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ARTICLE

New MDA Transformation Process from Urban Satellite Image Classification to Specific Urban Landsat Satellite Image Classification

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ABSTRACT

In a context where urban satellite image processing technologies are undergoing rapid evolution, this article presents an innovative and rigorous approach to satellite image classification applied to urban planning. This research proposes an integrated methodological framework, based on the principles of model-driven engineering (MDE), to transform a generic meta-model into a meta-model specifically dedicated to urban satellite image classification. We implemented this transformation using the Atlas Transformation Language (ATL), guaranteeing a smooth and consistent transition from platform-independent model (PIM) to platform-specific model (PSM), according to the principles of model-driven architecture (MDA). The application of this IDM methodology enables advanced structuring of satellite data for targeted urban planning analyses, making it possible to classify various urban zones such as built-up, cultivated, arid and water areas. The novelty of this approach lies in the automation and standardization of the classification process, which significantly reduces the need for manual intervention, and thus improves the reliability, reproducibility and efficiency of urban data analysis. By adopting this method, decision-makers and urban planners are provided with a powerful tool for systematically and consistently analyzing and interpreting satellite images, facilitating decision-making in critical areas such as urban space management, infrastructure planning and environmental preservation.

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1. Introduction

In recent years, the use of satellite imagery for urban classification has grown considerably, supported by rapid technological advances and increased availability of spatial data [1, 2]. Although this progress has opened new perspectives, existing methods still have some important limitations that hamper their effectiveness in complex and varied urban contexts.

Firstly, many current approaches are based on classification models specific to a particular platform or geographical area, making it difficult to generalize them to other regions or urban environments. These methods often lack flexibility and require significant manual adjustments to be applied to new contexts or to images from different satellites. Secondly, conventional algorithms struggle to deal effectively with the heterogeneities of urban patterns and the rapid variations in urban dynamics, particularly in environments where infrastructure and natural areas coexist in complex ways. What's more, while some techniques succeed in identifying basic classes such as built-up areas or water zones, they often perform less well for more complex classes, such as arid zones or fragmented urban forests. These limitations underline the need for a standardized, flexible approach to urban satellite image classification, capable of adapting to different contexts and platforms. It is within this framework that this article proposes a new method based on model-driven architecture (MDA) [3], aimed at transforming a generic meta-model into a meta-model specific to urban satellite image classification. Using the ATL (Atlas Transformation Language) [4] transformation language, our approach enables us to move from a platform-independent model (PIM) to a platform-specific model (PSM) [4], thus ensuring increased interoperability and better efficiency in spatial data processing.

Unlike existing methods, our approach makes it possible to classify various types of urban areas (water areas, cultivated areas, sandy areas, built-up areas, arid areas, forest areas) in an automated and reproducible way, without requiring manual readjustments for each new region or satellite used. This marks a major step forward in urban data management and offers a more efficient and adaptable alternative to traditional approaches.

The article is structured as follows: Sections 2 and 3 present the background and related work that contributed to the development of our approach. Section 4 describes our proposed approach. Sections 5 and 6 detail the source and target meta-models used. Section 7 introduces the ATL transformation rules defined to perform the transition from the generic metamodel to the specific metamodel. Section 8 describes the tests and experiments carried out to validate our contribution. Finally, Section 9 interprets the results obtained and discusses prospects for our model-driven engineering approach.

2. Background

Satellite image classification is a constantly evolving field of research, particularly relevant in the context of urban planning. Accurate and rapid analysis of spatial data is crucial for the planning [5] and management of urban territories, enabling decision-makers to monitor changes in land use, detect urban transformations, and manage resources more efficiently. Although numerous studies have explored different methods for improving the accuracy of image classification, the need for a systematic and automated approach remains a major challenge.

Our approach is distinguished by using model-driven engineering (MDE) and ATL transformations to standardize and automate the process of satellite image classification [6]. By integrating these tools into the urban planning domain, we propose an innovative method that aims to structure complex image processing processes, reducing dependency on manual intervention and improving the consistency and reproducibility of analyses.

3. Related Work

Previous research in the field of satellite image classification has focused on the use of different algorithms, such as random forests, support vector machines, and decision trees, to improve classification accuracy. However, these studies have often used pre-existing algorithm-specific models, without addressing the transformation of generic models into specific ones.

