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A knowledge-driven service composition framework for wildfire prediction

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Abstract

Wildfire prediction has drawn a lot of researchers' interest, but still presents a computational difficulty since it necessitates real-time data collected from several distributed data sources. Furthermore, because environmental Web services have, now, access to a wider range of environmental data sources, services might be functionally similar but of varying quality. In this paper, we propose a knowledge-driven framework for service composition that is based on a layered architecture. Based on these layers, the proposed framework aims to select the optimal service instances participating in a service composition schema, through a modular ontology to infer the quality of data sources (QoDS) and an outranking approach. Moreover, it aims to executing the service composition schema at runtime by dynamically readjusting both the service composition schema and the service instances via a machine learning-based service composition approach. The conducted experiments showed that the proposed framework enables (i) a reasonable reasoning time for assessing the data sources' quality, (ii) a decrease in the ELECTRE III MCDM method's execution time achieved by combining the skyline and α-dominance methods, (iii) dynamic generation of the most relevant service composition schema with the appropriate wildfire risk classes, and (iv) a high prediction accuracy using our proposed outranking approach compared to the randomly selected services.

Keywords Dynamic service composition · Machine learning (ML) · Knowledge-driven approach · Multi-criteria decision making (MCDM)

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1 Introduction

Natural hazards such as earthquakes, typhoons, floods, and fires are severe threats. Wildfire occurrences, our application use case, present severe challenges that must be handled before they occur to take protective measures. Furthermore, building the wildfire prediction model is a computational challenge since it requires the collection of several environmental observations in real-time (e.g., air temperature, wind speed, etc.) from several heterogeneous distributed data sources. In this context, our PREDICAT (PREDIct natural CATastrophes)[1] project focuses on the prediction of natural disasters.

The main problem of the existing data sources lies in effectively exploiting and integrating various data services (i.e., named services in the rest of the paper) into a composite service for prediction purpose. Consider, for instance, choosing from a pool of services retrieving the essential features of interest relevant to wildfire, such as wind speed, relative humidity, air pressure, etc., accessing several distributed data sources. These data sources, along with their related services, are with different quality dimensions: Quality of Services (QoS) (e.g., response time, availability, cost, etc.) and Quality of Data Sources (QoDS) (e.g., trustworthiness, availability, accuracy, etc.). The data services can be provided by the data sources or any other meteorological service provider over the Internet [1]. They compete to provide the same feature with varying QoS. For instance, one can choose the cheapest service, the fastest service, or a compromise between the two. Hence, the first issue is which of these services one has to choose optimally, which persists as a significant problem in the service composition task while simultaneously considering the QoS and the QoDS. The second issue is determining the optimal service composition, which becomes more complex as new services are developed, upgraded, and as the Web environment goes dynamic, providing distributed large datasets that need to be qualified. The composition schema that orchestrates service calls needs to be constructed on the fly, considering on the one hand, services with particular QoS depending on the wildfire-context (i.e., a high or low wildfire risk) and the expert's needs, enabling them to assign high weights to the QoS and the QoDS, and on the other hand, considering observations of past wildfires and expert feedback. This issue consists of the composition schema to be performed, based on the historical observations and the wildfire danger context.

Thus, to address these raised challenges, the analysis of such competitive qualities and dynamically new emerging services necessitates innovative analytic techniques providing improved decision-making strategies for both the service selection and the service composition problems intended for wildfire prediction.

We propose in this paper a knowledge-driven and automatic framework for service composition based on quality-aware selected services for wildfire prediction. Our contribution promotes services with specific qualities (based on the wildfire context and experts' demands) rather than one-size-fits-all services. Also, the context-specific situation is figured out by executing the services within the composition schema, which predicts whether there is a high or low risk of a wildfire happening shortly. Our value-added contributions can be summarized as follows:

- The first contribution addresses the first issue, namely optimal service selection, by proposing a quality-aware and knowledge-driven solution for ranking and selecting optimal services. To guarantee the freshness and trustworthiness of the data sources, we propose an ontology defining quality dimensions along with their associated inferences for the data source quality assessment. Apart from the QoS of the candidate services, these dimensions are considered inputs in the skyline operator [2] and the MCDM technique, in particular ELECTRE III MCDM method [3], provides optimally ranked services with optimal qualities.
- The second contribution addresses the second issue of determining the optimal service composition. To this end, we propose a knowledge-driven approach for dynamic service composition intended for wildfire prediction. Furthermore, to guarantee automated and dynamically composed services while considering prior environmental domain knowledge, we present a wildfire prediction model based on machine learning (ML) methods, particularly decision-tree-based methods (DT). The DT helps produce service composition schemas for wildfire danger prediction and helps track the services' execution to identify possible readjustments.

The remainder of this paper is organized as follows: Sect. 2 overviews related works dealing with QoS-aware Web service selection and composition. Section 3 presents an overview of the layered architecture of the proposed framework. Section 4 details first our definition of the quality dimensions related to the data sources through our proposed Modular Environmental Source (MESOn) Ontology. Second, our outranking approach for optimal service selection. Section 5 presents our knowledge-driven approach to service composition. Section 6 details our framework's applicability and evaluation through several experiments. Finally, we summarize our results and present our future work in Sect. 7.

[1] https://sites.google.com/view/predicat/predicat

2 Related work

This section overviews related works about QoS-aware Web service selection participating in service composition and dynamic and automatic service composition approaches, including machine learning and MCDM approaches. Several approaches were proposed in the literature [4] to facilitate the composition of Web services by describing the services semantically. Furthermore, ontology-based approaches such that; [5] allow discovering Web services that meet the requested functional or non-functional parameters. Hence, automatic Web service composition is needed to enable automated logic-based service composition planning and more accurate service discovery.

Several approaches were provided to guarantee service composition dynamicity and automation. These include approaches based, on the one hand, on Artificial Intelligence (AI) planning [6], and on the other hand, on QoS-aware service selection for the composition using heuristics and meta-heuristics. However, AI planning approaches do not support the discovery of an optimal solution and necessitate a significant amount of time and memory to evaluate all feasible solutions with processing costs. Other works used Evolutionary Computing (EC) to automate the generation of composition solutions and the optimization of QoS Web service composition by dealing with an extensive service search space. A genetic algorithm (GA) is used in [7], to propose a composition solution. Although these solutions are a promising direction, efforts are still needed to enforce composition constraints and optimize the quality of solutions.

In the QoS-aware service selection problem, quality dimensions, or commonly named quality criteria, have always been considered paramount due to their direct impact on the selection process of the optimal services participating in a service composition problem. Many quality dimensions [8] are associated with the data sources, such as trustworthiness, accuracy, and timeliness. The survey carried out by [9] organizes the building blocks of the quality dimensions as a dataset profiling in a taxonomy, along with their assessment, summarization, and characterization processes. The dataset profiling is defined according to [9], as a set of characteristics, both semantic and statistical, that allow describing a dataset in the best possible way by taking into account the diversity of domains and vocabularies on the Web of data. However, one of the challenges in dataset profiling is performing the computation and interpreting the profiling results. Therefore, there is a need to reason about and evaluate the used dataset through a dedicated solution. Ontology can be a good candidate that interprets and explicitly evaluates the quality related to environmental data sources. Consequently, we promote in this work the usage of ontology to ensure the reasoning of the qualities on both levels: the data source and the data returned by the service accessing the data source.

Besides, the problem of QoS-aware Web service selection problem relies on exponential space complexity. Accordingly, recent studies focus on reducing the critical number of services candidates by using the skyline paradigm, introduced by Börzsönyi et al. [2]. However, the skyline method must still address the incomparability between service skyline candidates. Therefore, this solution may not give the users a hand in controlling the size of the returned skyline set, which may increase with a high number of quality dimensions. Furthermore, there is no information about the relationship comparison between the different candidates of the skyline services to select an optimal one. To tackle the QoS-based selection problem and rank the services, only a small number of research papers combined the skyline with MCDM-based techniques. Additionally, it is essential to emphasize that knowledge-driven MCDM approaches have recently been taken into account. Authors, in [10], proposed a new data- and knowledge-driven MCDM method to reduce the experts' assessment dependence. The authors used the extended data-driven DEMATEL method to specify the weight of the criteria. Moreover, the knowledge-driven ELECTRE and VIKOR methods ensure the alternatives' ranking. The TOPSIS [11] method was used in several studies as a decision support method, with different topics such as selecting property development location, etc. [12] or also implemented to mobile applications [13]. Authors, in [14], proposed a comprehensive ranking of Web services based on the CRITIC-TOPSIS method. In [15], authors used TOPSIS to select optimal services on the cloud. Moreover, authors in [16] developed a Web service selection approach based on sensitivity analysis, in which they compared the LSP (i.e., Logic Scoring of Preference) method with other MCDM methods (e.g., AHP, VIKOR, and TOPSIS). Authors in [17] proposed a novel framework called Optimal Service Selection and Ranking of Cloud Computing Criteria (CSS-OSSR). In this work, the authors used the TOPSIS method to obtain the final rank of the cloud services. Serrai et al. [18] combined the skyline with some MCDM methods (e.g., SAW, VIKOR, and TOPSIS) for service selection and ranking.

