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Updated methodology to quantify forest-sector employment

Global and regional estimates

Funded by the European Union

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Abbreviations

FAO	Food and Agriculture Organization of the United Nations
FE	female employment
FEM	Forest EMployment
FRA	Global Forest Resources Assessment
ICLS	International Conference of Labour Statisticians
ILO	International Labour Organization
ISIC	International Standard Industrial Classification of all Economic Activities
LFS	labour force survey
ME	male employment
NWFPs	non-wood forest products
PPP	purchasing power parity
RMSE	root mean squared error
SDGs	Sustainable Development Goals
TE	total employment
WBM	wave-based method

Executive summary

Key messages

- The Forest EMployment (FEM) model provides annual estimates of forest-sector employment by gender between 2011 and 2022 for 182 countries and territories, accounting for 99 percent of global forest area.
- In 2022, the forest sector provided employment to at least 42 million people worldwide, which amounted to about 1.2 percent of total employment.
- The manufacture of wood and products of wood accounted for the largest share (58 percent) of employment in the forest sector in 2022.
- In 2022, approximately 11 million women were employed in the forest sector, representing 25 percent of its total workforce.
- Between 2011 and 2022, about 0.8 percent of women and 1.5 percent of men in the global workforce were employed in the forest sector.

Forest EMployment (FEM) model

The number of people employed in the forest sector serves as a long-standing and tangible measure for assessing the socioeconomic importance of forest-related economic activities. Internationally comparable data on employment in the forest sector are needed to ensure evidence-based policymaking and foster a sustainable and resilient forest sector.[1] This study introduces an updated methodology – the Forest EMployment (FEM) model – for assessing the magnitude of global forest-sector employment. The forest sector is defined in accordance with the International Standard Industrial Classification of all Economic Activities, encompassing three subsectors: forestry and logging, the manufacture of wood and products of wood (wood manufacturing), and the manufacture of pulp, paper and products of paper (pulp and paper manufacturing).

The FEM model utilizes weighted fixed-effects panel regression, selected through the cross-validation procedure. In a finite number of possibilities, the cross-validation exercise identifies the statistical relationship between employment indicators of interest and country-level attributes that yields the lowest pseudo-out-of-sample root mean squared error. The country attributes cover socioeconomic and demographic characteristics, forest resources, labour market indicators and the supply and demand for forest products. The primary input data for estimating forest-sector employment were retrieved from ILOSTAT, FAOSTAT, the World Bank and the Population Division of the United Nations Department of Economic and Social Affairs. The FEM model successfully provides the first annual gender-disaggregated employment estimates for each forest subsector across 182 countries from 2011 to 2022, covering 99 percent of the global forest area.

[1] In this document, the term "employment" denotes an individual's main job activity within the specified sector. This definition follows the international standards on labour statistics established by the 13th International Conference of Labour Statisticians, thereby ensuring the consistency, reliability, and comparability of data at both national and global levels. Consequently, individuals who hold multiple jobs for whom employment in the forest sector is a secondary activity are excluded. Further methodological details can be found in Section 2.

Forest-sector employment

According to the FEM model, the forest sector provided employment to at least 42 million people globally in 2022, with wood and wood product manufacturing accounting for about 58 percent of total forest-sector employment.[2] The role of the forestry and logging subsector in job creation has remained relatively stable over the past decade, consistently representing nearly one-third of the total forest-sector employment worldwide. In 2022, the manufacture of pulp and paper subsector represented approximately 16 percent of total employment in the forest sector.

The forest sector accounted for 1.2 percent of the global employment in 2022 – a decline of approximately 3.1 percent with respect to 2011. Asia has consistently maintained the largest share of total employment in the forest sector, on average around 1.4 percent over the past decade. In Europe, the share of forest-sector employment declined slightly from 1.3 percent in 2011 to 1.2 percent in 2022, reflecting a modest reduction in the sector's contribution to employment. Africa experienced fluctuations, starting at 1.2 percent in 2011, peaking in 2016, and subsequently declining to 1.0 percent by 2022. The Americas exhibited a relatively stable trend, with a rate of around 0.8 percent and minor fluctuations following the COVID-19 pandemic. In Oceania, the forest sector's employment share of total employment stood at 0.9 percent in 2011 but showed slight variability between 2013 and 2015, then declined to 0.8 percent by 2022, following the pandemic.

Female employment in the forest sector

In 2022, an estimated 10.6 million women were employed in the global forest sector, accounting for 25 percent of its workforce. Between 2011 and 2022, approximately 0.8 percent of women and 1.5 percent of men worked in the forest sector worldwide, highlighting a persistent gender employment gap evident across all regions. In Europe, the disparity was widest, with 1.8 percent of men and only 0.5 percent of women employed in the forest sector in 2022. In contrast, the gender gap in the forest employment share was narrower in Africa, the Americas and Asia, ranging from 0.6 to 0.7 percentage points, with men still accounting for a slightly larger share than women. Africa saw a slight decline in forest-sector employment for both genders between 2016 and 2022. Despite the sector remaining predominantly male across all regions, the gender employment gap has narrowed in parts of Asia – particularly in South and Southeast Asia, declining from 0.36 percentage points in 2011 to 0.15 percentage points in 2022.

Methodological advantages and uncertainties

The FEM model is an updated methodology published by Lippe *et al*. (2022) and developed to close data gaps in cross-country time series, enabling the estimation of forest-sector employment figures worldwide and, for the first time, providing employment estimates disaggregated by gender. Compared with previous estimates, the latest FEM model offers several methodological improvements for addressing employment data gaps in the forest sector. It generates annual estimates instead of the previously used three-year intervals, allowing for more detailed trend analysis. In

[2] For the definition of forest sector and subsectors, please refer to Section 2 of this document.

addition, it utilizes country-specific socioeconomic and demographic characteristics, labour market and forest sector variables to predict missing data, rather than relying on regional averaging applied by earlier wave-based method (WBM). The FEM model also preserves the relationships between variables using panel regression techniques, ensuring consistency with observed data patterns.

Despite these strengths, the FEM model has some limitations. The model's reliance on country-level predictors makes it sensitive to missing covariate data, often necessitating linear interpolation or exclusion of data-poor countries. Moreover, many predictors include imputed values, resulting in layered uncertainty in the final estimates. There are also persistent subsector-specific limitations, including the absence of country-level data on non-wood forest products in forestry and logging, or on wood and cork products in wood manufacturing, which may lead to underestimation. The limited availability of gender-disaggregated employment data further restricts model accuracy, particularly for countries that do not report data and where imputations rely solely on patterns from reporting countries. As a result, employment estimates for these countries should be interpreted with caution.

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1. INTRODUCTION

Forests, forest products and forest ecosystem services significantly contribute to the achievement of the UN Sustainable Development Goals (SDGs), with impacts on several SDGs, including SDG 2 (Zero Hunger), SDG 8 (Decent Work and Economic Growth), SDG 12 (Sustainable Consumption and Production), SDG 13 (Climate Action) and SDG 15 (Life on Land) (Baumgartner, 2019). The forest sector plays a vital role in national economies and sustainable development by generating employment, creating economic value and supporting environmental sustainability, among other contributions. It is also a cornerstone of the transition to a sustainable bioeconomy, supplying renewable biological resources and bio-based products that foster societal well-being and sustainable economic development (Jonsson *et al.*, 2021). In this context, forest-sector employment[3] contributes to economies by creating additional livelihood options (FAO, 2022a), especially in rural areas where sources of income generation are often limited (Arce, 2019). Quantifying the contribution of forests to job creation is therefore essential – especially at meaningful spatial scales – to fully understand their economic impact. The number of people employed in the forest sector serves as a long-standing and tangible measure for assessing the socioeconomic importance of forest-related economic activities (Robertson and St. Hilaire, 2024). These data are essential for enabling evidence-based policymaking, and they play a decisive role in promoting a sustainable and resilient forest sector while advancing the SDGs, particularly SDG 8.

