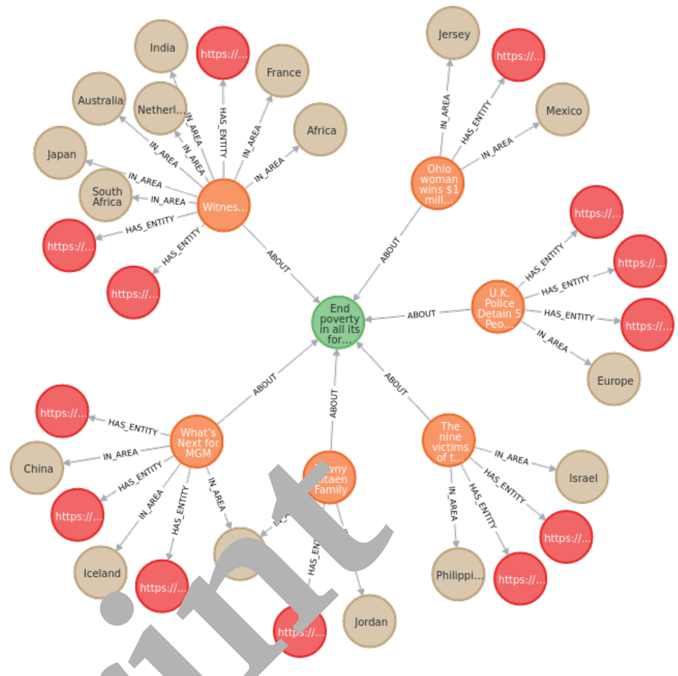

Fig. 5. Identified relationships for a specific Sustainable Development Goal.

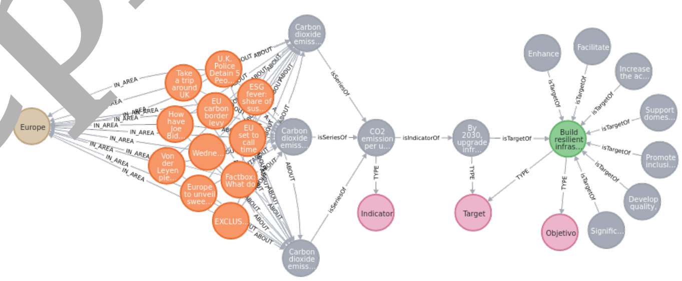

Fig. 6. Identification of popular subjects in the media in a specific area.

Based on the produced results, it is noticed high interest in news related to the carbon dioxide emissions from fuel combustion in Europe. To examine the level of emissions and their impact on the environment, we have adopted an existing ABM model (step 7) [21] that considers the greenhouse gases that block infrared light that is emitted by the earth. This model can be fed with real data (step 8) regarding the carbon dioxide emissions from fuel combustion (millions of tonnes) [22] per area. The model depicts the earth as rose colored, while its surface is represented by a green strip (Figure 7). Above the strip there is a blue atmosphere and black space at the top. Clouds and CO_2 molecules can be added to the atmosphere to examine the effect on the blocking of sun ray and the associated heating up of the examined area.

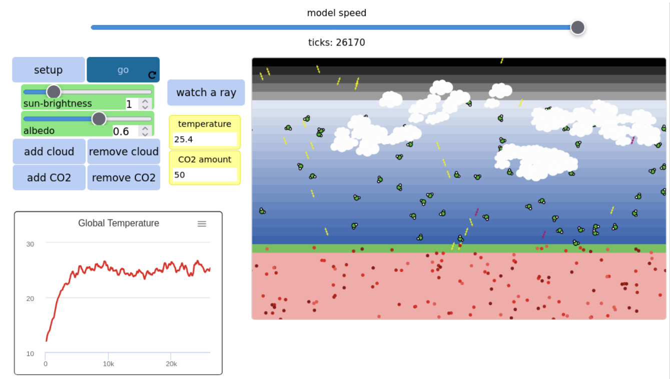

Fig. 7. Agent Based model regarding energy flow (heat) in the earth.

A set of simulations can be executed based on the adopted model to check how CO_2 emissions from fuel combustion affect the temperature in the various areas of our planet. Based on the analysis results, the impact of the evolution of CO_2 emissions on the temperature can be examined, considering various projections and testing scenarios (step 9).

V. Conclusions and Future Work

In the current manuscript, we have presented an approach for enabling participatory SES modeling and analysis, taking advantage of the transition from the traditional data world perspective towards a knowledge world perspective. Data representation and access is provided through a Knowledge Graph, enabling the homogeneous representation of data across various disciplines and the tracking of the evolution of the established relationships across time. The presented approach tackle the overall lifecycle of socio-environmental data aggregation, fusion, modeling and analysis, while it is open and modular in order to be easily adoptable and extensible in the future. A proof of concept has been implemented and made openly available, related to the development of a KG for tracking the evolution of SDG indicators.

In our upcoming work, we plan to develop an open source framework that will provide access to the proposed mechanisms to interdisciplinary scientists through user-friendly interfaces. We also envisage to further populate the developed KG for SDGs by covering further data sources and techniques.

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References

[1] S. Elsawah, T. Filatova, A. J. Jakeman, A. J. Kettner, M. L. Zellner, I. N. Athanasiadis, S. H. Hamilton, R. L. Axtell, D. G. Brown, J. M. Gilligan, M. A. Janssen, D. T. Robinson, J. Rozenberg, I. I. T. Ullah, S. J. Lade, Eight grand challenges in socio-environmental systems modeling, Socio-Environmental Systems Modelling 2 (2020) 16226.