Our study can be related to previous works on the QoS-aware service selection problem to select the optimal services based on their quality dimensions automatically. However, these previous works do not consider the quality of the data sources (QoDS) or the dynamically changing environment of services. Furthermore, since the QoDS and QoS may constantly be changing, the service composition must be automatic, dynamic, and knowledge-driven. To our best knowledge, these studies overlooked the importance of providing analytical support to describe and infer the continually changing quality of the environmental data sources. At the same time, the composition solution may be able to learn from the environmental observations collected. As the dynamic composition of services is largely treated in the literature, our aim is not only to generate dynamically and adaptively composition schemas but also to consider both levels of qualities: QoS and QoDS. Therefore, we deem it relevant to consider the potential value impact of using Artificial Intelligence (AI), specifically machine learning techniques. Subsequently, the main emphasis of our study is on applying machine learning techniques to dynamically guide the build of the service composition schema in a knowledge-driven fashion.

3 Overview of the layered architecture of the proposed framework

To present our framework, we must first establish the precise specifications that meet the PREDICAT experts' needs. Our studied use case imposes the following requirements: (1) Real-time access, via service-based technology, to several data sources while taking their heterogeneity and geographic distribution into account. (2) Identifying the most important environmental features of interest, having a relevant impact on fire disasters. (3) Collecting based on dedicated services, the weather, and environmental features of interest in real-time, integrating them, and combining expertise to support decision-making. (4) Enabling PREDICAT experts to work with the accurate data returned by the optimal services while considering their related optimal quality in real-time. (5) Generating fire danger alerts based on the collected real-time data and on the real-time reasoned qualities considered for the data source and the data returned by the service accessing the data source. To fulfill all these specific requirements, our proposed knowledge-driven framework for service composition is based on a layered architecture (see Fig. 1). This architecture encompasses six layers, namely: (1) data source layer, (2) service layer, (3) application layer, (4) semantic layer, (5) data processing layer, and (6) user interface layer. Based on these layers, the knowledge-driven framework first targets the optimal services selection step while relying on the *Optimal Service Selection Module* and the *Quality Source Assessment Module*, colored in blue, in Fig. 1. Then, it considers the composition step thanks to the *Service Composition Module* and the *Prediction Module*, which are colored in red, in Fig. 1.

The data source layer contains the data sources related to environmental observations (e.g., NASA, Copernicus, OpenWeather, etc.).

The service layer contains the automatically generated RESTful (Representational State Transfer - [19]) services providing access to the heterogeneous environmental data sources [1].

The semantic layer includes the *Quality Source Assessment Module* that aims to assess the quality related to the environmental data sources by relying on an ontology called the Modular Environmental Source Ontology (MESOn). MESOn ontology describes and evaluates the environmental sources and their dynamically captured quality dimensions presented in Sect. 4.1. Furthermore, to infer and reason on the quality dimensions for a given data source, the *Quality Source Assessment Module* relies on SWRL (Semantic Web Rule Language) rules and the Pellet reasoner. Consequently, it provides, as an output, the QoDS inferences that will be used by the Bα-DSS (Best_α-Dominant_Skyline_Service) outranking approach to select an optimal service.

The data processing layer deals with both processes of selection and composition of services while achieving the following objectives: (i) selecting optimal service instances participating in a service composition schema through an outranking approach, (ii) executing the service composition schema at runtime, (iii) dynamically readjusting both the service composition schema and the service instances to fasten the wildfire predictions. To this end, the data processing layer encompasses the *Optimal Service Selection Module* and the *Service Composition Module*. The first module relies on the proposed Bα-DSS outranking approach to discard the non important services (i.e., the dominated services) and to rank the best alternatives that will participate in a service composition schema. While the second module considers, for each particular execution, the path from a decision tree model that is built based on the historical environmental observation dataset and the service instances selected through the Bα-DSS outranking approach. The composition schema could be dynamically readjusted after the execution of a service instance to be able to change the path if necessary, which requires selecting again, via the Bα-DSS outranking approach, the associated instances.

The application layer encompasses the *Prediction Module*, which is composed of two sub-modules: the *Learning Module* and the *Awareness Module*. The *Prediction Module* produces the service composition schemas for the wildfire danger prediction. The *Learning Module* builds the wildfire prediction model by applying a supervised classification algorithm (i.e, Decision Tree-DT). The *Awareness Module* aims to map DT paths to abstract service composition schemas and tracks the services' execution to identify any possible readjustments.

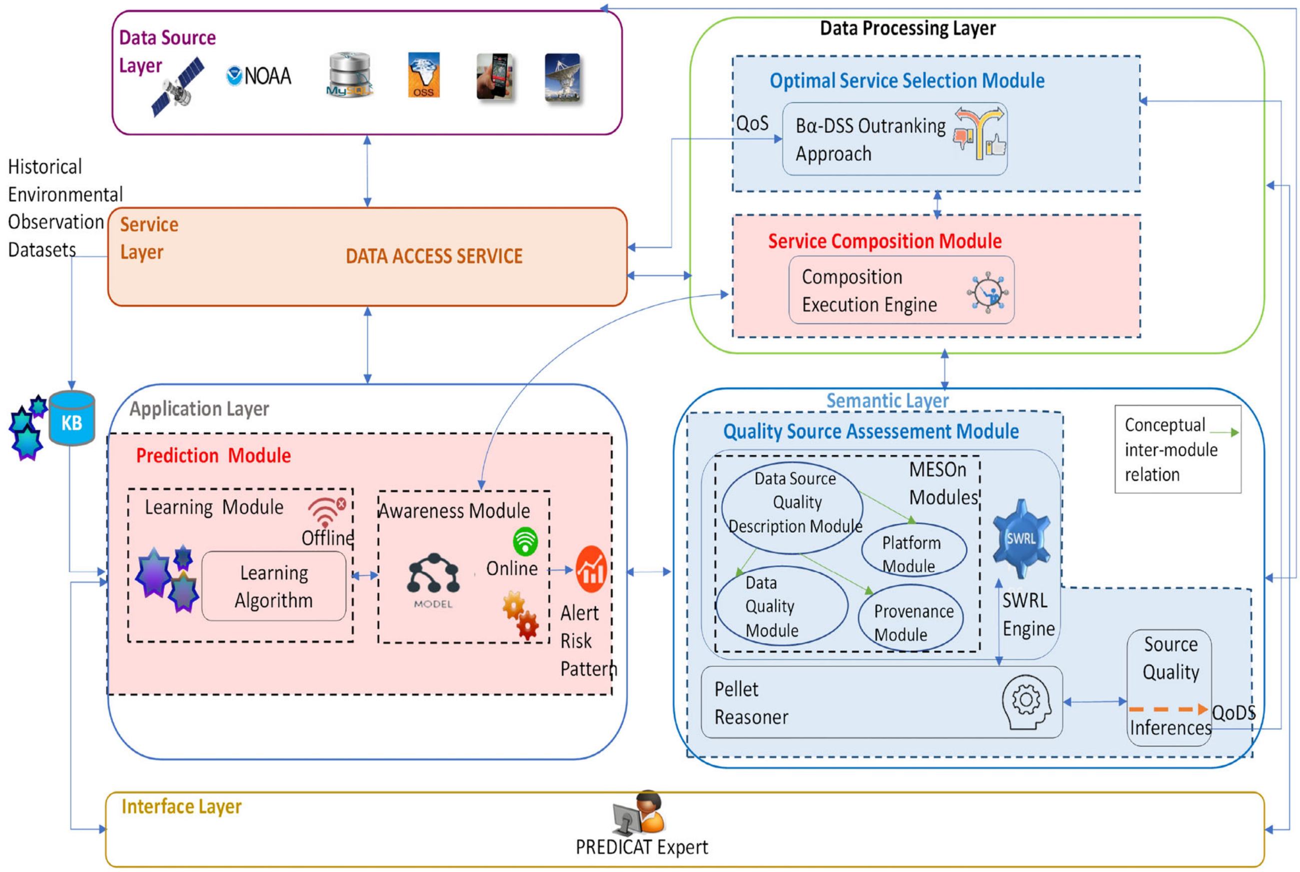

Fig. 1 Overview of the layered architecture of the proposed knowledge-driven framework

The user interface layer features a rich user interface that exposes the triggered fire danger alerts to the experts of the PREDICAT platform.