Over the past decade, significant efforts have been made to quantify the forest-sector employment and its share of the global labour force. Prior studies have offered valuable insights into this area. For example, Li *et al*. (2019) estimated that, in 2015, the global forest sector directly employed over 18 million people and supported 45 million jobs through direct, indirect and induced effects. Similarly, Lippe, Cui and Schweinle (2021) reported that at least 64 million full-time equivalent jobs were linked to the forest sector in 2015. Variations in reported figures stem from differences in input data, measurement units, the definition of the forest sector, the estimation methodologies and the number of countries included in the analysis (Lippe *et al*., 2022). To address these discrepancies, a study by FAO (2022b) and Lippe *et al*. (2022), which was conducted in support of the Global Core Set of Forest-related Indicators (FAO and CPF, 2022), adopted the concept of employment used by the International Labour Organization (ILO), drawing on the definition set out in the guidelines and resolutions of the International Conference of Labour Statisticians (ICLS). This alignment enables the production of internationally comparable labour statistics and harmonized employment estimates. Using a wave-based method,[4] the study estimated that at least 33 million people were employed in the global forest sector from 2017 to 2019 (FAO, 2022b; Lippe *et al*.,

[3] In this study, the term "forest-sector employment" refers to employment related to the forest sector as well as the people employed in the forest sector. These two meanings of the term are used interchangeably throughout the paper.

[4] The wave-based method, in Lippe et al. (2022), is a ratio imputation technique that consists of two main steps. First, the ratio of forest employment in the ILO modelled employment estimates for broad economic sectors is calculated to bridge data gaps in countries that have at least one data point during the analysis period. Second, the balanced panel of forest-related employment data derived from the first step and the ILO modelled estimates are thus used to generate regional employment coefficients for each subsector and data point. A regional employment coefficient for the case of the forestry subsector is the share of forestry employment in the ILO modelled estimates for agriculture, whereas ILO modelled estimates for manufacturing are used as a benchmark for the case of wood manufacturing and pulp and paper manufacturing. The procedure works on the assumption that countries in the same geographical domain are likely to exhibit the same characteristics in terms of forest-related employment.

2022). These global and regional estimates highlight the forest sector's significant role in job creation and the need for continued efforts to ensure that reliable and comparable employment statistics within the sector are available.

Time series data on forest-sector employment allow for the analysis of labour market trends, revealing patterns, gaps and opportunities across regions and within individual countries. In addition, employment data broken down by gender help to better understand occupational segregation and the evolving role of women, which can support inclusive workforce practices (Follo *et al.*, 2017; Korhonen *et al*., 2024). Despite the ILO's efforts to compile and disseminate comprehensive labour statistics, and notwithstanding recent advancements in research, quantifying annual employment in the forest sector and further disaggregating it by gender remains a complex task. This challenge is partly due to the nature of labour force surveys (LFS) or household surveys, which often result in fragmented employment data. The potential undercoverage bias in LFS further affects data availability and reliability (Lippe *et al.*, 2022). Moreover, the high degree of informality within the forest sector makes it even more difficult to adequately estimate the total workforce (Lippe *et al*., 2023).

To address these challenges, this technical background paper introduces an updated methodology for assessing the magnitude of global forest-sector employment, developed in the context of FAO's Global Forest Resources Assessments (FRA). It presents the latest annual employment estimates in the forest sector, disaggregated by geographic regions and gender, and covering 182 countries between 2011 and 2022.[5] The 182-country sample represents 99 percent of the global forest areas. The use of panel regression and best-model selection techniques makes results more robust by reducing the potential for subjectivity and improving the accuracy of employment estimates.

The next chapter sets out the definitions of the forest sector and employment, which form the basis for the analysis. It also provides an overview of the employment data and challenges in quantifying forest-sector employment. Chapter 3 describes the methodology and explains the selection of the most suitable model. Chapter 4 presents key findings, including global and regional estimates disaggregated by gender and trends within the forest sector. Chapter 5 discusses methodological constraints and considerations. The study concludes with key takeaways and future perspectives for improving the consistency and comparability of forest-sector employment data.

[5] The ILO modelled estimates cover 189 countries. In this study, seven countries are excluded because of the lack of available data on forest areas and forest product production.

2. DEFINITIONS AND EMPLOYMENT DATA

2.1 Definition of the forest sector

To accurately estimate global forest-sector employment, it is crucial to base the analysis on comparable, standardized terminology, definitions and measurement units. The International Standard Industrial Classification of all Economic Activities (ISIC) provides a structured framework for organizing and presenting economic data systematically. Its hierarchical, four-tier classification of mutually exclusive categories of economic activities facilitates data collection and analysis, informed decision-making and effective policy formulation (United Nations, 2008). In this study, the forest sector is defined according to the ISIC numerical codes, i.e. two-digit divisions, corresponding to the three divisions of economic activities (hereafter referred to as "subsectors"):

1. Forestry and logging (ISIC Revision 4, division 02 or A02): this subsector includes silviculture, raw wood-producing activities, the extraction and gathering of non-wood forest products, and products that undergo little processing in the forest, such as firewood and charcoal, as well as the transportation of harvested forest products within the forest. These activities can be carried out in both natural and planted forests.

2. Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials (ISIC Revision 4, division 16 or C16, hereafter "wood manufacturing"): this subsector includes the manufacture of semi-finished wood products (e.g. sawmilling, veneer sheets, wood-based panels), products of wood, cork, straw and plaiting materials, except furniture.

3. Manufacture of paper and paper products (ISIC Revision 4, division 17 or C17, hereafter "pulp and paper manufacturing"): this subsector covers the manufacture of pulp, paper, paperboard, corrugated paper, containers of paper and other articles of paper and paperboard.

2.2 Employment data by sector and gender

The ILOSTAT database, maintained by the International Labour Organization (ILO), serves as the most reliable publicly available data source, providing a comparable and harmonized set of indicators on labour statistics. The ILO harmonized microdata are a widely recognized and comprehensive resource derived from the systematic international standardization of national labour force surveys (LFS) or similar household surveys. The ILO Modelled Estimates (ILOEST) series offers a comprehensive set of comparable employment data, based on nationally reported observations and imputations for countries with missing information. Key employment indicators are extracted from ILOSTAT, based on the definition of the forest sector described in the previous section.

For the purpose of this analysis, three main indicators were retrieved from the ILOSTAT data repositories in August 2024: (1) employment by sex and economic activity – ISIC level 2 (thousands) (ILO, 2023a); (2) employment by sex and economic activity (thousands) (ILO, 2023b); and (3) employment by sex and economic activity – ILO modelled estimates (thousands) (ILO, 2023c). The first and second indicators refer to sex-disaggregated employment data harmonized from the Labour Force Survey (LFS). They differ in the level of disaggregation of economic

activity, namely ISIC two-digit divisions and aggregate economic activity. The third indicator refers to ILO modelled employment estimates, disaggregated by sex and by aggregate economic activity. It is important to note that the ILO microdata used in this analysis is based on the 13th ICLS definition of employment. Accordingly, the employed population comprises all persons of working age who, during a specified period, were engaged in any activity to produce goods or provide services for pay or profit. This includes employed persons at work (i.e. who worked in a job for at least one hour) and employed persons not at work due to temporary absence from a job or to specific working time arrangements. Employed persons can be in either paid jobs or self-employed, and they can work in formal or informal conditions (ILO, 2013). Persons engaged in own-use production work and subsistence foodstuff producers are also considered in the 13th ICLS definition.[6] Consequently, in this study, forest-sector employment corresponds to the sum of male and female persons in employment whose formal and informal main jobs are in the forest sector. Therefore, the employment statistics presented throughout this paper refer to an individual's main job in the forest sector; individuals who hold multiple jobs and whose employment in the forest sector is a secondary activity are excluded. Persons engaged in forest-related production for their own use, which constitutes an essential basis of their livelihood, are also included in these employment estimates.

