



École Nationale Supérieure d'Informatique et d'Analyse des Systèmes

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## Data Warehouse Assignment

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# ForestAI - Building a Data Warehouse for Enhanced Model Validation and Client Insights

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## SUMMARY

This project developed a data warehouse and BI solution to address ForestAI's needs for streamlined model validation, improved data analysis, and interactive client dashboards. A data model was designed to efficiently store relevant metrics, and the solution was implemented using SSIS for data loading, an SSAS cube for analysis, and BI tools for visualization. This improved system empowers ForestAI with faster validation, deeper insights, and effective client presentations.

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## ABSTRACT

Ce projet a permis de développer un data warehouse et une solution BI complète pour répondre aux besoins de ForestAI en matière de rationalisation de la validation des modèles, d'amélioration de l'analyse des données et de tableaux de bord interactifs pour les clients. Un modèle de données a été conçu pour stocker efficacement les indicateurs pertinents. La solution a été implémentée à l'aide de SSIS pour le chargement des données, d'un cube SSAS pour l'analyse et d'outils BI pour la visualisation. Ce système amélioré permet à ForestAI de réaliser des validations plus rapides, d'obtenir des analyses plus approfondies et de présenter ses résultats aux clients de manière convaincante.

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## GENERAL INTRODUCTION

This report presents the design and implementation of a data warehouse solution for ForestAI, a company specializing in applying Data Science to predict forest inventories. The primary objective of this project is to overcome the current limitations of ForestAI's platform by improving the benchmarking process of the models, which is important for validating model quality and building client trust in ForestAI's products.

ForestAI uses climate, geospatial, and customer process data To effectively pinpoint possible buying and harvestable areas in forests with fewer field visits. However, the current model validation process is fragmented and lacks standardization, leading to inefficiencies and poor user experience.

To address these issues, this project aims to create a standardized data pipeline that integrates data from various sources (ground truth, company predictions, client models, and competitor models) into a common destination. This will enable quick data analysis for technical and business insights while ensuring consistent data quality. Additionally, the introduction of intermediate storage is intended to improve overall system performance.

The project involves designing a data warehouse and creating interactive dashboards, thus enhancing visualization and improving the user experience for ForestAI's clients. This report details the conceptual choices, data modeling, implementation steps, and provides a demonstration of the developed solution.



### 1.1 Introduction

Forest inventory assessment is essential for sustainable forest management. ForestAI exploits the advantages of data science to predict key forest metrics like tree volume and species composition. However, streamlining model validation, improving data analysis, and providing client-friendly insights remain challenges. This project outlines the development of a data warehouse to address these needs and empower ForestAI with a robust data analysis platform.

### 1.2 Project Background

ForestAI's current workflow involves data acquisition, model development, and model validation for forest inventory prediction. Data resides in various sources, making analysis overly complicated and obstructive in-depth validation. Additionally, presenting insights to clients often requires manual data manipulation, leading to inefficiencies.

### 1.3 Project Objectives

This project aims to:

- Establish a centralized data warehouse to integrate and store forest inventory data from different sources.
- Design interactive dashboards for efficient model validation and data visualization.
- Provide clients with user-friendly access to key metrics and forest inventory insights.

### 1.4 Expected Outcomes

A successful project will achieve the following outcomes:

Improved model validation efficiency: Easier access to historical data and streamlined analysis will facilitate faster and more robust model validation.

Enhanced data analytics capabilities: The data warehouse will enable advanced data exploration and analysis, leading to deeper insights into forest health and composition.

Actionable client insights: Interactive dashboards will empower clients to readily access and comprehend key forest inventory data, aiding decision-making.

Increased efficiency: Streamlined workflows and automated reporting will free up resources for further innovation and client support.

### 1.5 Project Scope

This project focuses on building a data warehouse that integrates internal and potentially external forest inventory data sources. The scope includes:

- Data modeling and warehouse design
- Data extraction, transformation, and loading (ETL) processes
- Interactive dashboard development for model validation and client communication
- Data security and user access management

### 1.6 Conclusion

Building a data warehouse is an investment in ForestAI's future. It will enhance model development, empower data analysis, and provide valuable insights to clients. This project will lay the foundation for a data-driven approach to forest inventory prediction, leading to better decision-making and improved forest management practices.

## 2.1 Introduction

Data modeling is an important step in designing a data warehouse as it structures information in a way that optimizes analysis and reporting. In this chapter, we will detail the process of creating the data modeling schema by identifying the necessary dimensions and facts to meet the needs of the dashboards and reports of the BI solution.

## 2.2 Reverse Engineering and Requirements

The first step in designing our data warehouse involves reverse-engineering the existing reports and understanding the current metrics, dimensions, and visualizations used. This process helps to identify the gaps and additional requirements needed to create a more comprehensive and efficient data warehouse.

The existing reports primarily focus on various performance metrics such as [1][2]:

- Y-MEANS (Mean of observed values)

$$y_{\text{mean}} = \frac{1}{n} \sum_{i=1}^n y_i$$

Figure 2.1: Formule de Y-MEANS

- PRED-MEANS (Mean of predicted values)

$$\text{pred}_{\text{mean}} = \frac{1}{n} \sum_{i=1}^n \hat{y}_i$$

Figure 2.2: Formule de PRED-MEANS

- RMSE (Root Mean Square Error)

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

Figure 2.3: Formule de RMSE

- MSE (Mean Square Error)

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

Figure 2.4: Formule de MSE

- MAE (Mean Absolute Error)

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i|$$

Figure 2.5: Formule de MAE

- MNAE (Mean Normalized Absolute Error)

$$\text{NMAE}_1 = \frac{\text{MAE}}{\text{mean}(\text{actual values})}$$

Figure 2.6: Formule de MNAE

- NRMSE (Normalized Root Mean Square Error)[4]

$$\text{NRMSE} = \frac{\text{RMSE}}{\bar{y}}$$

Figure 2.7: Formule de NRMSE

- Bias

$$\text{bias} = \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)$$

Figure 2.8: Formule de bias

- NBIAS (Normalized Bias)

$$\text{nbias} = \frac{\text{bias}}{y_{\text{mean}}}$$

Figure 2.9: Formule de Nbias

These metrics are essential for evaluating the performance of different models and understanding the accuracy of predictions.

We aim to create visualizations that highlight these performance metrics, allowing for easy comparison and analysis. The dashboards will display scatter plots comparing observed values and predicted values, efficient tables that shows the evolution of these measurement.

### 2.3 Metrics List

The second step is to identify the metrics that will be visualized in the dashboards and reports. Based on research on existing MLOps solutions, we have determined the following metrics:

- Total Volume (m3/ha)
- Total Timber (m3/ha)
- Average Height (m)
- Total Basal Area (m2/ha)
- Average DBH (cm)
- Pine Volume (m3/ha)
- Pine Timber (m3/ha)
- Average Pine Height (m)
- Pine Basal Area (m2/ha)
- Average Pine DBH (cm)
- Spruce Volume (m3/ha)
- Spruce Timber (m3/ha)
- Average Spruce Height (m)
- Spruce Basal Area (m2/ha)
- Average Spruce DBH (cm)
- Deciduous Volume (m3/ha)
- Deciduous Timber (m3/ha)
- Average Deciduous Height (m)
- Deciduous Basal Area (m2/ha)
- Average Deciduous DBH (cm)

### 2.4 Dimensions

Dimensional modeling is a design technique used to structure the data warehouse schema. It involves creating fact tables that store quantitative data and dimension tables that provide context to the facts. This approach supports efficient querying and reporting.