We present in the following section more details on the knowledge-driven approach for optimal service selection relying on both modules: the *Quality Source Assessment Module* and the *Optimal Service Selection Module*.

4 Knowledge-driven approach for optimal service selection

Considering that there are various data sources with varying qualities, either for the data or for the service retrieving the data, considering different quality dimensions is critical. These dimensions should be associated with the data source, the data, and the service that retrieves the data. The proposed knowledge-driven approach to optimal service selection seeks to identify the most relevant services for service composition based on the qualities of the data sources and the data (QoDS), apart from the Quality of Services (QoS). It relies on the data processing and semantic layers and undertakes a quality assessment process to achieve this goal. We tackle, in this section, the service selection approach, which considers, at the same time, the two levels of qualities. At first, we present the semantic aspects through the *Quality Source Assessment Module*, representing the MESOn ontology with its related quality dimensions. Second, we detail the processing aspects through the *Optimal Service Selection Module* with its related analytic methods.

4.1 Quality source assessment module

In what follows, we detail the selected quality dimensions the *Quality Source Assessment Module* uses. Then, we present the proposed MESOn ontology that helps infer the quality related to data sources and their inherent data.

4.1.1 Quality dimensions

In our study, quality dimensions include both data source and data qualities. Quality dimensions are commonly conceived as a multidimensional construct, where each dimension represents a quality-related characteristic relevant to the consumer (e.g., accuracy, timeliness, completeness, relevancy, objectivity, believability, understandability, consistency, conciseness, etc.) [20]. Furthermore, most of the time, quality dimensions are grouped into categories referred to as quality categories. The quality dimension groups one or more computed quality metrics; their values are considered quality indicators. We count 127 data quality dimensions from the literature as stated in [21]. Among these quality dimensions, and taking into consideration the objectives of our study for the *Quality Source Assessment Module*, we present, in the following, the ones considered with their related descriptions: *source accuracy*, and *trustworthiness* for the data source and *volatility*, *currency*, and *timeliness* for the data.

4.1.2 Computing the quality dimensions

Following, we propose to define and present how to compute the various dimensions considered in this work.

Source Accuracy: is defined as the percentage of its provided values that are consistent with the given gold standard, as described in [22].

$$SourceAccuracy = \frac{NG}{NT} \tag{1}$$

With NG Number of instances of data flagged as Good. NT Number of total values

Volatility: describes the time period for which information is valid in the real world. It is the length of time, where data remains valid, as in [22].

Currency: concerns how promptly data are updated regarding changes occurring in the real world, as in [22].

$$Currency = Age + Delivery\,Time - Input\,Time \tag{2}$$

With

- DeliveryTime: the time when the data are delivered to the user.
- InputTime: the time when the data are received by the system.
- Age: age of the data when first received by the system.

Timeliness: is the extent to which age of the data is appropriate for the task at hand.

$$Timeliness = \max(0, 1 - \frac{Currency}{Volatility}) \tag{3}$$

Trustworthiness: the trustworthiness category is composed of three dimensions: Believability, Reputation, and Verifiability.

- Believability: data are accepted or regarded as true, real, and credible [22].
- Verifiability: degree and ease with which the information can be checked for correctness [22].
- Reputation: is a judgment made by a user to determine the integrity of a source. It can be associated with a data publisher, a person, an organization, a group of people, or a community of practice, or it can be a characteristic of a dataset [22].

We decided to make trustworthiness a block because believability, verifiability, and reputation are all connected. A variety of computation methods for trustworthiness, including models, algorithms, summarizing and averaging user ratings, probabilistic systems, and reputation systems, were proposed by several authors. We choose models and tools as the two methods to evaluate trustworthiness. We used the 7Ws Model [23], which consists of replying to 7 questions; then, we calculate a score ranging from 0 to 7 based on the answers.

4.1.3 MESOn: a source ontology with quality dimensions

To evaluate the quality related to data sources and their inherent data, the *Quality Source Assessment Module* relies on the proposed ontology called Modular Environmental Source Ontology (MESOn). MESOn aims to define a common and shareable understanding of environmental data sources and to reason on the data sources' quality and their related data (QoDS). To the best of our knowledge, no ontology in the literature achieves this objective.

The MESOn is built modularly, a well-known good practice for high-quality ontologies that makes it easier to maintain and reuse. Several methodologies for ontology construction are proposed in the literature, such as: METHONTOLOGY [24] On-To-Knowledge [25], and Ontology Development 101 [26]. However, since we aim to design a modular ontology, we used the Agent Oriented Modeling (AOM) methodology [27], which is specifically adapted for this purpose. This methodology encompasses four phases, presented as follows: the exploration, the planning, the module development, and the release and maintenance phases. We explored the domain in the first phase and identified the concepts to be reused from ontology fragments and vocabularies. Besides, MESOn is built upon existing data quality ontologies and vocabularies to promote its interoperability. It includes, in particular, the quality dimensions related to the environmental data sources already described in the previous section, as well as imported fragments from the ontologies validated from the Dataset Quality Ontology (daQ) [28], Data Quality Vocabulary (DQV) [29], Data Catalogue Vocabulary (DCAT) [30], Data Usage Vocabulary (DUV) [31], PROV-O ontology [32], and SOSA/SSN Ontology. In the second phase, we identified several questions that helped clarify the ontology's design, such as: which data source is the most accurate? How is the data generated? What is a data

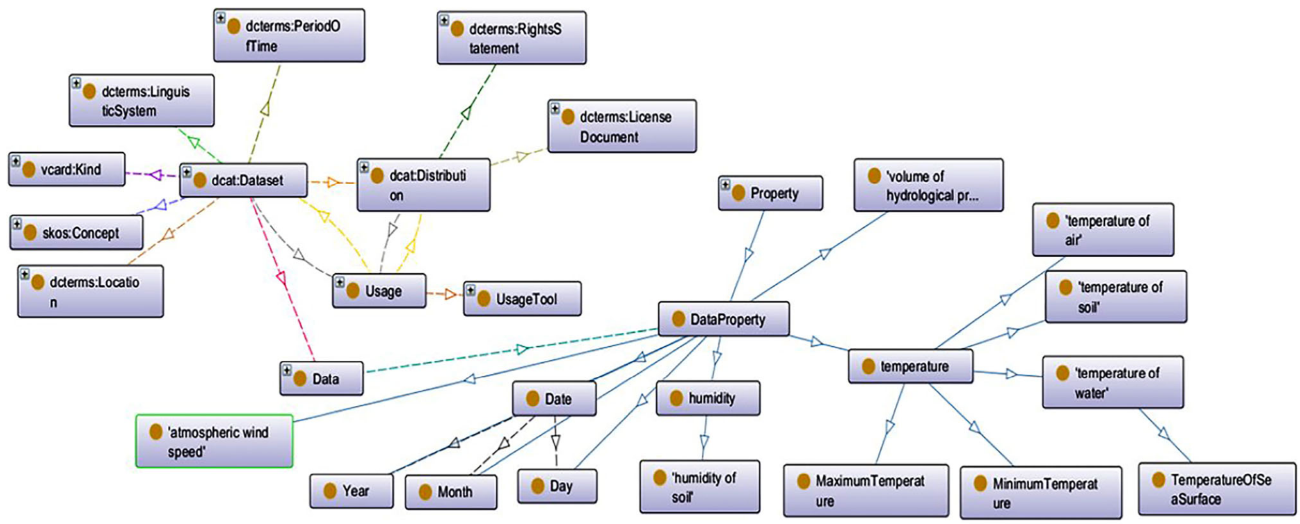

Fig. 2 The data source description module

source's file format? What is the tool allowing for the management of a data source? What instruments are used to capture the data?

The third phase of the ontology design is the module development phase, which consists of developing the following modules in the MESOn ontology.