2.3 Employment data cleaning

To ensure reliable estimates, the forest employment data retrieved from ILOSTAT underwent preliminary cleaning. Country-level employment data disaggregated by subsector and gender were found excessively noisy and therefore excluded from the estimation process. Special attention was given to cross-checking the consistency of data sources using LFS or similar household surveys with a labour module. For each country, data points that deviated substantially from the overall pattern were individually assessed to determine whether they represented plausible outliers or potential data anomalies.

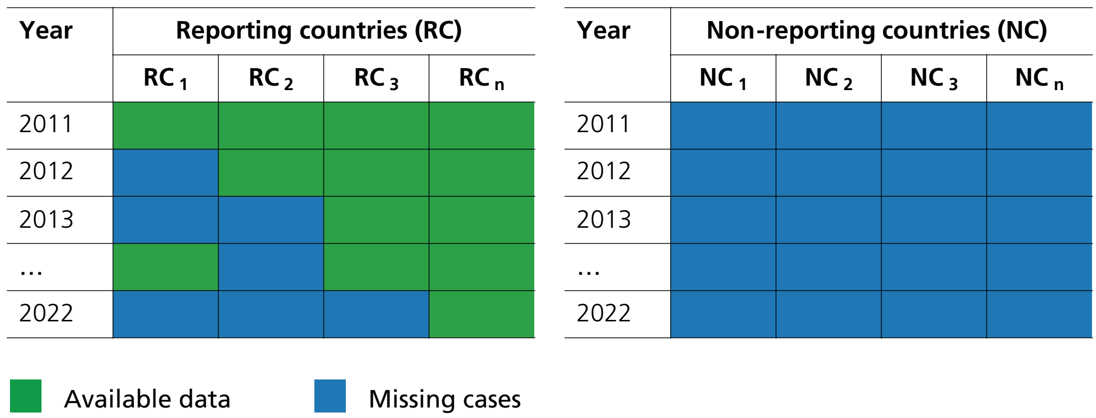
2.4 Reporting and non-reporting data countries

Although ILOSTAT Labour Force Statistics database provides employment statistics disaggregated by ISIC two-digit divisions and gender, there are two types of missing data (Figure 1). First, "missing data points" occur when LFS or similar household surveys are unavailable for certain years in a given country. Any potential undercoverage bias in the LFS, resulting from limited sample size when data are disaggregated by sex and economic activity at the ISIC two-digit divisions, may further affect data availability, as employment data are not published for a given country and year when the corresponding sample count falls below five (Lippe *et al.*, 2022). In this study, countries with at least one data observation are referred to as reporting countries.[7] Second, data may be missing for all reporting years due to several factors, including the absence of an LFS or the use of non-comparable industrial classifications. Such cases are referred to as non-reporting countries.

[6] The 19th ICLS measures persons engaged in own-use production work and subsistence foodstuff producers separately. This also implies that employment and work are not synonymous, as employment represents only a small portion of all work done by people (ILOSTAT, 2019).

[7] ILOSTAT data at the two-digit divisions are not available for Canada; however, forest-sector employment figures were derived directly from the Labour Force Survey (LFS) database in collaboration with Statistics Canada (FAO, 2025b). As a result, Canada is included among the reporting countries used in the estimation procedure.

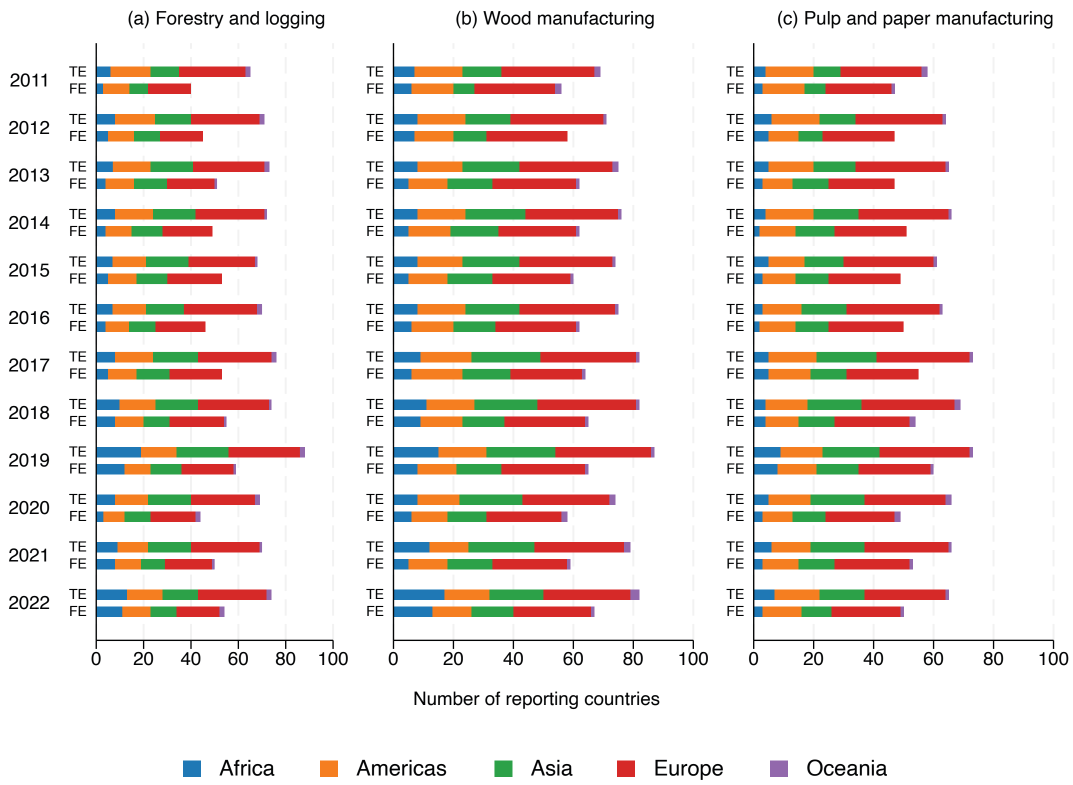
Figure 1. Reporting and non-reporting countries



Source: Authors' own elaboration

Further disaggregation of survey data may reveal missing data patterns within a country, often resulting from small sample sizes or the absence of recorded workers in a specific sector. Consequently, the number of available data points can vary across ISIC two-digit divisions, particularly when disaggregated by gender. As shown in Figure 2, the availability of employment data at the ISIC two-digit divisions has increased gradually until 2019 across all subsectors, with the number of countries reaching approximately one-third of the total number of countries and territories. However, after the first wave of the COVID-19 pandemic, the number of reporting countries appears to have declined, particularly in Africa. In 2022, total employment data were available for 74 countries and territories in forestry and logging, 82 in wood manufacturing, and 64 in pulp and paper manufacturing. Overall, Europe consistently has the highest share of reporting countries, followed by Asia and the Americas, with relatively stable trends across all subsectors. However, when disaggregated by gender, the availability of female employment data remains relatively lower for all years and subsectors, covering 54, 67 and 50 countries and territories in forestry and logging, wood manufacturing, and pulp and paper manufacturing, respectively, in 2022.