Dimensions Identified:

- Time Dimension: Captures date-related information to allow analysis over different time periods.
- Location Dimension: Provides geographical context, including country, region, and specific plot details.
- Metric Dimension: Defines the various forestry metrics being measured and their units.
- Tree Species Dimension: Categorizes data by tree species, such as Pine, Spruce, and Deciduous.
- Model Dimension: Details the predictive models used, including their versions and descriptions.
- Client Dimension: Contains client-specific information, such as client names and regions.

### 2.5 Granularity of Facts

In our project, the granularity of the fact tables has been carefully determined to ensure that the data captures the required level of detail for each type of fact: Observed Value, Client Estimate, and Model Prediction. We have chosen these specific fact tables because **all other metrics can be calculated from these core data points**. We have determined the following levels of granularity for each fact:

1. Observed Value
  - a By time period (day, month, year)
  - b By location (plot, region)
  - c By tree species
  - d By metric
2. Client Estimate
  - a By time period
  - b By location
  - c By tree species
  - d By metric
  - e By client

## 3. Model Prediction

- a By time period
- b By location
- c By tree species
- d By metric
- e By model

Here is the table that summarizes these granularities.

Facts	Time	Location	Metric	Tree Species	Model	Client
Observed Value	x	x	x	x		
Client Estimate	x	x	x	x		x
Model Prediction	x	x	x	x	x	

## 2.6 Fact tables list

Fact tables store the measurable, quantitative data. Based on the previous section, each fact is analysable by a different set of dimensions, therefore we have three fact tables:

## 1. Observed Values Fact Table (Ground Truth):

- Columns: Time ID, Location ID, Metric ID, Species ID, Observed Value
- Granularity: Individual plot measurements over time for different metrics and species.

## 2. Client Estimates Fact Table:

- Columns: Time ID, Location ID, Metric ID, Species ID, Client ID, Client Estimate
- Granularity: Client-provided estimates for various metrics and species over time and location.

## 3. Model Predictions Fact Table:

- Columns: Time ID, Location ID, Metric ID, Species ID, Model ID, Model Prediction, Model Performance
- Granularity: Model predictions and performance indicators for different metrics, species, and locations over time.

## 2.7 Data Modeling Schema

Based on the identified dimensions and facts, we have designed a star schema to structure the data. This schema includes:

- A main fact table for each type of fact (Observed Value, Client Estimate, Model Prediction).
- Associated dimension tables for time, location, metrics, tree species, models, and clients.

Additionally, we choose the **star schema** as database schema for our data mart because **our dimensions do not involve hierarchies**. Each dimension is treated as an independent entity, directly connected to the fact tables. This lack of hierarchies simplifies the design and usage, ensuring that users can easily query and analyze the data without navigating complex hierarchies.

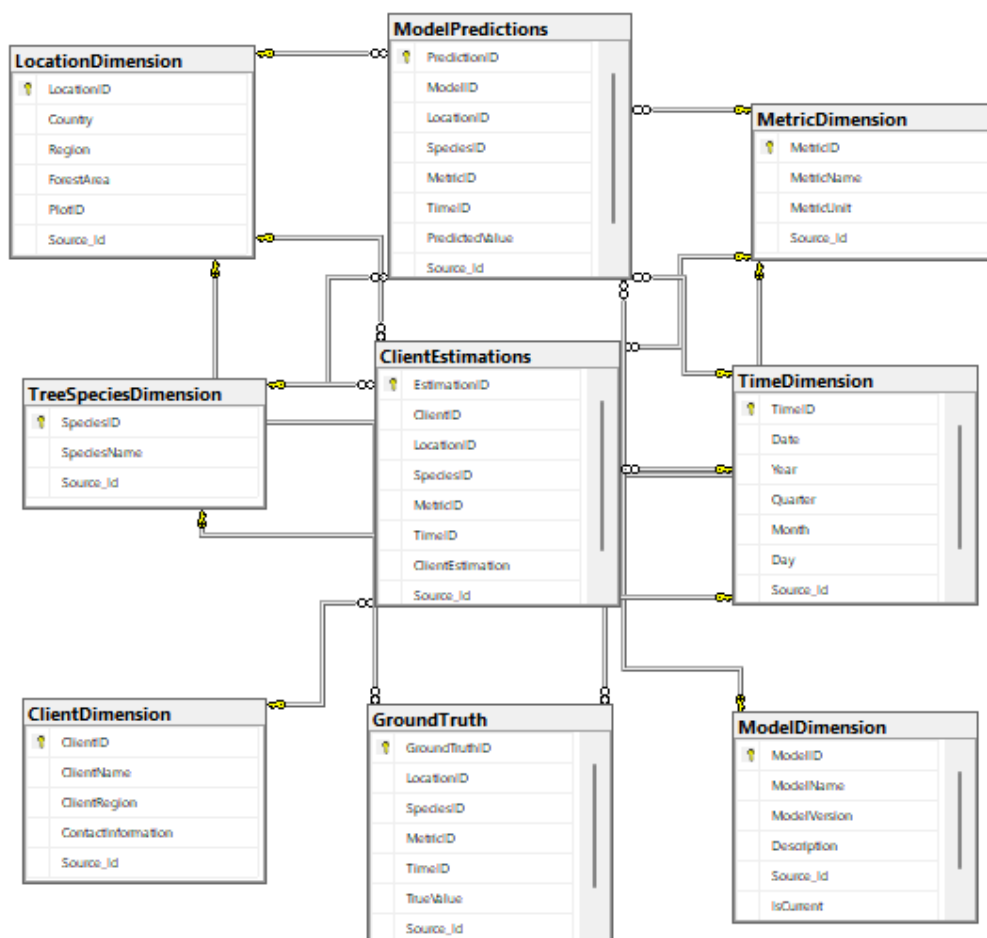


Figure 2.10: Forest AI datawarehouse schema

## 2.8 Conclusion

The design of the data warehouse for forestry metrics analysis provides a comprehensive framework to capture, store, and analyze various metrics, supporting robust reporting and performance monitoring. By utilizing dimensional modeling and a star schema, the data warehouse enables efficient querying and detailed analysis across multiple dimensions. The architecture en-



sure scalability and performance, supporting the business needs for accurate and timely insights into forestry metrics and model performance. This design will facilitate better decision-making and enhance the ability to track and improve predictive models.

## CHAPTER 3

# DATA WAREHOUSE IMPLEMENTATION

### 3.1 Introduction

In this section, we will delve into the details of implementing our data warehouse, a crucial step in our project. We will first explore the data sources used, describing their nature and structure. Next, we will discuss the ETL (Extract, Transform, Load) process that was implemented to extract data from sources, prepare it, and load it into our data warehouse environment. Finally, we will focus on the design and construction of the cube using SSAS (SQL Server Analysis Services), highlighting design choices, dimensions, facts, and aggregated measures available for analysis. This section provides a comprehensive overview of how our data warehouse was practically implemented, from the flow of raw data to the creation of a robust analytical environment.

### 3.2 Data Source

We have established a critical data source in the form of a relational database. This database was created and populated using Microsoft SQL Server Management Studio, a robust and efficient tool for database management.