- **The data source description module** This module deals with the description of the data source (see Fig. 2). The description consists of detailing the dataset (*dcat:Dataset*), with its characteristics; such that: the period of time (*dcterms:PeriodOfTime*), location of observations (*dcterms:Location*), the linguistic system used (*dcterms:LinguisticSystem*), the different forms of data it contains (*vcard:Kind*), and (*dcat:Distribution*), such as an XML dataset, a Web service, a database, etc., along with the specified data properties, such as the URL, the username, etc.
- **The data quality module** This module details the different quality characteristics, including the quality dimensions, standards, certificates, quality policies, and user quality feedbacks (see Fig. 3). It aims to provide an assessment of the quality of the environmental data sources and their related data, through the *SourceQuality* and the *DataQuality* classes. We have represented the computed quality dimensions according to the details given, in Sect. 4.1.2.
- **The provenance module** This module gives information about the data lineage (i.e., the origins of a data unit) and reuses fragments from the provenance ontology (PROV-o). The main concepts of this module are: *Entity*, *Activity*, and *Agent* (see Fig. 4). The *Agent* class represents the agent who manipulates the activities. An agent can be a *SoftwareAgent*, a *Person*, or an *Organization*. The *Activity* class is designed to show the activities responsible for generating the data. Agents and entities carry out these activities. The class *Entity* is designed to show entities dealing with data units.
- **Platform module** Fig. 5 represents the *Platform Module* with its related classes. It describes platforms that capture the environmental observations (e.g., temperature) and the hosted sensors (e.g., smartphones and satellites). Each sensor tracks an observable Property and its Feature Of Interest. As an example, air temperature is the observation required, measured by an IPhone. The platform is a smartphone represented by an individual named "IPhone 9-IMEI 35-207776-824955-0", containing a sensor represented by the individual "Bosch SensortecBMA253". The Observable Property is the "Air Temperature" and its Feature Of Interest is "Earth Temperature".

The created modules are used to develop the modular ontology, thanks to the interconnection between them, throughout the final phase, which is the release and maintenance phase.

In what follows, we present how the MESOn ontology was applied to evaluate the Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS) data source. CHIRPS is a 35+ year quasi-global rainfall data set offered by UCSB/CHG. It incorporates in-house climatology, satellite imagery, and in-situ station data to create gridded rainfall time series for trend analysis. We chose, for example, the dataset dealing with the year 2022, which contains precipitation observations [2] from January 1, 2022, to December 31, 2022. Since the MESOn ontology is empowered by inference rules that aim at reasoning and

[2] https://data.chc.ucsb.edu/products/CHIRPS-2.0

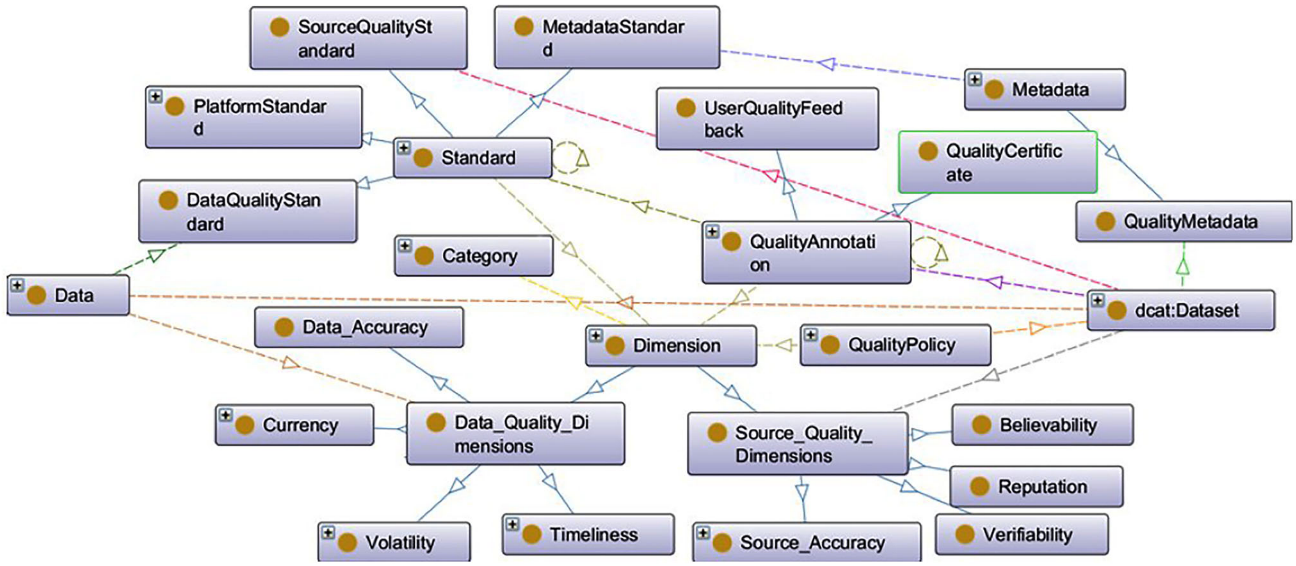

Fig. 3 The data quality module

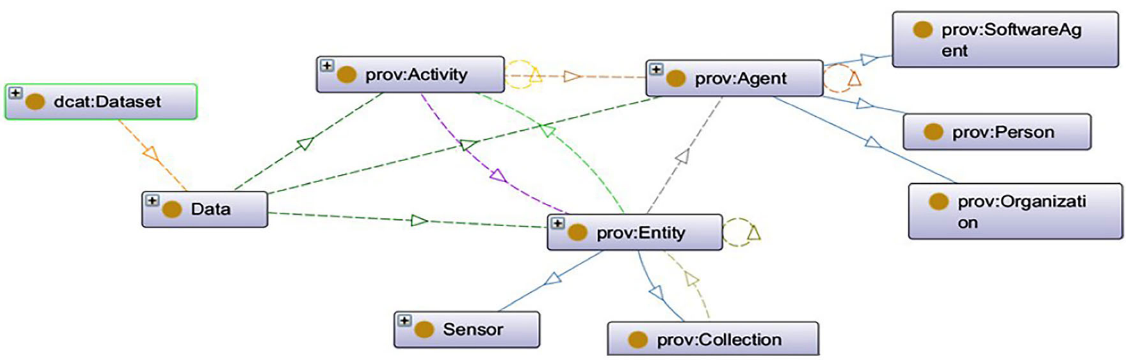

Fig. 4 The provenance module

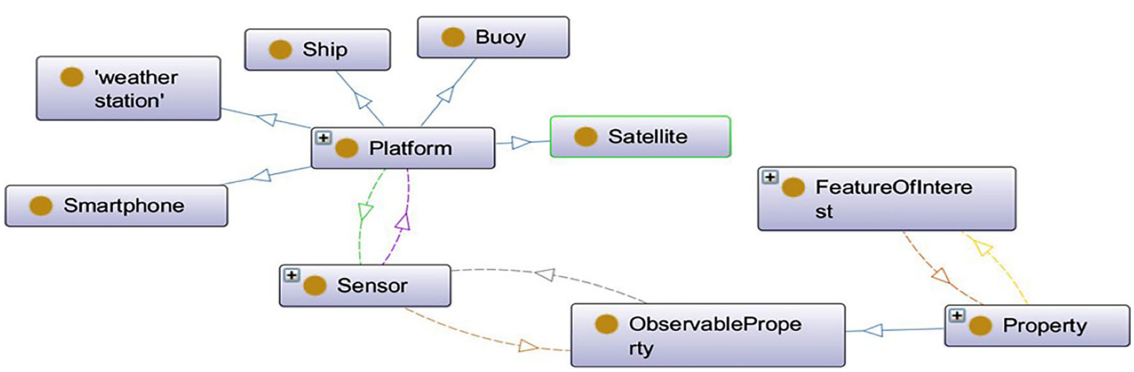

Fig. 5 The platform module

assessing environmental data sources and their related data (QoDS) while considering the different quality dimensions, we queried the QoDS related to the CHIRPS data source through the inference rules of the MESOn ontology. These inference rules are outside the scope of the paper, but readers can refer to [33] for more details. The evaluation results generated the following QoDS values: Accuracy: 95%, Volatility: 354, Currency: 23, Timeliness: 94%, and Trustworthiness: 100%. It is essential to note that these inferences are performed on each data source that needs to be evaluated in the use case. Furthermore, the assessed QoDS qualities are used by the *Optimal Service Selection Module*, which is presented in what follows.

4.2 Optimal service selection module

The *Optimal Service Selection Module* is based on the Bα-DSS outranking approach. It aims to select effectively optimal services considering both of the quality levels: QoDS and QoS. In what follows, we detail the main steps of our proposed Bα-DSS outranking approach.