Figure 2. Number of countries with available total employment (TE) and female employment (FE) data from 2011 to 2022, broken down by subsector and region



Source: Authors' own elaboration.

3. METHODOLOGICAL APPROACH TO FILL DATA GAPS

Estimating the global forest-sector employment requires broader country coverage than currently available in ILOSTAT. Several approaches are commonly used for imputing missing data, generally falling into two main categories: parametric and nonparametric approaches (Waal *et al*. 2011). The choice of method depends on the data characteristics and the extent of missing values. In some regions and subsectors, country coverage for forest-sector employment data remains limited (Annex 1). Non-parametric methods such as hot deck imputation, where missing values are replaced with data from similar countries, may not provide accurate estimates for the purpose of this study. To increase the accuracy of the estimates, this study uses a deterministic parametric approach to data imputation (used interchangeably with "filling data gaps"). The FEM model uses the panel regression technique, grounded in the methodological framework and estimation procedures similar to the ILO modelled estimates (ILO, 2025, 2017; Pasteels, 2013). Conceptually, the FEM model defines a statistical function that links employment indicators to country-level attributes, including socioeconomic and demographic characteristics, forest resources, and the supply and demand for forest products. The estimation process consists of seven main steps presented in Annex 2 and described in what follows.

Step 1: Preparation of dependent variables

To estimate TE and FE in each subsector, six dependent variables (DVs) are derived from ILOSTAT database at the ISIC broad structure (section) and two-digit divisions. In the case of total employment, DV represents the percentage of subsectoral forest employment within the total employment of the corresponding broad economic sector. For female employment, DV denotes the percentage of female employment within each subsector's total employment. By constructing the TE and FE, the share of male employment (ME) is subsequently calculated as TE - FE.

Normalizing the dependent variables by using the unit of percentage share helps to control for variations between countries in terms of population and labour force size. A log transformation is then applied to the dependent variable to keep the estimates within valid bounds.

DV1: $\text{Employment share}\left(\text{A02}\right) = \left(\frac{\text{Forestry and logging TE}}{\text{Agriculture TE}}\right) * 100$

DV2: $\text{Employment share}\left(\text{C16}\right) = \left(\frac{\text{Wood manufacturing TE}}{\text{Manufacturing TE}}\right) * 100$

DV3: $\text{Employment share}\left(\text{C17}\right) = \left(\frac{\text{Pulp and paper manufacturing TE}}{\text{Manufacturing TE}}\right) * 100$

DV4: $\text{Female employment share}\left(\text{A02}\right) = \left(\frac{\text{Forestry and logging FE}}{\text{Forestry and logging TE}}\right) * 100$

DV5: $\text{Female employment share}\left(\text{C16}\right) = \left(\frac{\text{Wood manufacturing FE}}{\text{Wood manufacturing TE}}\right) * 100$

DV6: $\text{Female employment share}\left(\text{C17}\right) = \left(\frac{\text{Pulp and paper manufacturing FE}}{\text{Pulp and paper manufacturing TE}}\right) * 100$

Step 2: Preparation of potential explanatory variables (covariates)

The explanatory variables included in the FEM model are selected based on their correlation with the dependent variables and their ability to capture socioeconomic, demographic and subsector-specific characteristics for each country. The selection process also considered the availability and reliability of cross-country data, which is crucial for maintaining model integrity. As Denk and Weber (2011) caution, "filling holes in Swiss cheese with whipped cream" can produce misleading results, highlighting the importance of carefully selected covariates in determining model outcomes (Pasteels, 2013). Since the FEM model is designed for predictive purposes, all available variables that can improve predictive accuracy should be included. Considerations such as explaining causal relationships between variables or addressing issues like multicollinearity are less important in this context. Failure to include all useful predictors may reduce the predictive accuracy (Austin *et al.*, 2021; Denk and Weber, 2011). In general, stronger correlations between explanatory variables and employment shares lead to more accurate imputations (Pasteels, 2013).

In theory, employment levels are influenced by aggregate demand components such as consumption, government spending and net exports (Keynes, 2018). Key macroeconomic determinants of employment growth include economic performance (GDP), inflation, foreign direct investment and population growth (Mohamed *et al*., 2024). Likewise, GDP per capita, unemployment rates and fertility rates positively affect female participation (Taşseven *et al.*, 2016). Within the forest sector, employment is influenced by multiple factors. The price of forest products directly impacts employment and indirectly supports job growth through wage increases. Mechanization has an increasingly long-term effect on employment (He *et al*., 2022). Moreover, countries with large or growing forest areas are expected to contribute significantly to forest-sector employment (Fraser, 2019; Lippe *et al.*, 2023). Building on these conceptual foundations and the available country data, the selected covariates – categorized into socioeconomic and labour market indicators as well as forest-related determinants – are summarized in Table 1. These variables are expected to provide the most accurate predictive results for employment in the forest sector, based on the data currently available.

Table 1. Potential covariates for the FEM model

ATTRIBUTE	PROXY VARIABLE	ORIGINAL SOURCE
Socioeconomic determinants		
Economic performance	GDP per capita (constant 2017 international USD at PPP)[1] (log)	ILO, 2023d
Demographic indicators	Urban population (% of total population)	United Nations Department of Economic and Social Affairs, Population Division, 2024
	Population growth (%)	
	Fertility rate, total (births per woman)	World Bank, 2024
Labour market indicators	Labour dependency ratio, ILO modelled estimates	ILO, 2023e
	Female labour force participation rate (%), ILO modelled estimates	ILO, 2023f
	Unemployment rate (youth, adults:15+), ILO modelled estimates (%)	ILO, 2023g
Infrastructure	Individuals using the Internet (% of the population)	World Bank, 2024
Labour productivity	Output per worker (GDP constant 2015 USD), ILO modelled estimates	ILO, 2023h
Forest-related determinants		
Forest resource	Forest area (% of land area), accessed in 2024.	FAO, 1997
Wood demand	Apparent consumption of wood fuel[2] (log, m^3 per capita) FAOSTAT: wood fuel (item 1864), published in 2024	FAO, 1997
	Apparent consumption of sawn wood and wood-based panels[3] (log, m^3 per capita) FAOSTAT: sawn wood (item 1872) and wood-based panel (item 1873), published in 2024	FAO, 1997; United Nations Department of Economic and Social Affairs, Population Division, 2024
	Apparent consumption of wood pulp, paper and paper board[4] (log, tonne per capita) To control the variability of the country's population, consumption per capita is generated FAOSTAT: Wood pulp (item 1875) and paper & paper board (item 1876), published in 2024	FAO, 1997; United Nations Department of Economic and Social Affairs, Population Division, 2024
Sector contribution to the economy	Forest rents (% of GDP)	World Bank, 2024
	Agriculture, forestry, and fishing value added (% of GDP)[5]	World Bank, 2024
	Manufacturing value added (% of GDP)[6]	World Bank, 2024

Notes: Apparent consumption = production + import – export. To control the variability of the country's population, apparent consumption per capita is generated. [1]PPP denotes purchasing power parity. [2]Used in the FEM model for forestry and logging subsector. [3]Used in the FEM model for wood manufacturing. [4]Used in the FEM model for pulp and paper manufacturing. [5]Used in the FEM model for forestry and logging subsector. [6]Used in the FEM model for wood manufacturing and pulp and paper manufacturing.