On the other hand, several studies have explored the use of the ATL language for model transformation in various domains, such as software engineering. However, the application of ATL in the field of urban satellite image classification remains underexplored, thus justifying the relevance of this study.

In the field of satellite image classification [7, 8], many researchers [9–14] have explored the use of machine learning algorithms to improve the accuracy of results. For example, techniques such as random forests (RF) [15], support vector machines (SVM) [16], and convolutional neural networks (CNN) [17, 18] have been widely adopted for the detection and classification of various urban landscape features. While these approaches focus primarily on improving algorithms, they do not address the issue of standardizing or automating processes through a conceptual model, as proposed in our approach.

Satellite images [19] are widely used in applications specific to urban planning, such as land-use mapping, monitoring urban growth, or detecting changes in urban areas [20]. Studies have applied various classification techniques [21–25] to identify residential areas, green spaces and urban infrastructures. However, these works are often limited to the practical application of classification methods without proposing a systematic or automated approach to manage these large-scale processes, which is the main objective of our research.

Model-driven engineering (MDE) [26] has been explored in various fields to structure and automate complex processes, notably in image processing and spatial data analysis. However, these studies have generally focused on applications in contexts other than urban planning, such as biomedical or industrial contexts. Although this research demonstrates the effectiveness of MDE for organizing complex processes, it has not applied this approach to the specific domain of satellite image classification for urban planning, nor has it used ATL for these transformations.

ATL (Atlas Transformation Language) [27] is a model transformation language widely used in software engineering and information systems. Numerous studies have demonstrated its effectiveness in transforming conceptual models in complex systems, thus facilitating change management and the evolution of software systems. However, the application of ATL in the context of satellite image classification, particularly for urban planning, has not been explored in the literature. Our approach, which integrates ATL to standardize and automate classification, represents a novel extension of its application.

Traditional approaches to satellite image classification remain largely manual and non-standardized, requiring human intervention to configure and adapt algorithms to each new project. These methods lack the consistency and automation required to effectively manage the large amounts of data generated by satellites in urban contexts. In response to these limitations, our research proposes a new approach that not only standardizes these processes but also automates them, offering a more robust and reliable solution for satellite image analysis.

Finally, although many studies have applied satellite image analysis to answer specific urban planning questions, such as green space detection or urban density analysis, these works have not adopted as systematic an approach as ours. Most have focused on the direct use of existing algorithms, without proposing a methodological framework to structure and automate the classification process at a conceptual level.

4. Proposed Approach

Satellite images play a crucial role in the monitoring and management of urban areas. However, to take full advantage of these data, it is often necessary to transform generic conceptual models into specific models that meet the requirements of different classification methods. This process is particularly important in the context of the use of Landsat data, which requires adjustments to exploit their full potential in various applications, such as land cover mapping and land use assessment.

In this section, we present our meta-modeling approach dedicated to the classification of urban satellite images. Two types of metamodels have been designed for this study: a generic metamodel and a specific metamodel. The generic metamodel includes elements such as CollectingSatelliteDataset, ImagePreprocessing, FeaturesExtraction, ClassifierAlgorithm and LandCoverMap. The specific metamodel, on the other hand, includes elements tailored to classifiers and indices, such as LandsatSatelliteDataset, RFClassifier, SVMClassifier, and NDVI.

Our aim is to propose a generic meta-model covering all stages of the urban satellite image classification process, from data collection to the evaluation of classification results. By applying Model Driven Engineering (MDE) techniques, we have defined a generic meta-model for urban satellite image classification.

This meta-model, based on model-driven architecture (MDA), is designed as a platform-independent model (PIM). It represents in an abstract and generic way the different components and steps of the classification process, including data collection, image pre-processing, feature extraction, modeling and evaluation. To validate and test our approach, we decided to transform this generic meta-model into a platform-specific meta-model (PSM) for the classification of satellite images of any urban area. This transformation is carried out using the Atlas Transformation Language (ATL). **Figure 1** illustrates our overall transformation approach:

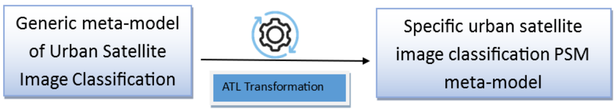

Figure 1. Overview of our approach.