4.2.1 Best_α-dominant_skyline_service (Bα-DSS) approach

The main objectives of our proposed Bα-DSS outranking approach are as follows: (i) reduce the overall number of services, which impacts the space discovery and computational time of the services. (ii) Support the comparison between the alternatives in the retrieved dominant skyline set by applying a fuzzy degree of dominance to discard the skyline services that do not belong to the fixed degree of dominance. (iii) Outranking mechanism of the compared set of the α-dominant skyline services based on an MCDM method. To do so, Bα-DSS includes three main steps (see Fig. 6). These steps will be presented in detail in what follows.

(A) **Skyline-based services filtering** This step aims to retrieve from similar functional services with their different QoS and QoDS quality, the dominant set of skyline services. It mainly considers the following six quantitative quality dimensions: Execution Time (*S_ET*), Availability (*S_Av*), and Cost (*S_Cost*) which are related to the quality of service (QoS), and Accuracy (*SO_Acc*), Trustworthiness (*SO_Trust*), and Data Timeliness (*SO_DTime*), which are related to the quality of data sources (QoDS). Besides, it adopts the BNL (Block-Nested-Loops) skyline algorithm to compute the set of dominant services. The choice of this algorithm is due to its popularity and simplicity of usage. The function **ComparisonFct(p, q, ListCrit)**, in Algorithm 1, compares the two services *p* and *q* pairwise, in all the criteria listed in the list *ListCrit*. This function returns a count of the maximum number of quality criteria for a given service. Furthermore, the main function **ComputeBNLSkyline**, in Algorithm 1 retrieves the set of all the dominant services in the *Sky* list. This latter is the input for the next step.

Algorithm 1 Calculate Skyline Services

```
S: Input List of Services on which is computed the Skyline
ListCrit: Input List of Criteria
p, q: Services
Sky: Output List of the Skyline Services
Function ComputeBNLSkyline
Foreach p in S do
if ( Sky = ∅) then
Sky ← {p};
else foreach q in S do
Res = ComparisonFct (p, q, ListCrit );//Comparison between services
//p and q pairwise, in all the criteria listed in the list ListCrit.
if ( Res > 0) then
Sky ⇐ Sky + {p};//Adds the service p in Sky list.
S ⇐ S - {q};
else if ( Res < 0) then
Sky ⇐ Sky - {p};//Removes the service p from Sky list.
end if;
end if;
end foreach;
end if;
end foreach;
return Sky;
End Function.
```

(B) **α-Dominant-based services filtering** The second step consists of applying a second filter through the definition of a fuzzy degree of dominance to discard services that have a degree lower than the degree of dominance. The fuzzy dominance relationship [34] relies on a particular comparison function expressing a graded inequality of the type "strongly greater than", using λ and ϵ values, which are subjective parameters, user-defined, and domain-specific. These parameters express the semantics of the (gradual) relation μ in a given domain for a given user as defined in [35]. Consequently, this second step provides all the skyline services that obey the condition of greater or equal to the fuzzy dominance degree. The variation in the α degree influences the size of the returned α-dominant skyline services. The increase (resp. decrease) of α leads to the inclusion (resp. exclusion) of services with a bad compromise. Furthermore, we varied the α parameter and fixed its degree value to 0.7. Also, the variations of λ and ϵ allow maintaining services with a good compromise between the QoS attributes. Since λ and ϵ are subjective parameters, we varied them and fixed them to 0.2 and 0.1, respectively. We noticed these values return α-dominant services with a good compromise between the QoS attributes. Algorithm 2 calculates the degree of dominance for each service and verifies if the degree of dominance of all pairwise services (i.e., between every two services) is greater or equal to the fixed α-dominance degree. Finally, it maintains all services with a degree greater than $\geq$ 0.7. This set of services is called α-dominant skyline services. The remaining issue is that the α-dominant skyline services are not ranked. The next step applies an outranking mechanism over the α-dominant skyline services set with the ELECTRE III method.

(C) **ELECTRE III-based services outranking** To best manage the ranking of the candidate services, our choice is focused on the ELECTRE III Roy [3]. The rationale of using the ELECTRE III is its ability to deal with inaccurate, imprecise, and uncertain comparisons. Furthermore, the ELECTRE III, as a knowledge-driven method is based on pseudo-criteria, which are considered as thresholds. These latter consider the uncertainty and ambiguity related to the calculations and to the performance evaluation between the compared services, which makes fuzzy comparisons. The fuzzy comparisons carried out by the ELECTRE III method derive conclusions upon the set of the α-dominant skyline services, that will be outranked. These comparisons produce useful decisions by exploiting the knowledge carried out from the quality dimensions inferred by the MESOn ontology. Additionally, the ELECTRE III outlines the decision maker's preferences, by assigning weights and pseudo thresholds to each quality criterion. Furthermore, ELECTRE III method is used to select the best compromise among all the considered service alternatives and their criteria. It is based on a pairwise comparison of alternatives, based on the extent to which evaluations of the alternatives and the preference weights confirm or contradict the dominance relationship between the pairwise alternatives. The quality criterion can be, in our case, one of these 6 quality dimensions (i.e., QoS: (*S_ET*:

Algorithm 2 Calculate α-Dominant Skyline Services

```
α: Input Degree
ϵ: Input of the ϵ value
λ: Input of the λ value
Sky: Input List of the Skyline Services
α_Sky: Output List of the α-Dominant Skyline Services
α_Sky ⇐ ∅;
Function Computeα-DominantSkyServices
foreach Element in Sky do
deg ⇐ Compute_Degree_Service (Element, NextElement);//Computes
//the degree for each service.
remove (Element);
if (deg ≥ α) then
α_Sky ⇐ List_Of_α_Dominant_Services(); //Lists all the services having
//a degree greater or equal to α.
End if;
end foreach;
return α_Sky;
End Function.
```

service execution time, *S_Av*; service availability, *S_Cost*: service cost), QoDS: (*SO_Acc*: source accuracy, *SO_Trust*: source trustworthiness, *SO_DTime*: source data timeliness)). For each criterion (QoS and QoDS), we defined three different pseudo-criteria, namely, the preference threshold (p), the indifference threshold (q), and the veto threshold (v). The experts should specify the weight values for each criterion related to the previously stated thresholds, respecting the following conditions: $(v \geq p \geq q)$ and assign an importance weight for (w_j) for each criterion j, as depicted in Table 2. For each criterion (QoS and QoDS), PREDICAT experts assigned the important weights. Then, we applied the Weighted Arithmetic Mean normalization through Eq. 4, upon the criteria weights. The sum of the normalized weights should be equal to 1.

$$x'_w = \frac{\sum_{i=1}^{n}(w_i x_i)}{\sum_{i=1}^{n}(w_i)} \qquad (4)$$

where: x_w is the weighted mean, w_i is the allocated weighted value, x_i is the observed values which are the criteria in our case.

ELECTRE III method encompasses several steps such that: (1) estimation of concordance indices, (2) estimation of discordance indices, (3) estimation of credibility scores, (4) performing distillation procedures, and (5) performing the complete ranking. Algorithm 3 details the optimal outranked and selected service from the set of the α-dominant skyline services, upon the application of the ELECTRE III MCDM method.

The optimal ranked services selected through the Bα-DSS outranking approach will be used in the service composition schema, produced by our proposed knowledge-driven approach for service composition.

5 Knowledge-driven approach for service composition

The proposed service composition approach is dynamic and knowledge-driven. First, it is knowledge-driven because the service composition schemas are based on observations of past wildfires and expert feedback. It uses machine learning techniques to make service composition schemas on the fly, especially the decision tree method. Second, the approach is dynamic because it can change the service composition schema at runtime based on the decision tree model and the level of wildfire danger (emergency or normal).

The knowledge-driven service composition approach relies on the application and the data processing layers. It will be explained in detail in what follows.