Source: Authors' own elaboration.

Covariates expressed as percentage units, rates and ratios are preferred in this modelling context for two compelling reasons. First, given that the dependent variable is itself a percentage unit (share of forest subsector employment), explanatory variables in rate or ratio form (e.g. forest area as a percentage of total land area) are more likely to display stronger and more meaningful correlations with the dependent variable than their level counterparts (e.g. total forest area in hectares). Second, using level variables introduces substantial heterogeneity and extreme outliers, particularly from large and populous countries, which can distort model estimates. Converting covariates to percentage units, rates, and ratios mitigates these outlier effects and yields a more homogeneous data distribution. This approach is conceptually akin to applying a logarithmic transformation to GDP to linearize relationships and reduce skewness. In sum, rate-based explanatory variables are more likely to maintain linearity with the dependent variable and improve model robustness.

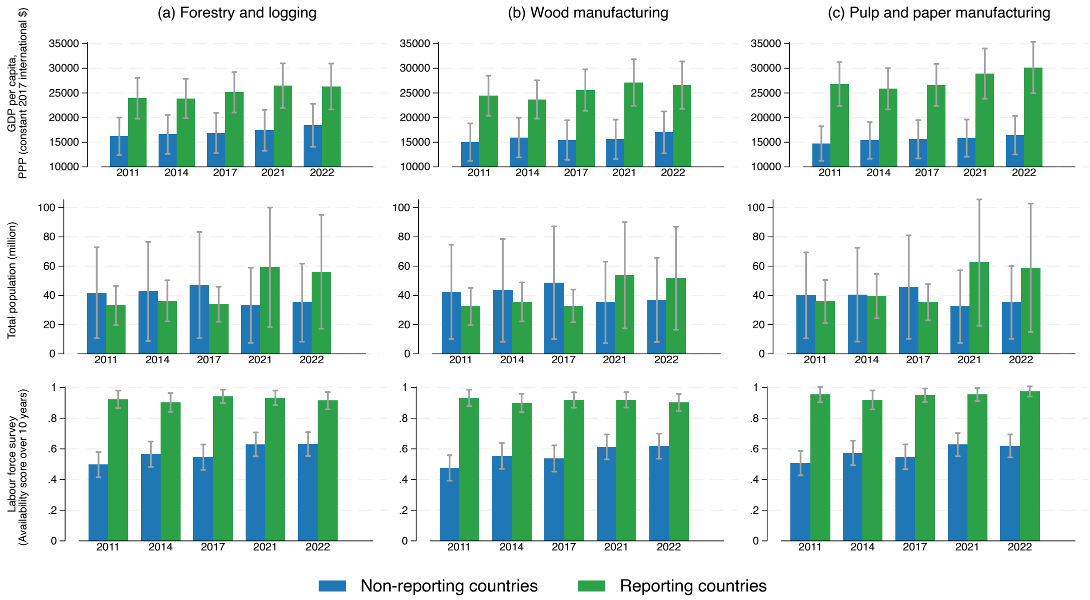
Step 3: Calculating response-probabilistic weights

Of the 182 countries analyzed, 129 reported data for employment in forestry and logging, 133 for wood manufacturing, and 109 for pulp and paper manufacturing for at least one year in the 2011–2022 period. Non-response bias may occur if forest-sector employment rates in non-reporting countries tend to differ significantly from rates in reporting countries. In this context, using a standard panel regression technique may result in biased estimates of the forest-sector employment share (ILO, 2017). Before selecting an estimation method, it is therefore essential to assess the characteristics of reporting and non-reporting countries to determine the type of non-response in the forest employment data. This is to ensure that the missing forest-sector employment data are not systematically related to the missing values themselves. Figure 3 confirms the observed differences in GDP per capita, total population and the availability index of the labour force survey in reporting and non-reporting countries by subsector.

The observed differences indicate that reporting and non-reporting countries do not share identical distributions of key characteristics. In all subsectors, reporting countries exhibit a statistically higher GDP per capita than non-reporting countries. However, non-reporting countries have moderately larger populations than reporting countries, although this trend reverses after 2017. As expected, across all subsectors, reporting countries have statistically higher LFS availability scores than non-reporting countries, given that employment data are derived from LFS or comparable national surveys. These systematic differences between reporting and non-reporting countries indicate that the missingness of forest employment data is linked to country characteristics, meaning that the missing data do not appear to be missing completely at random (MCAR). However, since data on GDP per capita, total population and available LFS scores are available for both reporting and non-reporting countries, the probability of missingness based on these factors can be modelled. This supports the assumption of missing at random (MAR), as any remaining missingness can be considered random after controlling for these country characteristics (Rubin, 1976). This assumption is crucial for qualifying valid statistical techniques to correct for non-response bias.

To correct sample selection bias, balancing weights are generated using a two-step process. In the first step, the probability of a country reporting forest-related subsectoral employment data is estimated using a logit regression model.

Figure 3. Socioeconomic characteristics of reporting and non-reporting countries by subsector



Notes:
GDP per capita is derived from gross domestic product (GDP constant 2017 international USD at PPP) – ILO modelled estimates (International Labour Organization, 2023b) and the total population (United Nations Department of Economic and Social Affairs, Population Division, 2024). PPP stands for purchasing power parity.
Population refers to the total population (United Nations Department of Economic and Social Affairs, Population Division, 2024).
Labour force survey (LFS) is a standard household-based survey of work-related statistics at the national and subnational employment or unemployment levels, rates or trends. One point refers to 3 or more surveys conducted within the past 10 years, whereas 0.6 and 0.3 points indicate 2 surveys and 1 survey carried out within the past 10 years, respectively. The zero points imply that no survey within the past 10 years (World Bank, 2024).
GDP per capita, population and LFS availability score were included to determine the type of non-response in the forest employment data. GDP per capita and population, reflecting the economic and demographic characteristics, may influence employment levels. The presence of LFS also plays a crucial role in determining the accessibility and completeness of labour statistics within each country. The data for these three indicators are available across both reporting and non-reporting countries.
The grey spike indicates the confidence intervals at 95 percent.
Source: Authors' own elaboration

The binary dependent variable indicates whether employment data are missing for a given country and year. Covariates in the logit model include GDP per capita (measured in constant 2017 international USD at PPP), the total population in log transformation, the availability score of the labour force survey and regional dummy variables. The results of the logit estimations for the probability of reporting total and female employment for each subsector are provided in Annex 3 and Annex 4, respectively. In the second step, a weight variable is constructed based on the inverse of the estimated probability of employment data availability in each subsector.

Step 4: Weighted FEM model

For each dependent variable, different models are estimated for reporting and non-reporting countries. The weighted FEM model follows the standard panel regression framework:

$$\ln(DV_{ct}) = \beta_0 + \beta\chi_{ct} + \alpha_c + \mu_{ct}$$

where:

- DV_{ct} is the dependent variable and represents the employment indicator of interest, varying by country c and time t.
- χ_{ct} is a vector of explanatory variables of country c and time t used to predict missing employment data.
- β_0 is the intercept, representing the fixed effect of the omitted category.
- β is the vector of the slope coefficients associated with the explanatory variable χ
- α_c accounts for country fixed effects for reporting country models and regional fixed effects for non-reporting country models. These fixed effects control for all country or regional specific factors that affect the forest employment share but are not captured by the other covariates.
- μ_{ct} is the error term.