[2] R. Calinescu, J. Cámara, C. Paterson, Socio-cyber-physical systems: Models, opportunities, open challenges, in: 2019 IEEE/ACM 5th International Workshop on Software Engineering for Smart Cyber-Physical Systems (SEsCPS), 2019, pp. 2–6. doi:10.1109/SEsCPS.2019.00008.

[3] A. Hogan, E. Blomqvist, M. Cochez, C. d'Amato, G. de Melo, C. Gutierrez, J. E. L. Gayo, S. Kirrane, S. Neumaier, A. Polleres, R. Navigli, A.-C. N. Ngomo, S. M. Rashid, A. Rula, L. Schmelzeisen, J. Sequeda, S. Staab, A. Zimmermann, Knowledge graphs (2021). arXiv:2003.02320.

[4] N. Noy, Y. Gao, A. Jain, A. Narayanan, A. Patterson, J. Taylor, Industry-scale knowledge graphs: Lessons and challenges, Commun. ACM 62 (8) (2019) 36–43. doi:10.1145/3331166.

[5] S. Abiteboul, Querying semi-structured data, in: F. Afrati, P. Kolaitis (Eds.), Database Theory — ICDT '97, Springer Berlin Heidelberg, Berlin, Heidelberg, 1997, pp. 1–18.

[6] M. Nickel, K. Murphy, V. Tresp, E. Gabrilovich, A review of relational machine learning for knowledge graphs, Proceedings of the IEEE 104 (1) (2016) 11–33. doi:10.1109/JPROC.2015.2483592.

[7] S. Schmid, C. Henson, T. Tran, Using knowledge graphs to search an enterprise data lake, in: P. Hitzler, S. Kirrane, O. Hartig, V. de Boer, M.-E. Vidal, M. Maleshkova, S. Schlobach, K. Hammar, N. Lasierra, S. Stadtmüller, K. Hose, R. Verborgh (Eds.), The Semantic Web: ESWC 2019 Satellite Events, Springer International Publishing, 2019, pp. 262–266.

[8] X. Dong, E. Gabrilovich, G. Heitz, W. Horn, N. Lao, K. Murphy, T. Strohmann, S. Sun, W. Zhang, Knowledge vault: A web-scale approach to probabilistic knowledge fusion, in: Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '14, Association for Computing Machinery, New York, NY, USA, 2014, p. 601–610. doi:10.1145/2623330.2623623.

[9] M. Kaltenböck, D. Recheis, S. Bharwani, J. Barrott, Creating a global climate action knowledge graph to leverage artificial intelligence and speed progress on the climate agenda, Tech. rep. (2020).

[10] N. M. Gotts, G. A. K. van Voorn, J. G. Polhill, E. de Jong, B. Edmonds, G. J. Hofstede, R. Meyer, Agent-based modelling of socio-ecological systems: Models, projects and ontologies, Ecological Complexity 40 (2019) 100728. doi:https://doi.org/10.1016/j.ecocom.2018.07.007.

[11] M. Will, J. Groeneveld, K. Frank, B. Müller, Combining social network analysis and agent-based modelling to explore dynamics of human interaction: A review, Socio-Environmental Systems Modelling 2 (2020) 16325. doi:10.18174/sesmo.2020a16325.

[12] R. Martin, M. Schlüter, Combining system dynamics and agent-based modeling to analyze social-ecological interactions—an example from modeling restoration of a shallow lake, Frontiers in Environmental Science 3 (2015) 66. doi:10.3389/fenvs.2015.00066.

[13] K. Lee, M. Rucker, W. T. Scherer, P. A. Beling, M. S. Gerber, H. Kang, Agent-based model construction using inverse reinforcement learning, in: 2017 Winter Simulation Conference (WSC), 2017, pp. 1264–1275.

[14] C. E. Stocks, S. Wise, The role of gis in environmental modelling, Geographical and Environmental Modelling 4 (2) (2000) 219–235. doi:10.1080/713668590.

[15] M. Salpeteur, L. Calvet-Mir, I. Diaz-Reviriego, V. Reyes-García, Networking the environment: social network analysis in environmental management and local ecological knowledge studies, Ecology and Society 22 (1), publisher: The Resilience Alliance (Mar. 2017). doi:10.5751/ES-08790-220141.

[16] E. Fotopoulou, A. Zafeiropoulos, Repository for the development of the sdg kg, last accessed 01 October 2021 (2021).
URL https://gitlab.com/netmode/kg-sdg

[17] A. Joshi, L. G. Morales, S. Klarman, A. Stellato, A. Helton, S. Lovell, A. Haczek, A knowledge organization system for the united nations sustainable development goals, in: R. Verborgh, K. Hose, H. Paulheim, P.-A. Champin, M. Maleshkova, O. Corcho, P. Ristoski, M. Alam (Eds.), The Semantic Web, Springer International Publishing, 2021, pp. 548–564.

[18] United nations statistics division sdg api, last accessed 01 October 2021 (2021).
URL https://unstats.un.org/SDGAPI/swagger/

[19] News api, last accessed 01 October 2021 (2021).
URL https://newsapi.org/

[20] Linked sdg api, last accessed 01 October 2021 (2021).
URL http://linkedsdg.apps.officialstatistics.org/

[21] R. Tinker, U. Wilensky, Netlogo climate change model, Publisher: Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL. (2007).

[22] Sdg series: carbon dioxide emissions from fuel combustion (millions of tonnes), last accessed 01 October 2021 (2021).
URL http://metadata.un.org/sdg/EN_ATM_CO2