5.1 Decision tree building for service composition & wildfire prediction

The proposed service composition approach relies on machine learning techniques, especially Decision Tree (DT), to automatically and dynamically organize and adjust the flow of services. The reason to use DT to build service composition schemas is that it can provide compelling sequential features of interest organized as a path. Each path can be thought of as a rule that can be easily mapped to an abstract composition schema. Thanks to the *Prediction Module*, abstract service composition schemas are built. This module contains the *Learning Module* and

Algorithm 3 Best_α-Dominant_Skyline_Service (Bα-DSS) Pseudo-Algorithm

```
input: S, α ⇐ 0.7;
SKY ⇐ ∅;
output: Best Ranked Service;
Function Best_αDominantSkyService
for each element in S do
Sky ⇐ ComputeBNLSkyline(); //Lists the Skyline Services
α_Sky ⇐ Computeα-DominantSkyServices();//Lists all the services
//having a degree greater or equal to α.
for each element in α_Sky do
Best_Ranked_Service ⇐ ELECTREIII()
end foreach;
return Best_Ranked_Service;//the 1st-ranked service from the set of ranked
//services.
End Function.
```

Table 2 Assigned weights for the quality dimensions

Weights	*S_ET*	*S_Av*	*SO_Acc*	*SO_Trust*	*SO_DTime*	*S_Cost*
$Assignedweights_i$	6	6	4	4	3	1
w_i	0.25	0.25	0.167	0.167	0.125	0.041

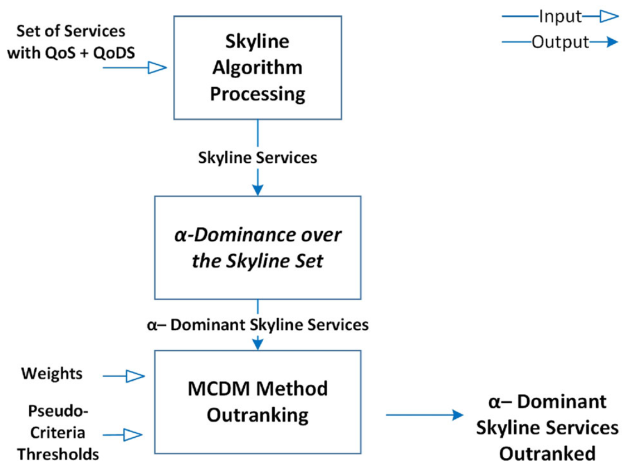

Fig. 6 Bα-DSS steps approach

the *Awareness Module*. As its name suggests, the *Learning Module* operates at design time and learns from historical environmental observations data collected from heterogeneous data sources to build a dedicated wildfire prediction model. For this purpose, it uses the Random Forest algorithm (RF) [36] that takes as input the set of features of interest that may ignite the fire (i.e., temperature, wind speed, humidity, wind direction, etc.) and produces as an output the classes of fire danger (i.e., moderate, low, high, very high, extreme, catastrophic, etc.).

The *Awareness Module* aims to map DT paths to abstract service composition schemas and tracks the services' execution to identify any possible readjustments. It works at both design and run times to reach this goal and takes two main steps. The first step, performed at design time, is to extract the essential features from the dataset of past wildfire observations. The rationale behind searching for the most important feature is that it will be the first node to begin the traversal of the decision tree to the leaf nodes. Identifying essential features helps eliminate unnecessary or duplicate attributes from the dataset, making the results more accurate and simplifying the process. The most important feature has the highest score. This feature significantly affects the model used to predict wildfires more than the other features used. Also, it is essential to know that if new wildfire features of interest are added, selecting and identifying features will be performed again.

Technically, the *Awareness Module* generates the feature scores thanks to applying the algorithm CMIF+ES [37]. In this algorithm, the most important feature is determined by applying the RF feature selection method [38], which produces a list of scored features within the wildfire prediction model. Second, the most important feature in the wildfire prediction model is determined by using the maximum equation on these values. Furthermore, once the most important feature is determined, the idea is to map it to the most convenient service. This service is executed to get a value to guide the tree traversal to search for the other features in the DT. For illustration purposes, for a particular execution, the *Awareness Module* suggested the "Drought Factor (DF)" as the most critical feature for the wildfire prediction model (see Fig. 7). According to the returned value by the DF service, the DF node will guide the tree traversal to search for the other features in the DT.

The second step of the *Awareness Module* runs at runtime and involves identifying and tracking the path from the DT through the various nodes to the leaf node containing the fire alert danger. The *Awareness Module* is fully connected to the service composition engine to decide and track the executed path. The service associated with the most important feature is executed, returning a value that is compared to the DT node's threshold to determine which sub-tree of the DT to extract to the leaf node. The execution of the most important feature's node and the rest of the features of interest constituting the path depends on a feature-matching process. This latter is applied to each extracted feature from the DT, mapped to an existing ranked service by our proposed Bα-DSS approach. Each DT feature that is extracted represents an abstract service that is then instantiated and run. Each service execution is tracked, and path and service instance readjustments can be performed. This execution is handled by the *Composition Execution Engine*, in the **data processing layer**.

5.2 Composition execution engine

The composition engine receives the abstract composition schema from the *Awarness Module*. It instantiates the services at runtime based on their optimal quality dimensions as determined by our proposed Bα-DSS approach. Hence, as the service composition is performed on the fly, the *Composition Execution Engine* favors services with particular QoS (depending on the context and the expert's needs) and is not focused on one-size-fits-all services. Also, how an expert sets the QoS weights depends on the

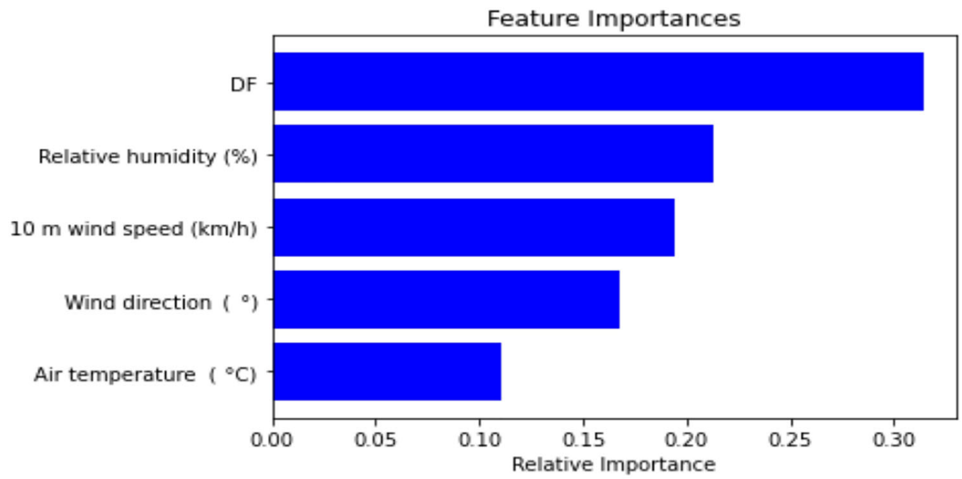

Fig. 7 The set of the important features in the fire model prediction

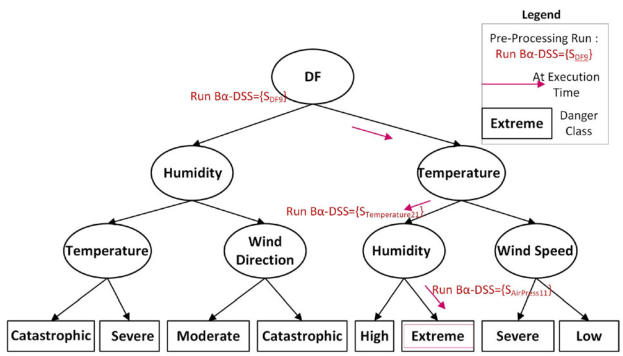

Fig. 8 Composition execution at runtime

situation and the needs of the expert. If there is an urgent or emergency case, the expert assigns high weights to the QoS and the QoDS. If it is an ordinary case, the expert gives low weights to the QoS and the QoDS. Furthermore, as our contribution is both knowledge-driven and context-specific, the execution of one service determines the wildfire context, whether there is a high or low wildfire risk. For example, suppose the execution of the temperature service returned 50°. In that case, one may assume that the current context indicates that the weather is hot and will impact the selection of services to participate in a composition schema. So, this current context will force the execution of the next feature of interest (the nodes in the DT) and the selection of the service instances while considering the weights given by the expert based on the current situation (for example, an emergency case). A unique path from the DT will be instantiated at execution time. Accordingly, the instantiated service composition schema indicates the wildfire alert occurrence is happening. Fig. 8 depicts an extraction from the DT showing how to dynamically execute the service composition schema at runtime. Subsequently, it performs each feature of interest according to its suitable service, mapping it with its corresponding service. Each executed service in the service composition schema is determined by relying on the Bα-DSS approach. Consequently, it is about invoking the 1^{st}-ranked service (i.e., the first service among all the outranked services) responding to the requested feature of interest in the DT.

We detail in what follows the implementation and evaluation related to our proposed framework, the knowledge-driven approach for optimal service selection, and the knowledge-driven approach for service composition for wildfire prediction.