Having defined our generic meta-model for the classification of urban satellite images, we focus here on transforming this meta-model into a specific meta-model for the classification of satellite images of any urban area. The following sections of this article will detail the ATL transformation rules applied to make this transition from the generic meta-model to a meta-model specific to the classification of satellite images of any urban area.

By integrating classes such as water areas, cultivated areas, sandy areas, built-up areas, arid areas and forest areas, our approach enables the efficient classification of different urban areas, providing a powerful tool for resource management, urban planning and environmental monitoring.

ATL transformation rules have been developed to convert elements of the generic metamodel into their specific equivalents. For example, the CollectingSatelliteDataset2LandsatSatelliteDataset rule transforms a generic satellite data collection element into one specific to Landsat data. Similarly, the rule ClassifierAlgorithm2MultipleClassifiers generates several specific classifiers from a generic classification algorithm.

The transformations generated specific models highly adapted to urban satellite image classification tasks. For example, the FeaturesExtraction model transformation produced specific models capable of extracting detailed features based on NDVI, NDBI, BSI, and MNDWI indices. Similarly, transformations of classification algorithms have produced classifiers adapted to Landsat data, improving the accuracy of land cover maps. The code extracts provided illustrate these transformations. Each ATL rule is designed to transfer the relevant attributes from the source model to the target model while adding specific features tailored to the requirements of the classifier or index.

As part of this study, we have developed a meta-modeling methodology dedicated to the classification of urban satellite images, considering the critical steps required to fully exploit satellite data, particularly Landsat data. The generic meta-model we have built includes elements such as satellite data collection, image pre-processing, feature extraction, classification algorithms and land cover map generation. Each element has been selected according to its crucial role in the classification process. For example, CollectingSatelliteDataset represents the satellite data source, essential for feeding the process. ImagePreprocessing is a key element in ensuring the correction of raw images, while FeaturesExtraction isolates features relevant to classification, such as NDVI or NDBI indices. In addition, ClassifierAlgorithm encompasses supervised learning algorithms, such as RF and SVM, commonly used for satellite image classification. To make our approach applicable to specific data, we then transformed this generic meta-model into a specific meta-model. The transformations, performed using ATL (Atlas Transformation Language), allow us to move from generic elements, such as CollectingSatelliteDataset, to specific elements, such as LandsatSatelliteDataset, adapted to Landsat data. Specific classifiers, such as RFClassifier and SVMClassifier, are integrated because of their reliability for urban classification tasks. Similarly, NDVI, NDBI and MNDWI were chosen for their relevance to urban landscape analysis. This transformation makes it possible to generate specific models that are highly adapted to urban satellite image classification tasks while improving the accuracy of the results. ATL rules, such as ClassifierAlgorithm2MultipleClassifiers, guarantee the creation of several specific classifiers from a generic algorithm, thus enhancing the adaptability and efficiency of the classification process. This methodology represents a significant advance, as it standardizes and automates the process, reducing reliance on manual intervention and making the analysis of urban data more reliable and reproducible.

5. Source Meta-Model of Urban Satellite Image Classification

In the age of advanced satellite observation, our urban and environmental activities leave valuable digital traces. Every day, a huge amount of satellite data is generated, providing a detailed overview of urban areas. This data is crucial for a variety of applications, from resource management to urban planning and environmental monitoring. Processing and analyzing these vast datasets play a key role in strategic decision-making. **Figure 2** shows the proposal for a Generic Meta-Model of Urban Geospatial Classification:

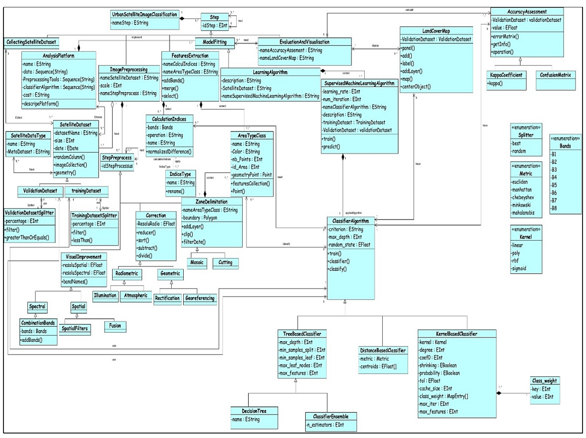

Figure 2. Proposal for a Generic Meta-Model of Urban Geospatial Classification.