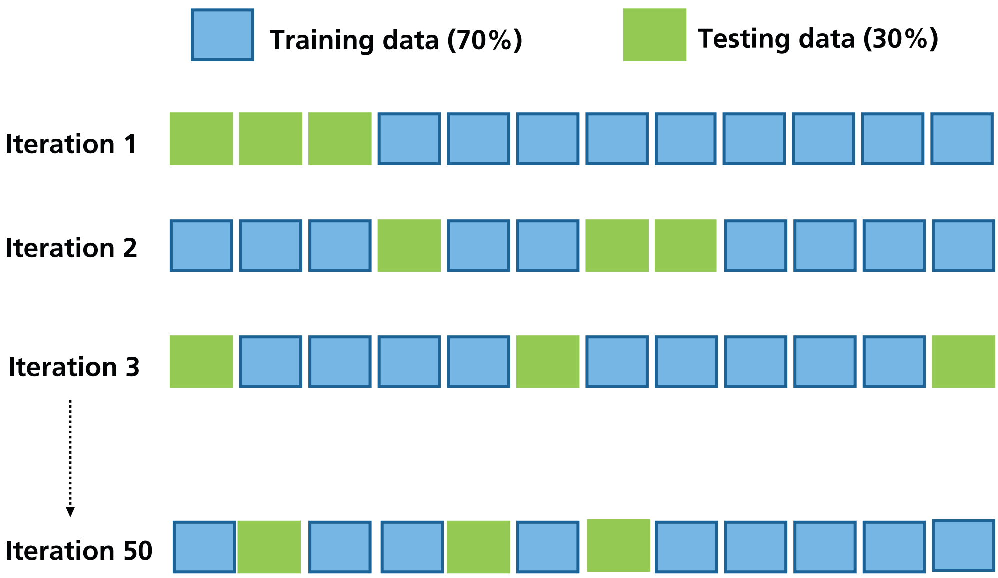
Data for 2020 were excluded from the regression to minimize the impact of the COVID-19 pandemic on the coefficients of the equation. However, the model estimates are subsequently adjusted to align with the actual data (step 6), which can include those from 2020, if available.

Step 5: Selecting the best model specification

The covariates listed in Table 1 are used in the weighted FEM model to create multiple potential model specifications. Letting the data determine the most suitable model specification for estimating missing values is a sound approach, as it significantly reduces subjective bias (Ribeiro and Freitas, 2021). To achieve this, a cross-validation technique is applied to identify the best model for each subsector and country group (i.e. reporting and non-reporting countries). The best-performing model is defined as the one that minimizes both estimation error and variance. Since the FEM model is designed for predictive rather than analytical purposes, the primary goal is to maximize imputation accuracy. Consequently, all available predictors that enhance estimation are included, while causal relationships and collinearity concerns take a secondary role (Makridakis *et al*., 1998; Pasteels, 2013).

The cross-validation technique is a simulation process that works by splitting the available observed employment data into two sets: a training set and a testing set (Figure 4). The FEM model is run using the training data and subsequently assessed based on its predictions for the testing data (Yates *et al*., 2023). In this study, the FEM model is trained on 70 percent of observed data and validated on the remaining 30 percent. The validation process is repeated 50 times for each subsector and country group to test the FEM model. Repeating the procedure 50 times strikes a balance between computational efficiency and the reliability of model evaluation. The guiding principle behind cross-validation is that it serves to assess whether the trained model can be generalized. Each candidate model is assessed based on the pseudo-out-of-sample root mean square error (ILO, 2025). However, quality measures such as R-squared, as well as the direction of coefficients and their statistical significance, are also considered as part of interpretability and robustness checks. This approach ensures that the selected model provides the most accurate estimate of

Figure 4. Iterative cross-validation approach



Source: Authors' own elaboration

employment share for each subsector and country group. It is important to note that the optimal set of covariates may vary by forest subsector and country group.

Step 6: Reconciliation with actual data

The employment share for each subsector is predicted using the best model specification for both reporting and non-reporting countries. At this stage, the regression estimates may not perfectly align with the original data for reporting countries, as the model generates predictions for all time periods, including those with observed data. To address this discrepancy, a scaling procedure is applied. First, the estimates are adjusted to match their observed values, where available. The remaining imputed values are then scaled using an interpolation approach to ensure a smooth transition over time. This process ensures consistency between observed and imputed employment shares while preserving overall trends.

Step 7: Calculating total and female employment (thousands of persons)

Total employment (TE) in each subsector is calculated by multiplying the employment share derived from FEM modelled estimates, by the ILO modelled estimates of employment in agriculture and manufacturing.

$$\begin{aligned}&\text{Forestry and logging TE,FEM modelled estimates}\\&\qquad = \text{Employment share (A02), FEM modelled estimates}\\&\qquad\ {}^{*}\text{Agriculture employment, ILO modelled estimates}\end{aligned}$$

$$\begin{aligned}&\text{Wood manufacturing TE,FEM modelled estimates}\\&\qquad = \text{Employment share (C16), FEM modelled estimates}\\&\qquad\ {}^{*}\text{Manufacture employment, ILO modelled estimates}\end{aligned}$$

$$\begin{aligned}&\text{Pulp and paper manufacturing TE,FEM modelled estimates}\\&\qquad = \text{Employment share (C17), FEM modelled estimates}\\&\qquad\ {}^{*}\text{Manufacture employment, ILO modelled estimates}\end{aligned}$$

In the case of ME and FE, the TE in each subsector – derived from the FEM model – is used as the benchmark. The share of male employment in each subsector is estimated as 100 minus the female employment share derived from the FEM model.

Finally, the number of men and women employed in each subsector is calculated as follows:

Forestry and logging FE, FEM modelled estimates
= Female employment share (A02), FEM modelled estimates
*Forestry and logging TE, FEM modelled estimates

Wood manufacturing FE, FEM modelled estimates
= Female employment share (C16), FEM modelled estimates
*Wood manufacturing TE, FEM modelled estimates

Pulp and paper manufacturing FE, FEM modelled estimates
= Female employment share (C17), FEM modelled estimates
*Pulp and paper manufacturing TE, FEM modelled

Forestry and logging ME, FEM modelled estimates
=(100-Female employment share (A02), FEM modelled estimates)
*Forestry and logging TE, FEM modelled estimates

Wood manufacturing ME, FEM modelled estimates
=(100-Female employment share (C16), FEM modelled estimates)
*Wood manufacturing TE, FEM modelled estimates

Pulp and paper manufacturing ME, FEM modelled estimates
=(100-Female employment share (C17), FEM modelled estimates
*Pulp and paper manufacturing TE, FEM modelled estimates

4. RESULTS

4.1 Forest-sector employment and subsector contribution

The FEM model estimates that, in 2022, at least 42 million people worldwide were employed in the forest sector as their main occupation. The estimates cover 182 countries and areas, representing 99 percent of the global forest area. Table 2 presents forest-sector employment by region from 2011 to 2022. Globally, total forest-sector employment increased by approximately 10 percent between 2011 and 2022, driven by employment growth in Asia, Africa and the Americas.

Asia accounts for half of all forest-sector employment, with China, India, Indonesia and Viet Nam being the main contributors. However, the estimates also indicate a decline in the forest-sector employment in Europe and Oceania over the study period.

Globally, employment in the manufacture of wood and products of wood accounts for approximately 58 percent of total forest-sector employment. The role of forestry and logging in job creation has remained relatively stable over the period, consistently representing nearly one-third of total forest-sector employment worldwide. In 2022, the manufacture of pulp and paper contributed to about 16 percent of total employment in the forest sector.