Figure 3.1: Microsoft SQL Server Logo

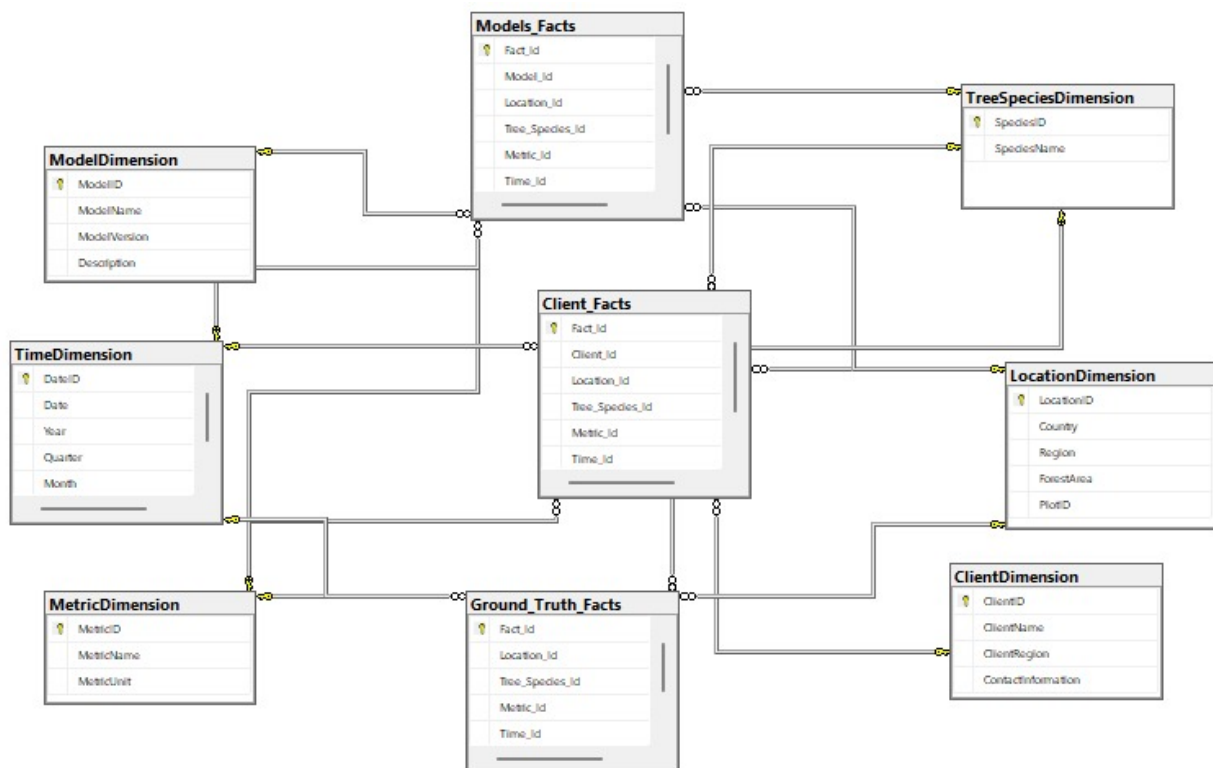


Figure 3.2: Relational Database Schema

### 3.3 Data Extraction, Transformation, and Loading (ETL)

To manage the ETL process between our relational database and our datamart, we used SQL Server Integration Services (SSIS).



Figure 3.3: SQL Server Integration Services Logo

### 3.3.1 Connection Manager Establishment

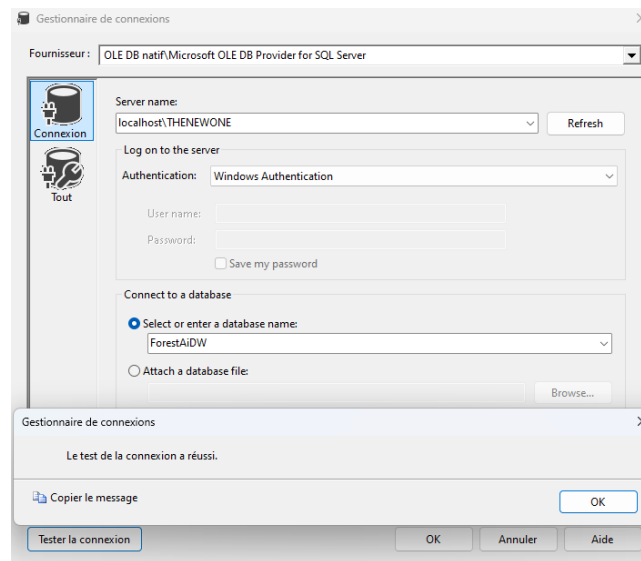


Figure 3.4: Connection to Data Source

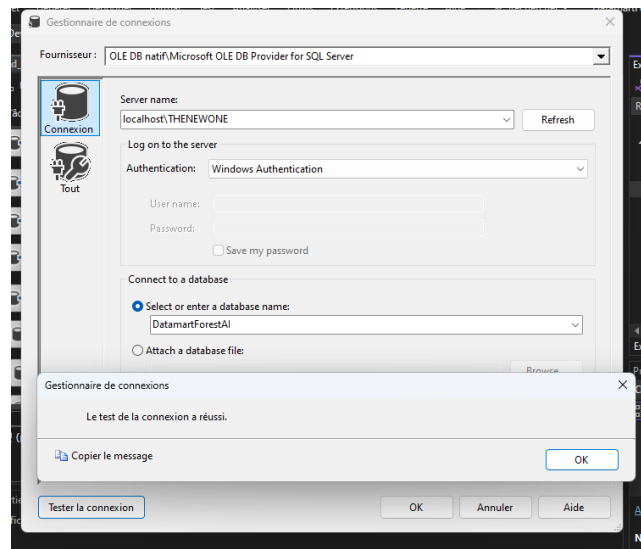


Figure 3.5: Connection to Data Destination

3.3.2 Control Flow and Data Flow Establishment

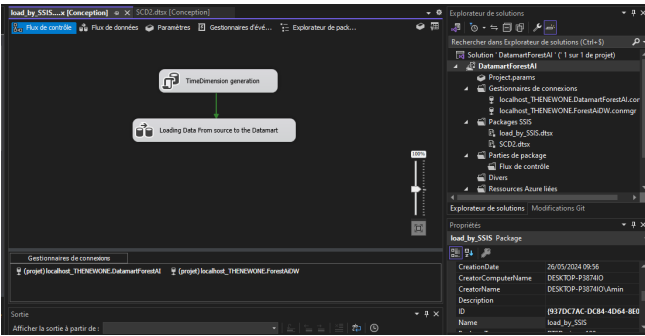


Figure 3.6: Control Flow Tasks

The screenshot shows the 'Éditeur de tâche d'exécution de requêtes SQL' (SQL Task Designer) window. The window is titled 'Éditeur de tâche d'exécution de requêtes SQL' and contains a configuration table for the task. The 'Général' tab is selected, showing the task name, description, connection type, connection, SQL source type, SQL statement, and other properties.

Général	
Name	TimeDimension generation
Description	Tâche d'exécution de requêtes SQL
Instruction SQL	
ConnectionType	OLE DB
Connection	localhost_THENEWONE.DatamartForestAI
SQLSourceType	Entrée directe
SQLStatement	DECLARE @StartDate DATE = '2022-01-01';DE
IsQueryStoredProcedure	False
BypassPrepare	True
Jeu de résultats	
ResultSet	Aucun
Options	
TimeOut	0
CodePage	1252
TypeConversionMode	Autorisé
Name	
Spécifie le nom de la tâche.	