6 Implementation and evaluation

We present the implementation and evaluation details related to our proposed knowledge-driven service composition framework for wildfire prediction in what follows.

We used the Protégé-OWL development environment to design the MESOn and reason about the quality of the data sources using SWRL rules. Then, to select the optimal QoS-aware services, we implemented the Bα-DSS approach using Java. The used dataset in the Bα-DSS includes six sets of services (i.e., the number of features of interest). Each set contains 500 functionally equivalent services with different QoS that respond to a given feature of interest, such as DF (Drought Factor), Temp (Temperature), Wind Speed, Wind Direction, and Humidity.

To select the optimal services, we used the ELECTRE III MCDM method implemented in Java. The ELECTRE III method requires assigning a weight to each quality dimension. Table 2 shows the assigned ones to each quality dimension QoS and QoDS, which we have normalized through the Weighted Arithmetic Mean formula according to Eq. 4. Also, to implement and build the wildfire prediction model, we relied on Python code implemented in Google Colab. For this purpose, we used the environmental observation dataset containing hourly collected weather data by the Observatory of Sahara and Sahel (OSS), our socio-economic partner in the PREDICAT project. The data were collected between November 1, 2017, and March 31, 2019. This period encompasses a wide range of temperatures (°C), relative humidity (%), wind speed (km/h), wind direction (°), and drought factor values pertinent to meteorological concerns. Furthermore, the McArthur Forest Fire Hazard Index (FFDI) and its rating, namely the fire danger rating scale for forests (FFDR), were employed as output of the decision tree algorithm. FFDR is classified into the following categories [39]: catastrophic (>100), extreme (75-99), severe (50-75) very high (25-49), high (12-24) and low-moderate (0-11). We conducted experiments based on the two discussed datasets: the Bα-DSS dataset and the environmental observation dataset. Statistics about the environmental observation dataset are depicted in Table 1. We performed all the experiments on the computer machine with Intel Core i7, CPU 2.60GHz, 2.59 GHz, and 8Go memory.

6.1 Evaluation metrics and analysis

We present in this section the five experiments that we have conducted to evaluate and analyze, mainly: (1) the data source quality reasoning time in the MESOn ontology, (2) our proposed Bα-DSS outranking approach, in terms of the pertinence related to the ELECTRE III MCDM ranking results compared with TOPSIS MCDM method, (3) the accuracy of the wildfire prediction model, (4) the accuracy of the composition and the prediction using the Bα-DSS with the DT compared to the Penalty-based GA approach, and (5) the impact of the Bα-DSS outranking approach on the prediction.

6.1.1 Experiment 1: data source quality reasoning time

The quality assessment of the data sources is realized through SWRL rules providing semantic reasoning over the data sources. We conducted several SWRL rule queries over different environmental data sources to assess the data sources' quality reasoning time. We used the Pellet reasoner for these SWRL queries on the Protégé 5.5.0 ontology editor. Table 3 shows the results that we obtained from the assessed data sources. For example, the reasoning times for the Copernicus and NASA data sources are 141 ms and 150 ms, respectively, which remain reasonable reasoning times. The reasoning execution time of the SWRL queries is often low and appropriate for all the data sources. Thus, the data sources' quality can not be changed within this period. Therefore, semantic reasoning may not cause the data processing layer to misselect inappropriate data sources in real-time scenarios.

6.1.2 Experiment 2: Bα-DSS execution time and ranking performance

This experiment aims twofold: (i) to evaluate the execution time of the ELECTRE III MCDM method compared with the TOPSIS MCDM method [11], with and without applying the skyline operator and the α-dominance, (ii) to evaluate the ranking performance of the ELECTRE III compared with the TOPSIS, using the Kendall Tau Distance (KTD) [40]. We used the TOPSIS thanks to its ability to find the best α-dominant skyline service alternatives by minimizing the distance to the positive ideal solution (i.e., the service) and maximizing the distance to the negative-ideal solution. TOPSIS is applied for benchmarking and ranking purposes according to [41]. We expanded the initial set of services to 950 services. The search space is reduced to 500 services by applying the skyline operator and the α-dominance. Besides, we noticed through the application of the skyline and the α-dominance methods a reduction in the execution time of both the ELECTRE III and TOPSIS, as depicted in Figs. 9 and 10. Consequently, we proved that applying the skyline and the α-dominance methods is essential to prune the dominated services before performing the ranking step through the MCDM method. The rationale behind reducing the search space of the services is to only operate on the most relevant services and, as a result, to simplify the selection process.

To evaluate the rankings of the ELECTRE III and TOPSIS MCDM methods, we proposed 500 ratings of the service candidates (i.e., the 1^{st}-ranked services) with environmental experts from the OSS. These experts were organized into four groups, each examining around 125 ranked service alternatives. Then, a cross-validation process is conducted among the different groups. The KTD coefficients are measured between the services ranked by the experts and the ones of ELECTRE III and TOPSIS. We noticed that the KTD ELECTRE III service rankings outperform the KTD TOPSIS rankings. Indeed, for the majority of the features of interest, the ELECTRE III KTD measures in (%) are lower than the TOPSIS, as depicted in Fig. 11. As the KTD measure decreases that means that the measured lists of the ELECTRE III ranked services are similar to the ones proposed by the experts.

Table 1 Number of samples per class in the environmental observation dataset

Class	#Samples
Low-Moderate	1000
High	1000
Very High	1000
Catastrophic	1000
Severe	1000
Extreme	1000

6.1.3 Experiment 3: performance of the wildfire prediction model

For the experimentation related to the prediction of the fire danger classes, we conducted a series of experiments to build the wildfire prediction models using the two machine learning algorithms: Random Forest and Decision Tree. We applied a 70/30 split for the training/testing of the datasets. Furthermore, to avoid overfitting and determine the optimal model performances, we used the "GridSearchCV" function from the "sklearn" library, to tune the model hyperparameters for both RF and DT classifiers. It consists in using a subset of the training collection as a validation dataset. We considered the following hyperparameters. For cv=5 in the DT classifier: max_depth=10, criterion='entropy' and, min_samples_split=2. For cv=3 in the RF classifier: criterion='gini', max_depth=10, and n_estimators=90. To evaluate both of the prediction models, we conducted training and testing steps using the dataset containing the five features of interest. Table 4 shows the performance of the different prediction algorithms in terms of accuracy, precision, and recall. The obtained evaluation results showed that the random forest (RF) model offers the best performance compared to the decision tree (DT) machine learning algorithm. This shows that the model generated by the RF algorithm is more performing in terms of learning for the prediction of the fire danger classes, to return the effective danger alert to the PREDICAT expert.

6.1.4 Experiment 4: evaluation of the composition and the prediction using the Bα-DSS with the DT and the penality-based genetic algorithm

This experiment aims twofold: (i) to evaluate the composition schema using our approach compared to the Penalty-based GA considered the baseline approach; and (ii) to evaluate the triggered wildfire prediction danger using our approach compared to the Penalty-based GA. The GA generates a population of usually random solutions that will be assessed according to a fitness function. We applied the Penalty-based GA approach introduced in [42], which penalizes an infeasible solution that violates restrictions. Table 5 presents the parameter settings for the Penalty-based GA. These parameters were obtained through trials on randomly generated test problems. In our case, a chromosome represents an executable service composition schema. An executable service should replace each gene on the chromosome. Each chromosome item includes an index to an array of possible service instances that may match a feature of interest. Within our knowledge-driven solution for service composition, we considered a composite service including several QoS-based services, selected optimally by our Bα-DSS. We evaluated a set of 500 composite services. We then computed the optimality of the returned composite service by comparing the overall utility value (u) of the composite service with the overall utility value (u_exact) of the optimal composition schema returned by the PREDICAT experts. The experts assess the valid composite services and their related composition schemas through a computed score. This score was inspired by the work proposed in [43] and was defined for both the Bα-DSS with the DT and the Penalty-based GA generated service composition schema. Then, we computed the precision and recall performance indicators to evaluate the service composition schemas generated by the Bα-DSS with the DT compared to the GA approach. We compared these two approaches with the composition schemas of the experts. Table 6 depicts the evaluation results of 500 composite services with their related composition schemas, generated by Bα-DSS with the DT approach and compared with the composition schemas of the Penalty-based GA. We noticed that Bα-DSS with the DT approach outperforms the Penalty-based GA while retrieving the most