Table 2. Forest-sector employment by subsector and region

REGION	FOREST-SECTOR EMPLOYMENT (THOUSANDS)				
	2011	2014	2017	2020	2022
Africa	4400.2	4748.9	5393.0	4954.7	4974.5
Americas	3524.5	3535.1	3599.3	3144.0	3652.2
Asia	25576.2	26865.6	27068.3	27263.2	29030.9
Europe	4429.8	4225.4	4081.0	4204.7	4162.1
Oceania	167.4	163.3	164.0	163.9	162.6
Global	38098.1	39538.3	40305.6	39730.5	41982.3
	FORESTRY AND LOGGING EMPLOYMENT (THOUSANDS)				
	2011	2014	2017	2020	2022
Africa	2189.1	2206.9	2522.2	1951.9	1804.5
Americas	962.6	1039.1	1100.3	912.3	1088.2
Asia	5807.1	5744.9	5725.3	5435.7	6469.6
Europe	1504.0	1472.6	1431.3	1462.7	1340.6
Oceania	34.9	43.2	43.9	41.4	42.3
Global	10497.8	10506.6	10823.0	9803.8	10745.2
	WOOD MANUFACTURING EMPLOYMENT (THOUSANDS)				
	2011	2014	2017	2020	2022
Africa	1702.0	2029.5	2401.0	2550.1	2776.8
Americas	1675.3	1582.7	1581.2	1403.1	1650.6
Asia	16267.2	17258.7	17201.3	17686.0	18055.9
Europe	1996.5	1879.0	1787.3	1844.4	1905.2
Oceania	103.6	86.7	96.8	95.5	96.6
Global	21744.6	22836.6	23067.6	23579.1	24485.1
	PULP AND PAPER MANUFACTURING EMPLOYMENT (THOUSANDS)				
	2011	2014	2017	2020	2022
Africa	509.2	512.5	469.7	452.7	393.3
Americas	886.6	913.3	917.9	828.6	913.4
Asia	3501.8	3862.1	4141.7	4141.5	4505.4
Europe	929.4	873.9	862.4	897.7	916.3
Oceania	28.9	33.4	23.2	27.1	23.7
Global	5855.8	6195.2	6414.9	6347.6	6752.1

Note: Estimates for all years between 2011 and 2022 can be found in Annex 5. Geographical domains are based on FAO. 2025a. FAOSTAT: Country/Region. [Accessed on 1 February 2025]. https://faostat.fao.org/en/#definitions
Source: Authors' own calculation.

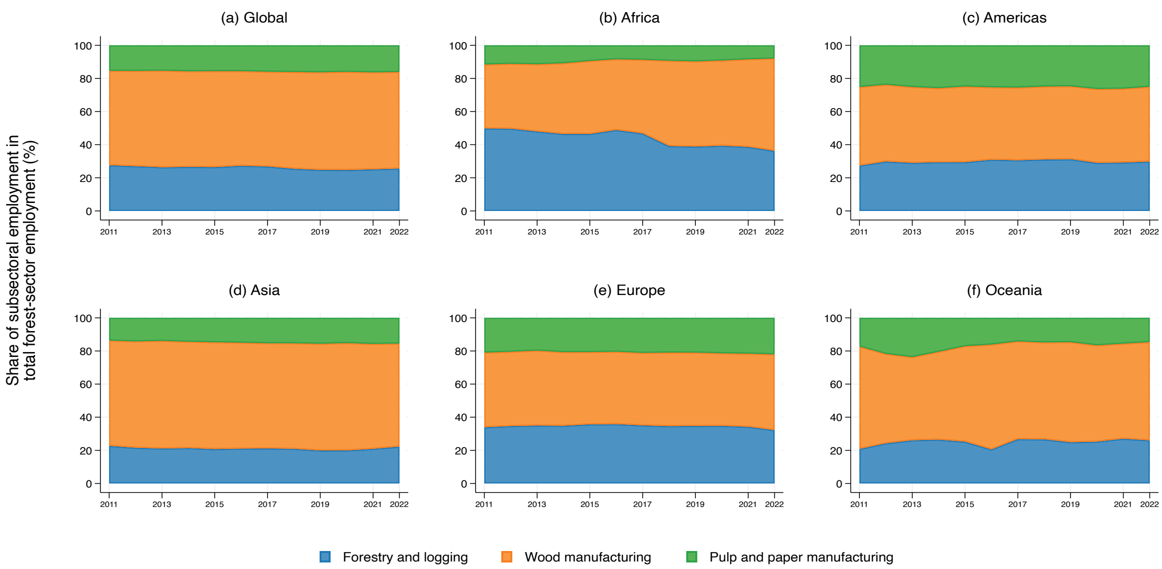
While the distribution of employment among these three subsectors has remained largely unchanged over the past decade, regional variations persist (Figure 5). In Africa, the forestry and logging subsector represents a higher proportion of total employment than in other regions. However, between 2016 and 2022, employment in wood manufacturing grew, while forestry and logging jobs declined, indicating a shift in labour demand and supply.

In the Americas and Europe, pulp and paper manufacturing employment represented about one-quarter of total forest-sector employment between 2011 and 2022. Nonetheless, wood manufacturing, forestry and logging continued to play vital roles in job creation in these regions. In Asia and Oceania, more than half of the total forest-sector employment was concentrated in the manufacture of wood and wood products. Forestry and logging accounted for approximately 20 percent and 25 percent of forest-sector employment in Asia and Oceania, respectively.

4.2 Employment trends in the forest sector and related industries

The share of forest-sector employment in total employment reflects its relative contribution to employment across all economic activities, as illustrated in Figure 6. In 2022, the forest sector accounted for 1.2 percent of total employment. Despite a slight increase in employment across all three forest-related subsectors, the forest sector's overall share declined by about 3.1 percent between 2011 and 2022. This is because total employment across all economic activities grew at a faster rate than the forest-sector employment during this period. Regional trends in the forest sector vary: Asia has consistently maintained the highest share

Figure 5. Distribution of subsectoral employment in total forest-sector employment by region, 2011–2022