Buttons: Parcourir..., Générer la requête..., Analyser la requête, OK, Annuler, Aide

Figure 3.7: Generation of Date Dimension using SSIS



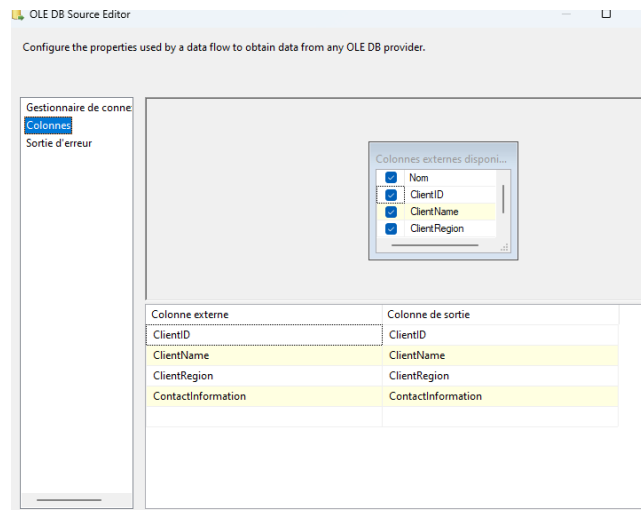


Figure 3.11: Data Source Columns Configuration

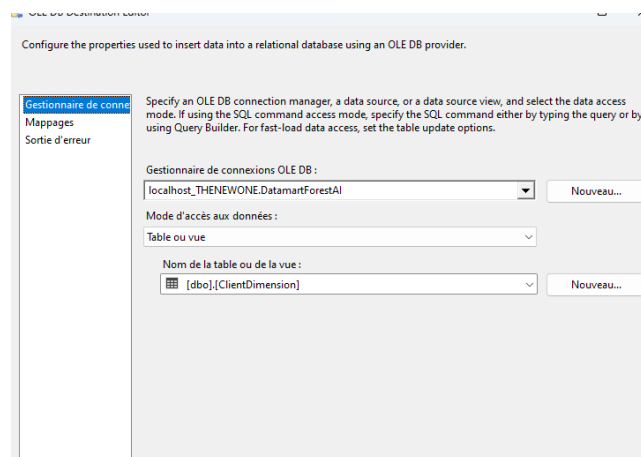


Figure 3.12: Data Destination Configuration

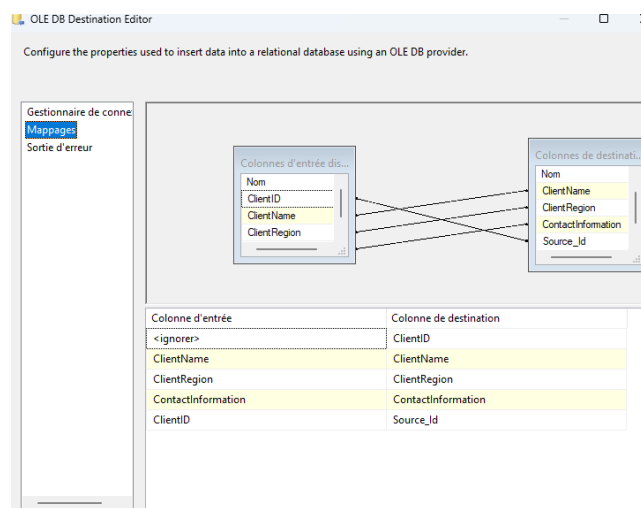


Figure 3.13: Mapping between Data Source columns and Data Destination columns



This is an example configuration for ETL data from our source to the Client Dimension, we proceeded with the same steps to populate all the rest of the tables in our data mart.

### 3.4 Slowly Changing Dimensions (SCDs)

We have applied Slowly Changing Dimension type 2 on the Model Dimension. We choose the model version as the historical data, and we added a column "IsCurrent" which can take two values : true and false, to keep track of the new and old data.

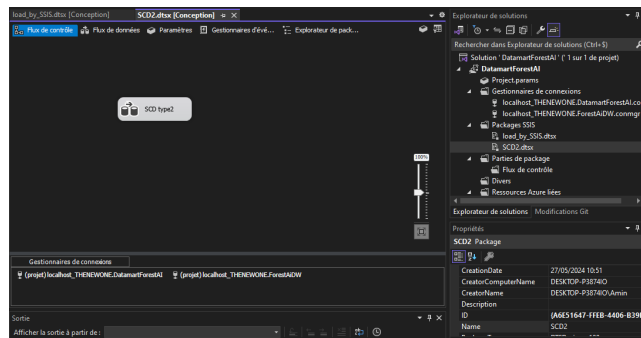


Figure 3.14: Control Flow Task

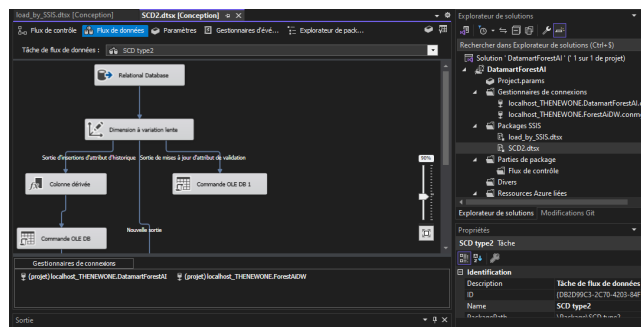


Figure 3.15: Data Flow Tasks

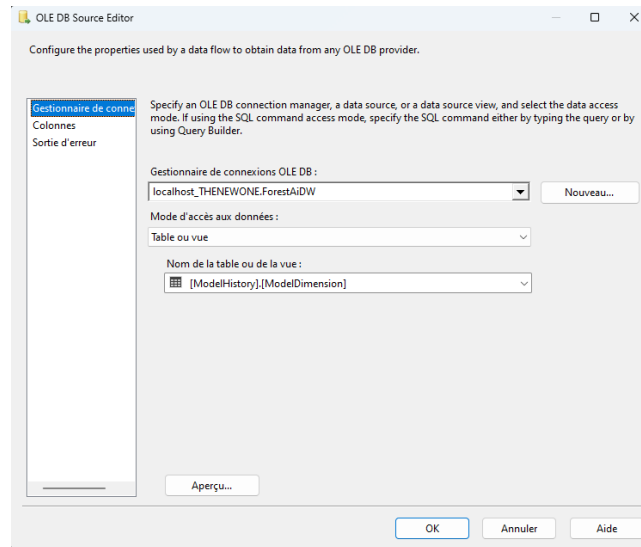


Figure 3.16: Data Source Specification

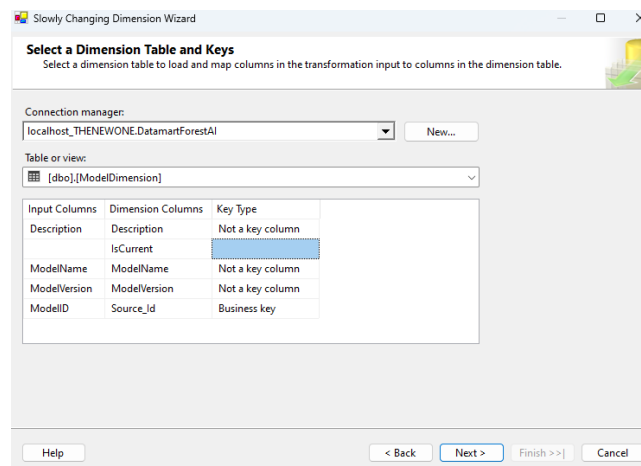


Figure 3.17: Selection of Dimension Table

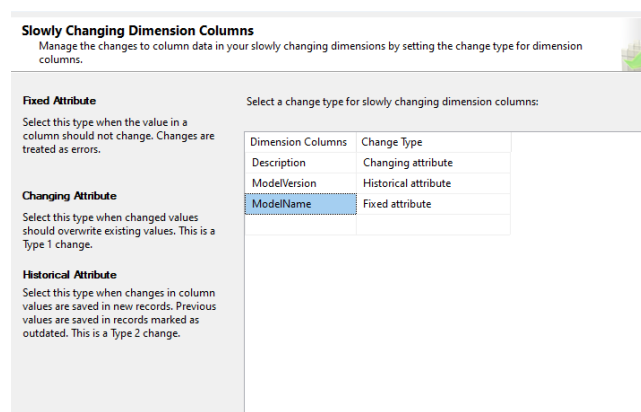


Figure 3.18: Selection of "Change" Type for Slowly Changing Dimension Columns

**Historical Attribute Options**  
You can record historical attributes using a single column or start and end date columns.