In the context of urban satellite image classification, data processing involves the application of various algorithms and methods to extract meaningful information. The generic meta-model we propose aims to structure this process in a systematic way. This meta-model covers the various stages of image classification, from satellite data collection to pre-processing, feature extraction, modeling and results evaluation.

The following figure presents the proposed generic meta-model for urban satellite image classification. It illustrates the various classes and relationships involved in the process, providing a structured overview of our meta-modeling approach. This meta-model serves as a foundation for the ATL transformation, enabling us to move from a generic model to a specific model for the classification of satellite images of any urban area.

6. Target Meta-Model for Specific Urban Satellite Image Classification

Having defined the generic source meta-model for the classification of urban satellite images, we will now present the proposed meta-model for the specific classification of satellite images of any urban area. It is important to note that this destination meta-model incorporates several specific classes, such as water areas, cultivated areas, sandy areas, built-up areas and forest areas. These classes enable detailed and precise classification of the various components of any urban area. ATL transformation ensures that generic satellite image classification concepts are adapted to the specific characteristics and needs of the region being classified. This approach enables satellite data to be fully exploited for urban applications, providing a structured and standardized view of the different types of surfaces and land uses in the city.

Figure 3 shows the proposed destination meta-model for the classification of satellite images of any urban area:

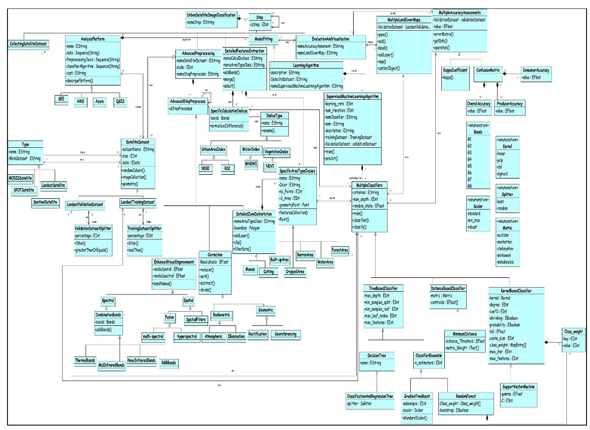

Figure 3. Meta-model proposed for the satellite image classification of any urban area.

By exploiting model-driven engineering (MDE) techniques, our approach standardizes and systematizes the satellite image classification process, facilitating efficient urban data management and improved decision-making based on accurate, up-to-date data. This destination meta-model plays a key role in urban planning and resource management, providing detailed and reliable information on land use and occupancy.

The main differences between the source and target metamodels lie in their level of abstraction and specificity. The source metamodel is generic and platform-independent, designed to cover the entire satellite image classification process in a flexible way that can be adapted to different platforms and data types. The target metamodel, on the other hand, is specific to a given platform or task, such as Landsat image classification. It incorporates elements, such as algorithms and indices adapted to the characteristics of the specific data. These differences affect the classification process by optimizing accuracy, efficiency and automation, enabling models to be tailored to specific contexts and needs, while guaranteeing greater reproducibility of results.

7. Transformation

After defining the source and destination meta-models for urban satellite image classification, we present in this section the transformation rules used to transform our generic meta-model into a specific model for urban satellite image classification. Each transformation aims to adapt a particular aspect of the generic model to suit the specificities of Landsat data.