Table 3 Reasoning time for the MESOn ontology

Data source	Reasoner	Reasoning time (ms)
Copernicus	Pellet	141
NASA	Pellet	150
OpenWeather	Pellet	110
NOAA	Pellet	159
CHIRPS	Pellet	133
GPCP	Pellet	139
UCSB Climate Hazard Center	Pellet	147
OSS	Pellet	127
HWSD	Pellet	130

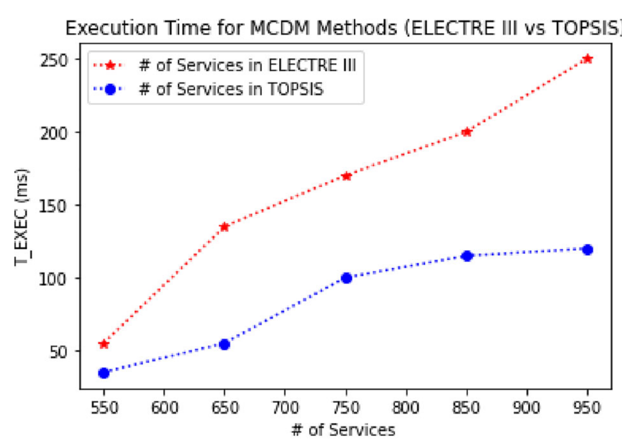

Fig. 9 Before skyline and α-dominance

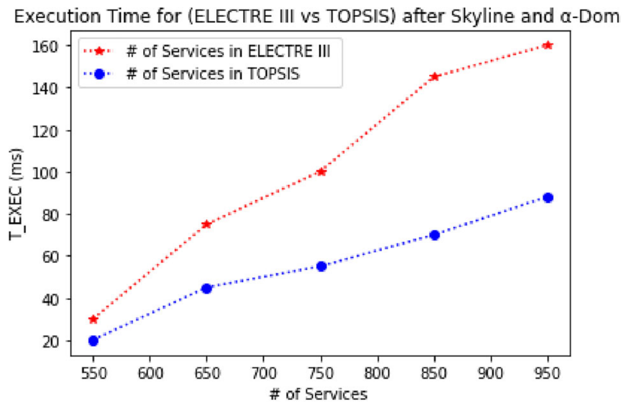

Fig. 10 After skyline and α-dominance

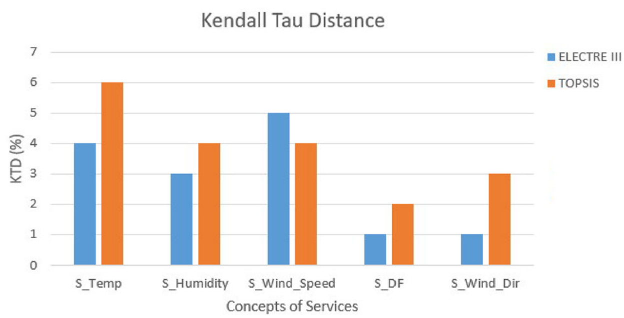

Fig. 11 Kendall Tau Distance (KTD) over ELECTRE III and TOPSIS rankings

relevant service composition schema with the suitable classes of wildfire danger. This positive overall evaluation is due to our accurate wildfire prediction model based on the most relevant features of interest. Performance indicators related to the precise wildfire prediction model are illustrated in Table 4.

6.1.5 Experiment 5: the impact of the Bα-DSS on the prediction

This experiment aims to show how applying the Bα-DSS impacts prediction accuracy. We conducted experiments for wildfire prediction with and without the Bα-DSS method. It is worth noting that the services are selected optimally with the Bα-DSS approach, whereas, without using the Bα-DSS, the service instances are randomly selected for the wildfire prediction.

Table 7 depicts the performance indicators related to the prediction accuracy enrolled with the Bα-DSS, without the Bα-DSS, and using the Penalty-based GA selection methods. Based on the experiment result, we noticed that the randomly-based selected services (i.e., those without Bα-DSS) have bad prediction accuracy. It is due to the selection of inadequate QoS-based services, which would access untrustworthy data sources, for instance, social media platforms (e.g., cell phones, smartphones, connected objects, etc.). Thus, the selection of a bad QoS Web service has a negative impact on the path in the DT and influences the choice of the following service to execute, resulting in a wrong path in the DT and an incorrect alert prediction.

Table 4 Performance indicators of the classification learning algorithms

Performance indicators	DT	RF
Accuracy (%)	84.06	86
Precision	0.840	0.860
Recall	0.840	0.860

6.2 Threats to validity

The final findings of our proposal gained much attention from the experts, as they can reduce wildfire disaster risks according to the proactive alerts triggered through our framework. The proposed framework, which includes an outranking approach to selecting the optimal services and a knowledge-driven solution for the dynamic generation of the service composition schema, is generic and applicable to any domain application. It is simply enough to accommodate the knowledge-base with the appropriate features of interest (i.e., along with an annotated historical dataset) pertaining to the domain application and to run the entire framework. Besides, the performance assessment of the framework (both execution time and prediction model accuracy), as outlined in the conducted experiments, demonstrates its capability to enable policymakers to take proactive measures to mitigate eventual damages. It is possible thanks to the reasonable service composition time and the accurate prediction model compared to the randomly selected services. The appropriate service composition time is thanks to many design time steps, such as the semantic reasoning for assessing the quality of the data

Table 5 Parameter settings for the penalty GA

Attributes	Value/condition
Population size	100
Initial population	Randomly generated solutions
Crossover probability	0.8
Mutation probability	0.1
Termination condition	No improvement for the optimal individual in 30 consecutive generations

sources and service ranking process. Furthermore, experts from the OSS enrolled in several evaluative tests, as presented in Sect. 6.1 to assess the results of our proposed knowledge-driven service composition approach for wildfire prediction. Also, our framework lets experts add weights based on the actual circumstances of the upcoming wildfire risk. The proposed framework is a prototype responding to the PREDICAT experts' requirements at the current state. When assessing the performance and quality of our framework, it is critical to consider the threats to the validity of the findings. The validity of our framework is seen while assessing how the results might be incorrect, i.e., the relationship between the framework outcomes and reality. If the number of services is extensively increased, the MESOn ontology no longer responds adequately and reasonably to the quality assessment. Likewise, this will impact the availability of information on service quality. Moreover, if the size of the environmental observation dataset increases profusely, reliance on classical machine learning methods is no longer possible. Subsequently, we may be forced to move to more complex structure algorithms, such as deep learning.

7 Conclusion

This paper proposed a novel approach that combines (i) machine learning and knowledge-driven engineering to dynamically compose services intended for the wildfire predictions, with (ii) ELECTRE III MCDM method performing fuzzy outranking to resolve the optimal selection of services participating in a service composition. At the same time, our approach takes into consideration (iii) the knowledge related to both quality levels of services (QoS) and the environmental data sources (QoDS) in the outranking process. Our framework is assessed by a series of experiments conducted in collaboration with OSS experts. The objective was to examine the effectiveness and pertinence of the proposed framework. Our results showed that it enabled: (1) a reasonable reasoning time for assessing the data source's quality, (2) a reduction of the execution time of the ELECTRE III method, through the application of the skyline and the α-dominance methods. We showed, also that the ELECTRE III MCDM method outperforms the TOPSIS MCDM method in the ranking process and selection of the optimal services, (3) the generation and dynamic readjustment of relevant service compositions with the suitable classes of wildfire risk, which outperforms the Penalty-based GA, and (4) a good prediction accuracy compared to the randomly-based selected services.

In future research, we will compare the proposed service selection and composition approaches by relying on a single approach that applies the reinforcement learning algorithm to simultaneously select optimal service composition with the optimal candidates' services at runtime. Moreover, we plan to assess the performance of the proposed framework while considering other non-functional requirements crucial for wildfire prediction, such as reliability and scalability. The purpose is to ensure that the framework will perform its intended purpose without failure, even under a significant number of wildfire risk queries.

Table 6 Performance indicators of the composite services generated by Bα-DSS with DT compared with the penalty-based GA

Performance indicators	Precision	Recall
Bα-DSS with DT	90	90
Penalty-based GA	78	78

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Table 7 Performance indicators of the learning-based wildfire prediction with and without Bα-DSS

	DT			RF		
Performance indicators	without Bα-DSS	with Bα-DSS	GA	without Bα-DSS	with Bα-DSS	GA
Accuracy (%)	75.0	84.06	80.0	70	86.0	79.0
Precision	0.75	0.840	0.8	0.7	0.86	0.79
Recall	0.75	0.840	0.8	0.7	0.86	0.79

Data availability Not applicable.

Declarations

Conflict of interest The authors declare that they have no conflicts of interest/competing interests.

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