☒ Use a single column to show current and expired records

Column to indicate current record:

Value when current:

Expiration value:

☐ Use start and end dates to identify current and expired records

Start date column:

End date column:

Variable to set date values:

Figure 3.19: Use of a Single Columns to Show Current and Expired Records

**Finish the Slowly Changing Dimension Wizard**  
Review the outputs that the Slow Changing Dimension Wizard will build to support a slowly changing dimension.

The following outputs will be configured:

- Slowly Changing Dimension Transformation
- New Records
- New Record Output
- Other Outputs
- Historical Attribute Output

Figure 3.20: Finish the Slowly Changing Dimension Configuration

## 3.5 Cube Construction

In constructing our cube, we leveraged the capabilities of SSAS (SQL Server Analysis Services). This powerful tool allowed us to model and organize our data efficiently, facilitating insightful analysis and reporting.



Figure 3.21: SQL Server Analysis Services

### 3.5.1 Data Source Configuration

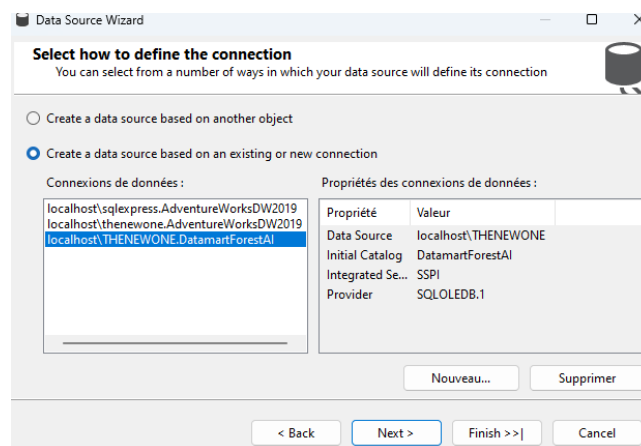


Figure 3.22: Selection of Connexion Type

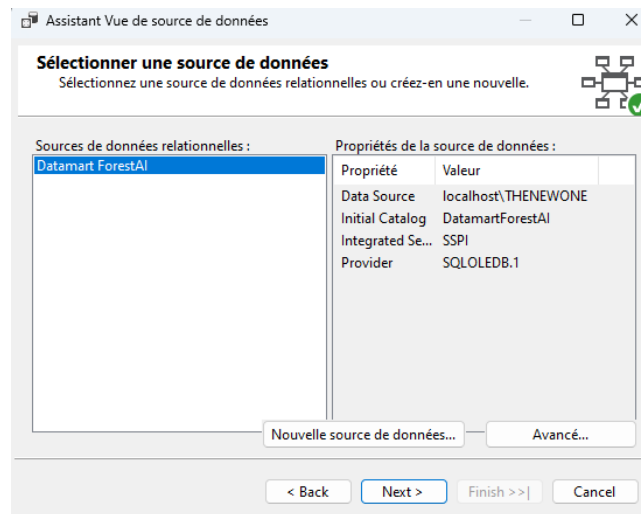


Figure 3.23: Data Source Configuration-Connexion

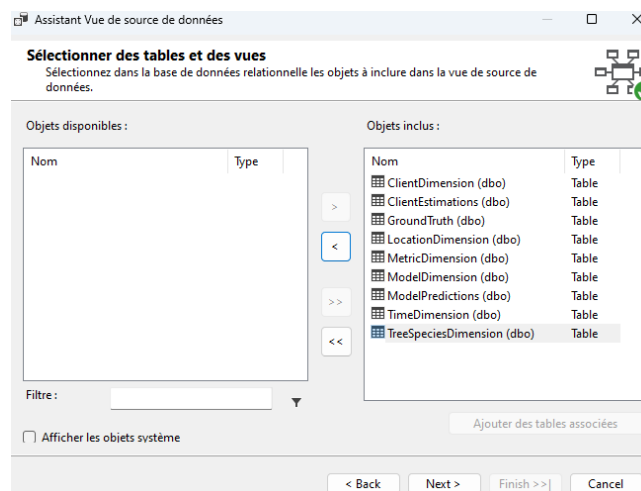


Figure 3.24: Data Source Configuration-Tables Selection

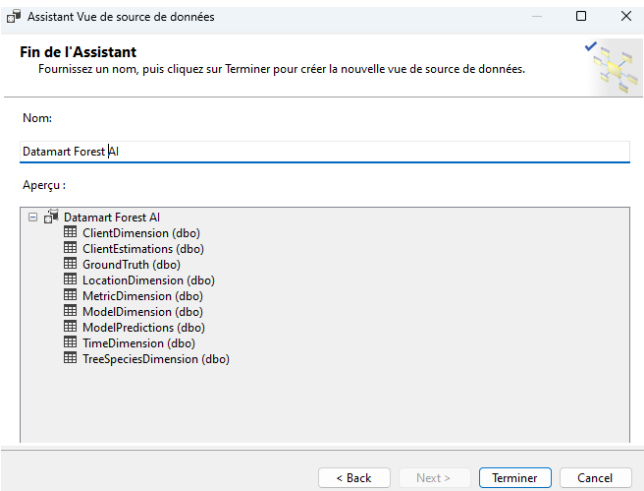


Figure 3.25: Data Source Configuration-Result

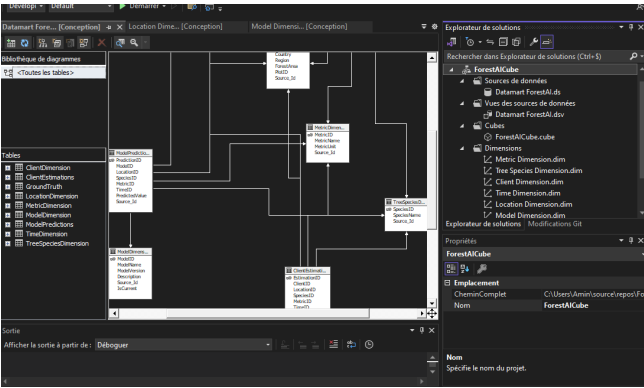
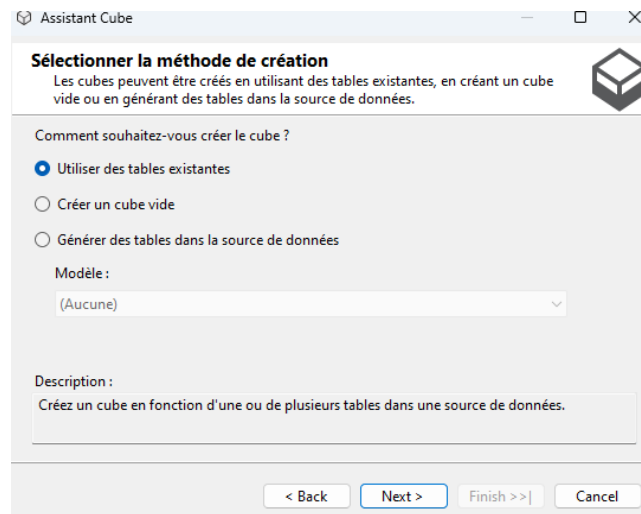


Figure 3.26: Data Source Configuration-Result Shema

### 3.5.2 Cube Construction



**Sélectionner la méthode de création**  
Les cubes peuvent être créés en utilisant des tables existantes, en créant un cube vide ou en générant des tables dans la source de données.

Comment souhaitez-vous créer le cube ?