Here is an extract from the ATL code used to transform our generic meta-model into a specific classification model for any urban area using Landsat satellite data (**Figrue 4**):

```
rule CollectingSatelliteDataset2LandsatSatelliteDataset {
  from
    c : Source!CollectingSatelliteDataset
  to
    l : Destination!LandsatSatelliteDataset (
      name <- c.name,
      date <- c.date,
      data <- c.data,
      geometry <- c.geometry
    )
}
rule SatelliteDataset2LandsatDataset {
  from
    c : Source!SatelliteDataset
  to
    l : Destination!LandsatDataset (
      datasetName <- 'Landsat OLI 8',
      size <- c.size,
      date <- c.date,
      randomColumn <- c.randomColumn,
      imageCollection <- c.imageCollection,
      geometry <- c.geometry
    )
}
```

```
rule AreaTypeClass2SpecificAreaTypeClasses {
  from
    c : Source!AreaTypeClass
  to
    builtUp : Destination!SpecificAreaTypeClasses (
      nameAreaTypeClass <- 'Built-Up area'
    ),
    water : Destination! SpecificAreaTypeClasses (
      nameAreaTypeClass <- 'Water area'
    ),
    barren : Destination! SpecificAreaTypeClasses (
      nameAreaTypeClass <- 'Barren area'
    ),
    forest : Destination! SpecificAreaTypeClasses (
      nameAreaTypeClass <- 'Forest area'
    ),
    cropped : Destination! SpecificAreaTypeClasses (
      nameAreaTypeClass <- 'Cropped area'
    )
}
```

```
rule ClassifierAlgorithm2MultipleClassifiers {
  from
    c : Source!ClassifierAlgorithm
  to
    md : Destination!MinimumDistanceClassifier (
      name <- c.name + '_MinimumDistance',
      parameters <- c.parameters
    ),
    rf : Destination!RFClassifier (
      name <- c.name + '_RF',
      parameters <- c.parameters
    ),
    svm : Destination!SVMClassifier (
      name <- c.name + '_SVM',
      parameters <- c.parameters
    ),
    cart : Destination!CARTClassifier (
      name <- c.name + '_CART',
      parameters <- c.parameters
    ),
    gtb : Destination!GTBClassifier (
      name <- c.name + '_GTB',
      parameters <- c.parameters
    ),
    dt : Destination!DTClassifier (
      name <- c.name + '_DT',
      parameters <- c.parameters
    )
}
```

```
rule LandCoverMap2MultipleLandCoverMaps {
  from
    l : Source!LandCoverMap
  to
    lmd : Destination! MultipleLandCoverMaps (
      classifier <- 'MinimumDistance',
      classificationType <- l.classificationType,
      accuracy <- l.accuracy
    ),
    lrf : Destination! MultipleLandCoverMaps (
      classifier <- 'RF',
      classificationType <- l.classificationType,
      accuracy <- l.accuracy
    ),
    lsvm : Destination! MultipleLandCoverMaps (
      classifier <- 'SVM',
      classificationType <- l.classificationType,
      accuracy <- l.accuracy
    ),
    lcart : Destination! MultipleLandCoverMaps (
      classifier <- 'CART',
      classificationType <- l.classificationType,
      accuracy <- l.accuracy
    ),
    lgtb : Destination! MultipleLandCoverMaps (
      classifier <- 'GTB',
      classificationType <- l.classificationType,
      accuracy <- l.accuracy
    ),
    ldt : Destination! MultipleLandCoverMaps (
      classifier <- 'DT',
      classificationType <- l.classificationType,
      accuracy <- l.accuracy
    )
}
```

Figure 4. An extract of the ATL transformation.

These ATL code extracts illustrate how elements of the source meta-model, representing the different stages of the urban satellite image classification process, are transformed into specific elements of the destination meta-model, suitable for the classification of satellite images of any urban area. The transformation rules ensure that each step of the generic process is correctly mapped to a specific classification step, preserving the relevant attributes and metadata. **Table 1** summarizes the transformations carried out between the generic conceptual model (Source) and the specific model (Destination) for a satellite image classification system applied to urban planning.

- CollectingSatelliteDataset2LandsatSatelliteDataset:

  This rule transforms the generic CollectingSatelliteDataset element into a LandsatSatelliteDataset. It transfers the name, date, data and geometry attributes from the source model to the target model, ensuring that the satellite collection data is tailored specifically for Landsat data.

- SatelliteDataset2LandsatOLIDataset:

  This rule creates a specific LandsatOLIDataset model from the SatelliteDataset model. It assigns a fixed name to the dataset (Landsat OLI 8) and copies relevant attributes such as size, date, randomColumn, imageCollection, and geometry.