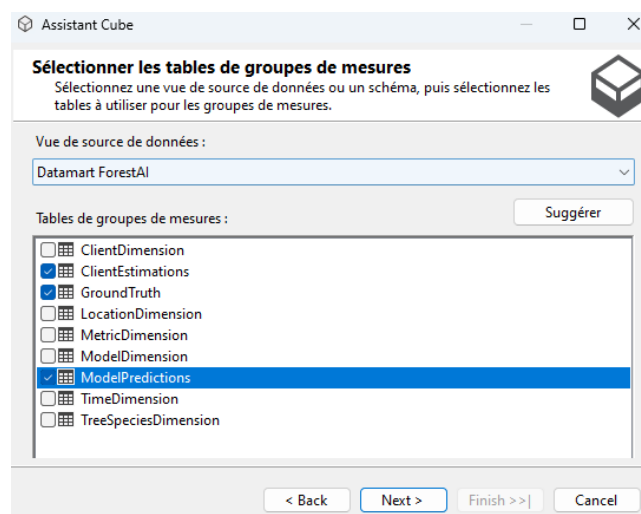
- ☒ Utiliser des tables existantes
- ☐ Créer un cube vide
- ☐ Générer des tables dans la source de données

Modèle :  
(Aucune)

Description :  
Créez un cube en fonction d'une ou de plusieurs tables dans une source de données.

< Back   Next >   Finish >> |   Cancel

Figure 3.27: Cube Construction-Selection of Creation Method



**Sélectionner les tables de groupes de mesures**  
Sélectionnez une vue de source de données ou un schéma, puis sélectionnez les tables à utiliser pour les groupes de mesures.

Vue de source de données :  
Datamart ForestAI

Tables de groupes de mesures :   Suggérer

- ☐ ClientDimension
- ☒ ClientEstimations
- ☒ GroundTruth
- ☐ LocationDimension
- ☐ MetricDimension
- ☐ ModelDimension
- ☒ ModelPredictions
- ☐ TimeDimension
- ☐ TreeSpeciesDimension

< Back   Next >   Finish >> |   Cancel

Figure 3.28: Cube Construction-Selection of Facts Tables

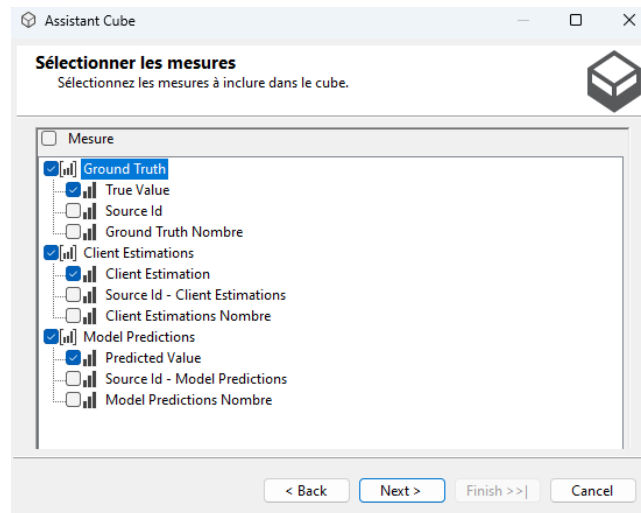


Figure 3.29: Cube Construction-Selection of Metrics

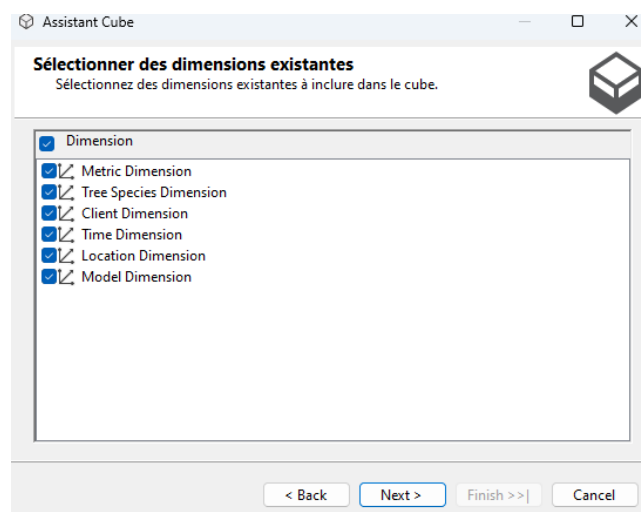


Figure 3.30: Cube Construction-Selection of Dimensions



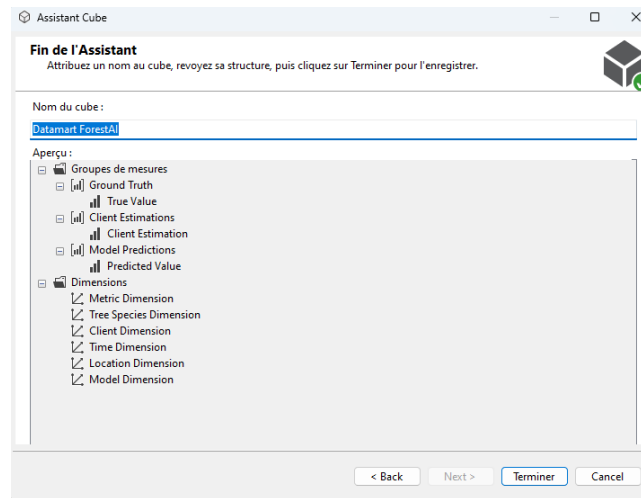


Figure 3.31: Cube Construction-Finish the Construction

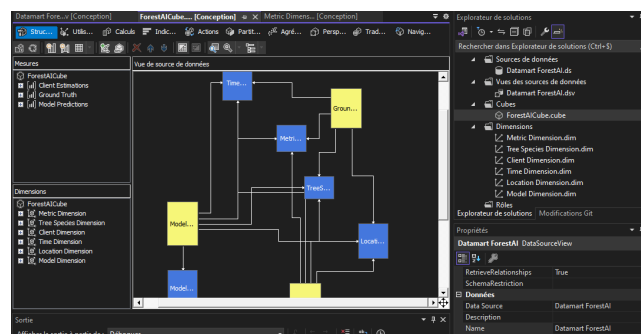


Figure 3.32: Cube Construction-Result

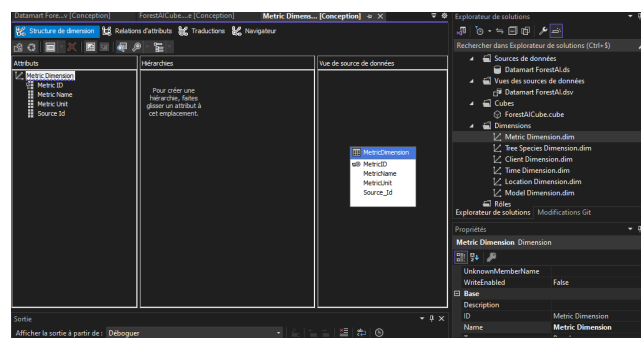


Figure 3.33: Attributes of metrics used in the cube - Example1

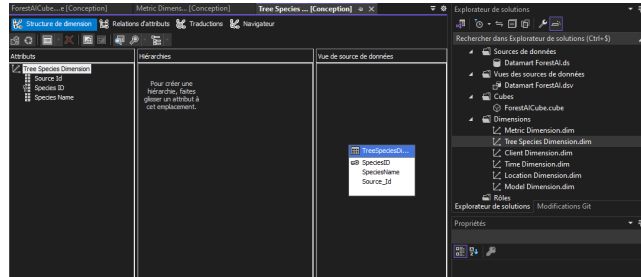


Figure 3.34: Attributes of metrics used in the cube - Example2

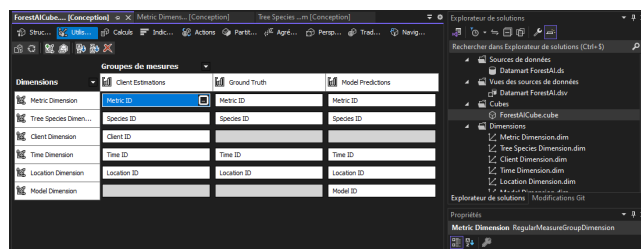


Figure 3.35: Cube Granularity

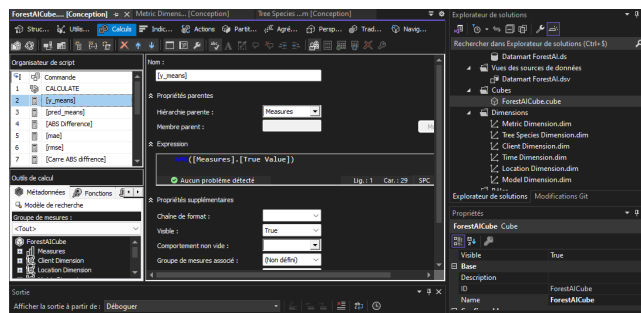


Figure 3.36: Adding Calculable Facts to the Cube

### 3.6 Conclusion

In conclusion, our data warehouse implementation was executed successfully. We established a critical relational database using Microsoft SQL Server Management Studio, then effectively designed and implemented the ETL process to ensure data integrity. Using SSAS, we constructed a cube with essential dimensions, facts, and aggregated measures, resulting in a robust and efficient analytical environment ready for comprehensive data analysis and visualization.

## 4.1 Introduction

The visualization phase of our data warehouse, achieved through Power BI connected to our cube, represents a critical step in interpreting and effectively communicating our data. This section highlights the different reports and visualizations created to analyze model performance, validate results, and compare predictions with real data. By combining the power of our data cube with the interactive features of Power BI, we have developed highly informative visual tools to guide decision-making and communicate our findings clearly and persuasively.



Figure 4.1: Microsoft PowerBI Logo

## 4.2 Model Performance Report

Model Performance Reports present characteristics and error metrics for the version of a model.

## Les performances du Modèle A V1.0

Model Name	Model Version	Metric Name	Species Name	y_means	pred_means	mae	rmse	mnae	nrmse	Bias	nbias
Model A	v1.0	Average DBH	Deciduous	54,214.00	55,627.00	-1,413.00	1,413.00	-0.03	0.03	1,413.00	0.03
Model A	v1.0	Average DBH	Pine	53,311.00	54,255.00	-944.00	944.00	-0.02	0.02	944.00	0.02
Model A	v1.0	Average DBH	Spruce	52,959.00	52,895.00	64.00	64.00	0.00	0.00	-64.00	0.00
Model A	v1.0	Average Height	Deciduous	55,263.00	52,278.00	2,985.00	2,985.00	0.05	0.05	-2,985.00	-0.05
Model A	v1.0	Average Height	Pine	55,440.00	54,167.00	1,273.00	1,273.00	0.02	0.02	-1,273.00	-0.02
Model A	v1.0	Average Height	Spruce	55,524.00	57,340.00	-1,816.00	1,816.00	-0.03	0.03	1,816.00	0.03
Model A	v1.0	Basal Area	Deciduous	55,028.00	54,516.00	512.00	512.00	0.01	0.01	-512.00	-0.01
Model A	v1.0	Basal Area	Pine	53,582.00	53,455.00	127.00	127.00	0.00	0.00	-127.00	0.00
Model A	v1.0	Basal Area	Spruce	53,330.00	54,319.00	-989.00	989.00	-0.02	0.02	989.00	0.02
Model A	v1.0	Timber	Deciduous	54,034.00	55,434.00	-1,400.00	1,400.00	-0.03	0.03	1,400.00	0.03
Model A	v1.0	Timber	Pine	55,962.00	54,140.00	1,822.00	1,822.00	0.03	0.03	-1,822.00	-0.03
Model A	v1.0	Timber	Spruce	51,962.00	55,670.00	-3,708.00	3,708.00	-0.07	0.07	3,708.00	0.07
Model A	v1.0	Volume	Deciduous	56,100.00	54,502.00	1,598.00	1,598.00	0.03	0.03	-1,598.00	-0.03
Model A	v1.0	Volume	Pine	54,188.00	54,051.00	137.00	137.00	0.00	0.00	-137.00	0.00
Model A	v1.0	Volume	Spruce	55,443.00	55,099.00	344.00	344.00	0.01	0.01	-344.00	-0.01
<b>Total</b>				<b>816,340.00</b>	<b>817,748.00</b>	<b>-1,408.00</b>	<b>1,408.00</b>	<b>0.00</b>	<b>0.00</b>	<b>1,408.00</b>	<b>0.00</b>

Figure 4.2: Model Performance Report

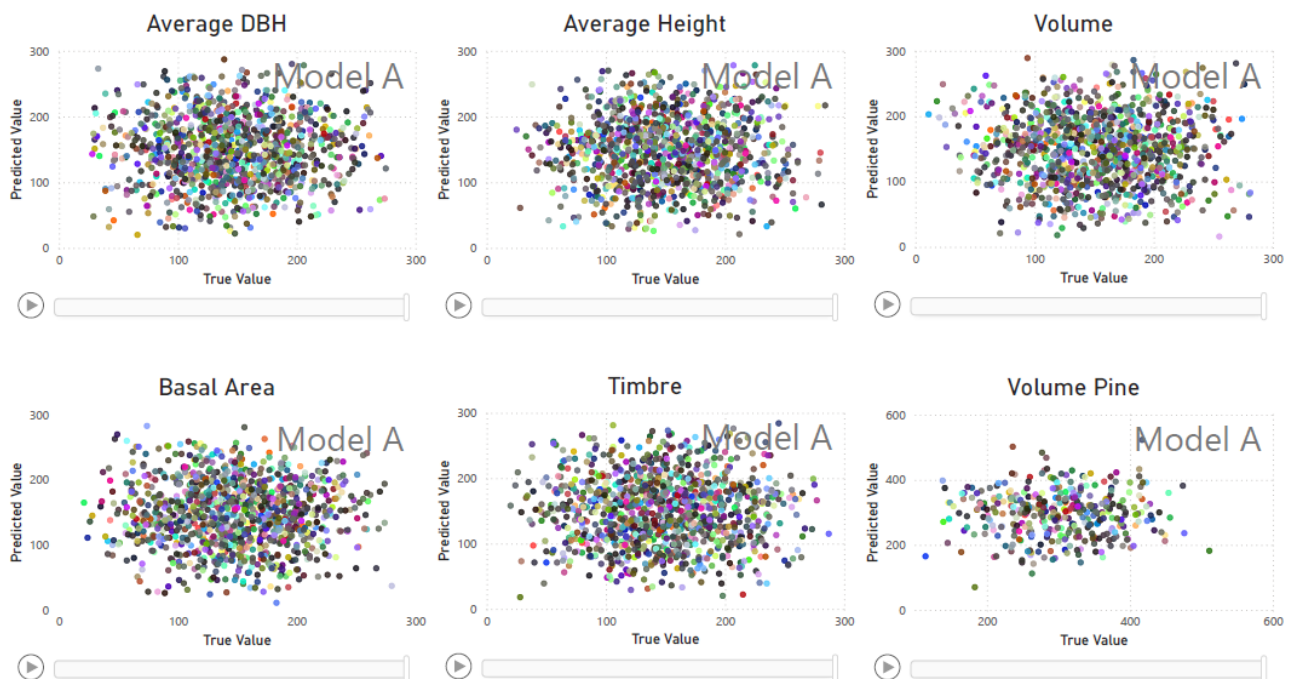


Figure 4.3: Comparison between Real Values and Prediction Values of Facts



Figure 4.4: Comparison between Real Values and Prediction Values of Facts

### 4.3 Model Validation Reports

The purpose is to compare the outputs of a new model with those of the previous version to demonstrate its improved performance. This comparison is very necessary to ensure that the new model is functioning as intended and is accurate. The validator evaluates all models against the actual data, using error metrics to identify the model with the most favorable performance.