- AreaTypeClass2SpecificAreaTypeClasses:

  The generic AreaTypeClass class is mapped to specific area types such as Built-Up area, Water area, Barren area, Forest area, and Cropped area. This enables precise categorization of area types in the context of urban satellite images.

- ClassifierAlgorithm2MultipleClassifiers:

  This transformation rule decomposes a generic ClassifierAlgorithm into several specific classifiers. The classifiers generated include MinimumDistanceClassifier, RFClassifier, SVMClassifier, CARTClassifier, GTBClassifier, and DTClassifier. Each classifier is tailored to the specifics of the target model.

- LandCoverMap2MultipleLandCoverMaps:

  This rule generates multiple land cover maps (LandCoverMap), each associated with a specific classifier. The maps produced correspond to different classification methods (MinimumDistance, RF, SVM, CART, GTB, and DT), and include information such as classification type and accuracy.

Table 1. Transformations from the source meta-model to the destination meta-model for the classification of urban satellite images.

Source (Generic)	Destination (Specific)
CollectingSatelliteDataset	LandsatSatelliteDataset
SatelliteDataset	LandsatOLIDataset
ImagePreprocessing	AdvancedPreprocessing (with specific filters)
FeaturesExtraction	DetailedFeaturesExtraction (specific indices)
ClassifierAlgorithm	MinimumDistanceClassifier, RFClassifier, SVMClassifier, CARTClassifier, GTBClassifier, DTClassifier
LandCoverMap	Multiple LandCoverMaps for each classifier
AccuracyAssessment	Multiple AccuracyAssessments for each classifier
CalculationIndices	SpecificCalculationIndices (NDVI, NDBI, BSI, MNDWI)
AreaTypeClass	AreaTypeClasses (Built-Up area, Water area, Barren area, Forest area, Cropped area)
TrainingDataset	LandsatTrainingDataset (with enhanced filtering options)
ValidationDataset	LandsatValidationDataset (with enhanced filtering options)
StepPreprocess	AdvancedStepPreprocess
ZoneDelimitation	DetailedZoneDelimitation (specific to urban areas)
VisualImprovement	EnhancedVisualImprovement (with advanced spectral and spatial enhancements)

This transformation makes it possible to customize and adapt the satellite image classification process to the specific needs of the region being classified, using a systematic and standardized approach. ATL transformation rules thus facilitate the transition from a generic to a specific model, while ensuring the consistency and accuracy of the processed data.

8. Experiences and Evaluations

In this section, we present the techniques we used to implement the approach illustrated in **Figure 1**. To do this, we used version 4.12 of the Eclipse IDE, with the addition of the Eclipse Modeling Framework (EMF) to draw the proposed meta-models. We also used version 4.1 of the ATL transformation language on Eclipse 4.12 to define the transformation rules introduced in the previous section, taking into account the specifications of the machine used (Intel(R) Core(TM) i7-7500U CPU 2.70GHz 2.90 GHz, 16.0 GB (RAM), 64-bit operating system, x64 processor). Our objective is to apply ATL transformation rules to move from our generic meta-model for urban satellite image classification to the specific meta-model. **Table 2** and **Figure 5** present the time of ATL transformations for urban satellite image classification.

Table 2. Time of ATL transformation urban satellite image classification.

Transformation	Transformation Time (s)
CollectingSatelliteDataset to LandsatSatelliteDataset	1.5
SatelliteDataset to LandsatOLIDataset	1.8
ImagePreprocessing to AdvancedPreprocessing	4.2
FeaturesExtraction to DetailedFeaturesExtraction	3.6
ClassifierAlgorithm to Multiple Specific Classifiers	12.4
LandCoverMap to Multiple LandCoverMaps	13.1
AccuracyAssessment to Multiple AccuracyAssessments	7.5
CalculationIndices to SpecificCalculationIndices	6.8
AreaTypeClass to Specific AreaTypeClasses	8.9
TrainingDataset to LandsatTrainingDataset	4.1
ValidationDataset to LandsatValidationDataset	4.7
StepPreprocess to AdvancedStepPreprocess	3.9
ZoneDelimitation to DetailedZoneDelimitation	8.3
VisualImprovement to EnhancedVisualImprovement	7.2

We created several Ecore model instances on the Eclipse tool using EMF, which contains a generic Ecore instance editor. The use of multiple data instances allows us to better measure the time of the transformations required to switch to PSM. The results show that the time of ATL transformations is strongly correlated with the complexity of the transformation rules. These results are typical for model transformation systems like ATL, where the efficiency of transformations depends on the nature of the operations performed and the structure of the source and target models.