**NRMSE des modèles par rapport aux metrics**

Model Version	Average DBH	Average Height	Basal Area	Timber	Volume	Total
☐ v1.0	<b>0.01</b>	<b>0.01</b>	<b>0.00</b>	<b>0.02</b>	<b>0.01</b>	<b>0.00</b>
Model A	0.01	0.01	0.00	0.02	0.01	<b>0.00</b>
☐ v1.1	<b>0.01</b>	<b>0.02</b>	<b>0.01</b>	<b>0.00</b>	<b>0.02</b>	<b>0.01</b>
Model A	1.00	1.00	1.00	1.00	1.00	<b>1.00</b>
Model B	0.01	0.02	0.01	0.00	0.02	<b>0.01</b>
☐ v1.3	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>
Model B	1.00	1.00	1.00	1.00	1.00	<b>1.00</b>
☐ v1.5	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>
Model A	1.00	1.00	1.00	1.00	1.00	<b>1.00</b>
☐ v1.8	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>
Model B	1.00	1.00	1.00	1.00	1.00	<b>1.00</b>
☐ v2.0	<b>0.03</b>	<b>0.01</b>	<b>0.01</b>	<b>0.00</b>	<b>0.00</b>	<b>0.01</b>
Model C	0.03	0.01	0.01	0.00	0.00	<b>0.01</b>
☐ v2.5	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>
Model C	1.00	1.00	1.00	1.00	1.00	<b>1.00</b>
☐ v2.9	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>
Model C	1.00	1.00	1.00	1.00	1.00	<b>1.00</b>
Total	<b>2.06</b>	<b>1.96</b>	<b>2.01</b>	<b>2.03</b>	<b>1.97</b>	<b>2.00</b>

Figure 4.5: NRMSE of models relative to metrics

**NRMSE des modèles par rapport aux species**

Model Version	Deciduous	Pine	Spruce	Total
☐ v1.0	<b>0.01</b>	<b>0.01</b>	<b>0.02</b>	<b>0.00</b>
Model A	0.01	0.01	0.02	<b>0.00</b>
☐ v1.1	<b>0.02</b>	<b>0.00</b>	<b>0.00</b>	<b>0.01</b>
Model A	1.00	1.00	1.00	<b>1.00</b>
Model B	0.02	0.00	0.00	<b>0.01</b>
☐ v1.3	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>
Model B	1.00	1.00	1.00	<b>1.00</b>
☐ v1.5	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>
Model A	1.00	1.00	1.00	<b>1.00</b>
☐ v1.8	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>
Model B	1.00	1.00	1.00	<b>1.00</b>
☐ v2.0	<b>0.00</b>	<b>0.01</b>	<b>0.02</b>	<b>0.01</b>
Model C	0.00	0.01	0.02	<b>0.01</b>
☐ v2.5	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>
Model C	1.00	1.00	1.00	<b>1.00</b>
☐ v2.9	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>	<b>1.00</b>
Model C	1.00	1.00	1.00	<b>1.00</b>
Total	<b>1.97</b>	<b>2.00</b>	<b>2.04</b>	<b>2.00</b>

Figure 4.6: NRMSE of models relative to species

## 4.4 Client Estimate Comparison Report

This report provides comparisons of the models predictions with client estimations. It is used as a sales tool to convince clients that ForestAI's models are better

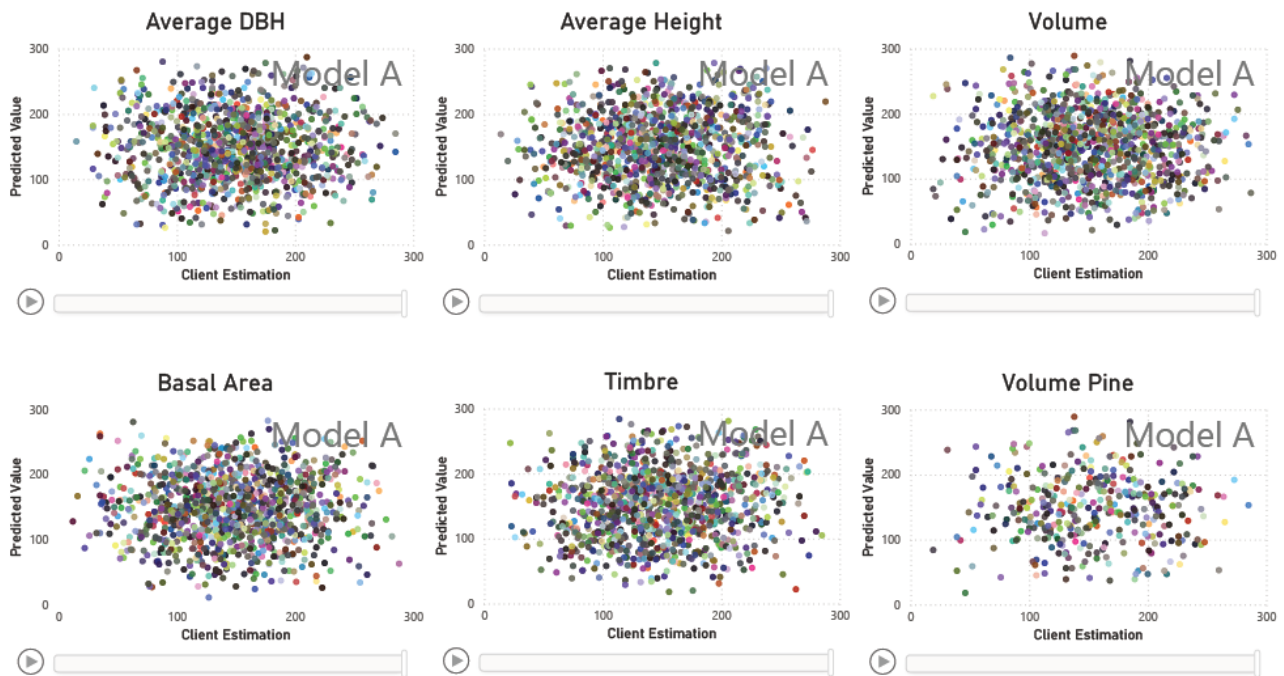


Figure 4.7: Comparison between Client Estimations and Prediction Values of Facts



### 4.5 Conclusion

Using Power BI as our visualization tool, we have created a range of essential reports to assess our models' performance and delve into our data comprehensively. These reports include comparative analyses of NRMSE relative to various metrics as well as species, providing a comprehensive view of the accuracy and effectiveness of our models. The integration of Power BI with our data cube has enabled us to present this information interactively and convincingly, facilitating informed decision-making and effective communication of results to stakeholders.

In conclusion, the development of the data warehouse for ForestAI has improved model validation, data analysis, and information delivery to clients. Using SSIS for data loading, a robust SSAS cube for detailed analysis, and Power BI for interactive visualizations, the project has achieved its goals of better data management and accessibility.

This technological integration has streamlined the model validation process, allowing for faster and more accurate evaluations, thereby enhancing internal efficiency and client presentations by providing clear, data-driven insights.

By focusing on key metrics and enabling detailed, real-time analysis, ForestAI can better understand model performance and offer superior services. This project demonstrates the crucial role of a well-designed data warehouse in supporting advanced analytics and business intelligence, laying the foundation for continuous growth and operational excellence.

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## REFERENCES

1. <https://www.datacourses.com/evaluation-of-regression-models-in-scikit-learn-846/> (Consulté le 20 mai 2024)
2. <https://sefidian.com/2022/08/18/a-guide-on-regression-error-metrics-with-python-code/> (Consulté le 20 mai 2024)
3. <https://www.statisticshowto.com/nrmse/> (Consulté le 20 mai 2024)
4. <https://www.techtarget.com/searchsoftwarequality/definition/reverse-engineering> (Consulté le 27 mai 2024)