The model we have created with ATL does not process real data, but prepares the conceptual structure needed for a real implementation. This means that if we remain at the conceptual level, ATL transformations are fast and abstract. For real calculations or satellite image processing, we will need to switch to another environment such as Jupyter or GEE[28, 29], etc., which will be able to manipulate real data according to the structure defined by our conceptual model.

In short, we have defined structures and flows without necessarily loading or manipulating the actual data. This includes the creation of attributes such as links to datasets or zone names. We then transformed the generic model into a more specific conceptual model. This transformation is fast because it does not process the actual data. Then, to process the real data, we need to integrate this conceptual model into a program (in Python, for example) that will load the images, apply the algorithms and manage the geometries.

This is perfectly logical and useful in the context of a thesis aimed at finding an approach to automating and structuring complex image processing processes, but it is important to understand that processing real data is a separate step requiring other tools and environments.

9. Results and Interpretations

The application of model-driven engineering (MDE) techniques to urban satellite image classification has overcome several key challenges, including adaptation to the different requirements of urban projects and standardization of classification processes. Firstly, we proposed a generic meta-model capable of capturing the fundamental concepts of satellite image processing and classification. This meta-model serves as a basis for structuring the various stages of the processing pipeline, from satellite data collection to pre-processing, feature extraction and classification.

Landsat data from Landsat 8 satellites are integrated into our model via the LandsatSatelliteDataset element, which is derived from the generic CollectingSatelliteDataset element. This component processes the raw data, which is then subjected to pre-processing and feature extraction steps. Landsat data includes several spectral bands (including visible, near-infrared, and thermal bands), and these bands are used to calculate indices such as NDVI (vegetation index), NDBI (built-up index), and MNDWI (water index). These indices are essential for classifying different urban areas, such as built-up areas, forests and water bodies.

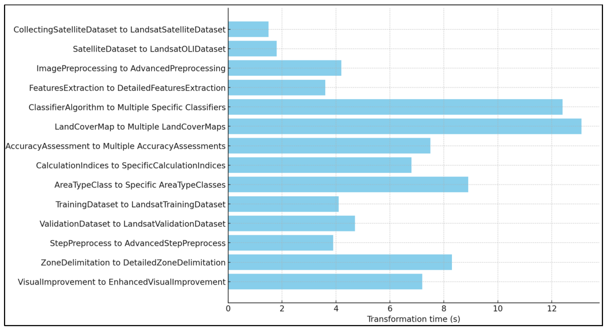

Figure 5. Transformation times for various urban satellite image classification processes.

The integration process begins with the radiometric and geometric correction of Landsat images, followed by the extraction of specific features using ATL transformation rules such as CollectingSatelliteDataset2LandsatSatelliteDataset, which adapts the generic process to the characteristics specific to Landsat data. This enables classification to be optimized using supervised algorithms such as Random Forest (RF) and Support Vector Machine (SVM), which are specially adapted to the Landsat satellite data in our model.

One of the major problems in this field is the diversity of existing classification solutions, which are often developed independently of each other and are not always compatible. This diversity complicates the integration of different tools into a unified pipeline, requiring manual adjustments and increasing the risk of errors. Our approach, using meta-models as a standard reference, has standardized these processes, facilitating the integration of heterogeneous solutions. The generic meta-model we have developed provides a unified framework for managing this diversity, significantly reducing the number of incompatible solutions.

Another challenge addressed in our work is that of flexibility and interoperability between different classification algorithms, such as SVM, Random Forest, and other machine learning techniques. Traditionally, adapting a classification pipeline to different algorithms requires manual modifications to adjust the parameters and configurations specific to each method. This process is not only time-consuming, but also introduces risks of inconsistencies and sub-optimal performance.

To meet this challenge, we designed a prototype based on ATL transformation rules, enabling us to automatically convert our generic meta-model into specific implementations adapted to various classification algorithms. By applying these transformation rules, we were able to automate the generation of configurations for specific algorithms such as SVM, Random Forest, CART, GTB and others, ensuring a smooth transition between different types of classification models.

Through a series of tests, we measured times for different ATL transformation rules. The results, summarized in **Figure 5**, reveal several trends:

- Simple transformations (1–2 seconds): Simple transformations, such as CollectingSatelliteDataset2LandsatSatelliteDataset and SatelliteDataset2LandsatOLIDataset, have very short times. This is because they mainly involve direct mappings and uncomplicated operations between the source and target models.
- Medium complexity transformations (2–5 seconds): Transformations involving more complex operations, such as ImagePreprocessing2AdvancedPreprocessing and FeaturesExtraction2DetailedFeaturesExtraction, showed longer times due to additional processing steps and more sophisticated data manipulations.
- Complex transformations (5–15 seconds): The most complex transformations, such as ClassifierAlgorithm2MultipleClassifiers and LandCoverMap2MultipleLandCoverMaps, have the longest times. These transformations require the creation of multiple target objects from a single source element, which explains the increased complexity and higher time.

Although the results obtained in this study are positive, it is important to note that our model has been designed to be standardized and flexible. This means that it can be adapted to different types of satellites, not just Landsat. In this study, we have chosen to focus on the specific case of Landsat data as an application example, but the model is designed to allow the integration of data from other satellites as required. Unlike some platform-limited approaches, our model allows other satellite types to be added simply by adjusting the metamodel parameters. As for transformations via ATL, while they are effective in this specific case, their adaptability means that they can handle more complex datasets if required. In addition, we have integrated mechanisms to handle a variety of input data, minimizing the impact on image quality, such as noise or cloud cover. Future work may focus on improving multi-temporal data processing and optimizing transformation processes for larger-scale analyses, while maintaining the model's flexibility for different types of satellite data.

In conclusion, this study shows that the application of model-driven modeling techniques, particularly the use of ATL transformations, represents a significant advance in the field of satellite image classification for urban planning. More specifically, in the context of image classification, our MDE-based approach enables us to switch from one algorithm to another more quickly than the traditional method, which involves manually uninstalling, reinstalling or reconfiguring each algorithm. This method not only standardizes and automates processes, but also offers greater flexibility to adapt to different algorithms and contexts while improving the performance and reliability of results.

10. Conclusions

In this article, we present an innovative approach to urban satellite image classification based on meta-model transformation using the ATL language. By integrating Model Driven Engineering (MDE), we were able to structure and automate the complex process of satellite image classification. One of the major contributions of this research lies in the transformation of a generic meta-model into a specific metamodel, enabling classification methods to be standardized and adapted to various urban environments while integrating algorithms such as SVM and Random Forest, etc. This method represents a significant advance in the field of urban satellite image classification, offering unprecedented flexibility. It allows rapid adaptation to new technologies and to the varied needs of urban planning projects. The integration of MDE and ATL transformations not only optimizes geospatial analyses, but also reduces reliance on manual intervention, thereby increasing process efficiency.

For urban planning practitioners, the results of this research offer concrete application possibilities. For example, this approach can be used to monitor the evolution of urban areas, identify changes in land use, or optimize the management of natural resources. Thanks to its ability to adapt quickly to specific projects and to integrate new types of data and algorithms, our method could also facilitate strategic decision-making in the fields of urban planning and environmental protection.

Future work will aim to extend this approach to other types of spatial data and integrate more advanced algorithms, including those derived from Deep Learning, to further improve the accuracy and adaptability of classifications. In summary, our research has advanced the field of urban satellite image classification by proposing a flexible and efficient solution while paving the way for practical applications in urban planning and management.

Author Contributions

Hafsa Ouchra designed and processed the data, analyzed the proposed methods, and edited the manuscript; Abdessamad Belangour and Allae Erraissi interpreted, analyzed and discussed the proposed methods; Maria Labied revised the manuscript.

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You'll find all my research data in scopus and research.

Conflicts of Interest

All authors have read and agreed to the published version of the manuscript.

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