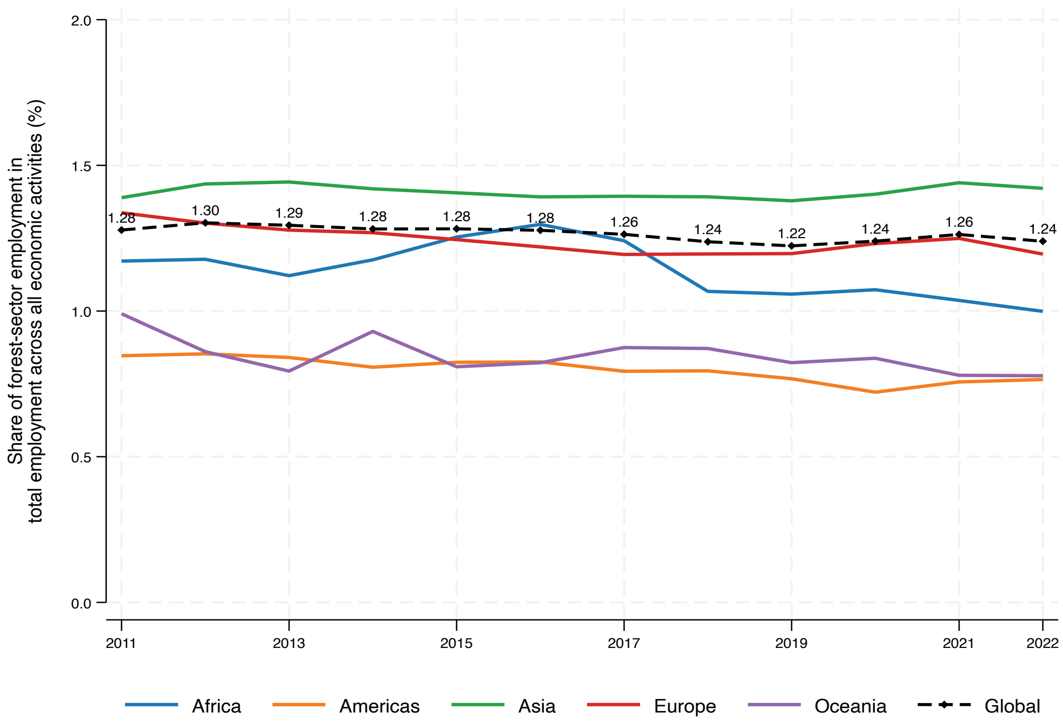


Notes:
Geographical domains are based on FAO. 2025a. FAOSTAT: Country/Region. [Accessed on 1 February 2025]. https://faostat.fao.org/en/#definitions. Licence: CC-BY-4.0.
All data used in this figure are based on 182 countries and areas.
Distribution by subregion is outlined in Annex 6.
Source: Authors' own elaboration.

of the forest sector in total employment, at around 1.4 percent over the study period. In Europe, the share of forest-sector employment declined slightly from 1.3 percent in 2011 to 1.2 percent in 2022, reflecting a modest reduction in the sector's contribution to employment. Africa experienced fluctuations, starting at 1.2 percent in 2011, peaking at 1.3 percent in 2016 and 2017, and then subsequently going down to 1.0 percent by 2022. The Americas showed a relatively stable trend, around 0.8 percent, with minor fluctuations following the COVID-19 pandemic. Similarly, Oceania's forest-sector employment share in the total employment stood at 1 percent in 2011 but showed slight variability between 2013 and 2015, then decreased to 0.8 percent by 2022, following the pandemic.

Employment trends across subsectors and regions reveal notable variations, with the impact of the COVID-19 pandemic on employment share being particularly evident after 2020. Figure 7 illustrates the proportion of forest subsector employment as a percentage of total employment in the corresponding broader economic sector, i.e. agriculture and manufacturing. In Europe, the share of total agricultural employment represented by forestry and logging notably increased between 2019 and 2021, before decreasing again in 2022.

Figure 6. Employment trends in the forest sector, by region, 2011–2022

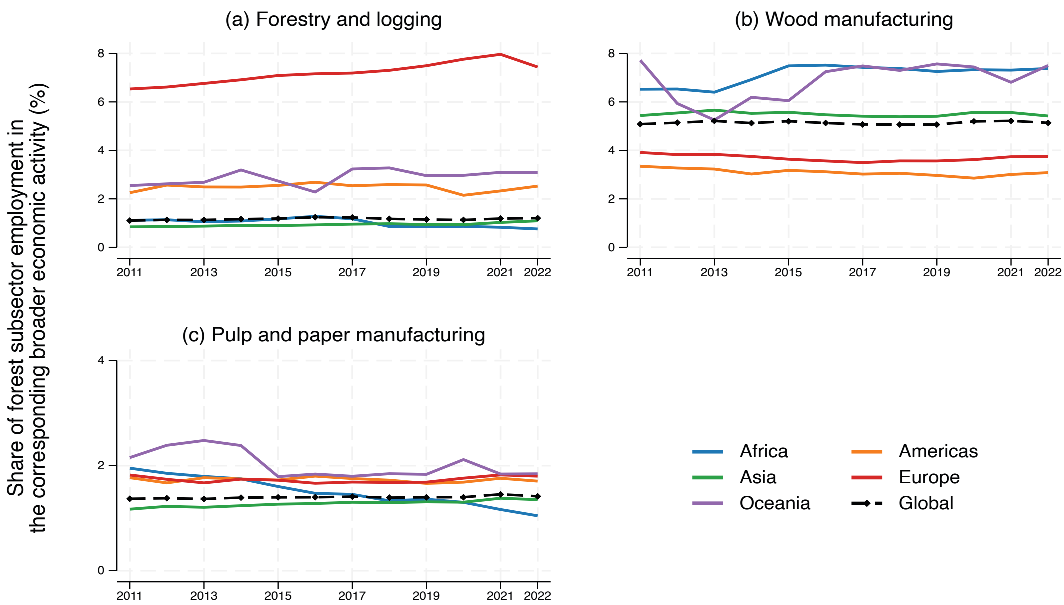


Notes:
Employment share refers to the share of total forest-sector employment using the Forest Employment (FEM) model estimates and the ILO modelled estimates for total employment (in the November 2023 version).
Geographical domains are based on FAO. 2025a. FAOSTAT: Country/Region. [Accessed on 1 February 2025]. https://faostat.fao.org/en/#definitions. Licence: CC-BY-4.0.
All data used in this figure are based on 182 countries and areas.
Employment trends by subregion are outlined in Annex 7.
Source: Authors' own elaboration.

In contrast, the Americas experienced the opposite trend, with a decline in the share of forestry and logging employment in total agricultural employment in 2020, followed by a gradual recovery. In Africa, forestry and logging employment experienced a slight decline from 2020 onwards, whereas Asia saw a modest increase during the same period.

Employment trends in the manufacture of wood and products of wood varied significantly within the period across regions, particularly in Africa and Oceania (Figure 7). In Africa, wood manufacturing employment rose from 6.4 percent in 2013 to 7.4 percent in 2022, driven primarily by a significant growth of employment in wood manufacturing in Eastern and Southern Africa (Annex 6). Oceania also experienced fluctuations, as between 2013 and 2017, the share of wood manufacturing employment increased from 5.3 percent to 7.5 percent, followed by a decrease between 2019 and 2021. However, the sector rebounded in 2022, reaching 7.4 percent of total employment in manufacturing in the region. Meanwhile, the Americas and Europe saw a rapid growth of employment in wood manufacturing after 2019, whereas Asia – and particularly East Asia (Annex 6) – experienced a slight downward trend over the same period. Employment in pulp and paper manufacturing also showed regional differences. In Africa and Oceania, employment in this subsector declined after 2020 onwards, although Oceania saw

Figure 7. Employment trends by subsector and region, 2011-2022



Notes:
Employment rate in Figure 7 (a) refers to the share of employment in forestry and logging using the FEM model and estimates of total agricultural employment based on ILO modelled estimates.
Employment rate in Figure 7 (b) refers to the share of employment in manufacturing of wood and products of wood using the FEM model and estimates of total manufacturing employment based on ILO modelled estimates.
Employment rate in Figure 7 (c) refers to the share of employment in manufacturing of pulp and paper using the FEM model and estimates of total manufacturing employment based on ILO modelled estimates (version Nov 2023).
Geographical domains are based on FAO. 2025a. FAOSTAT: Country/Region. [Accessed on 1 February 2025]. https://faostat.fao.org/en/#definitions. Licence: CC-BY-4.0.
All data used in this figure are based on 182 countries and areas.
Employment trends by subregion in Annex 7.
Source: Authors' own elaboration.

signs of stabilization after 2021. In contrast, Asia, the Americas and Europe experienced an increase in pulp and paper employment between 2019 and 2021, before returning to pre-pandemic levels by 2022.

4.3 Women's contribution to the forest-sector employment

In 2022, an estimated 10.6 million women were employed in the global forest sector, accounting for 25 percent of total forest-sector employment (Table 3). Asia recorded the highest number of women employed in the sector, followed by Africa and the Americas. Compared to 2011, female employment in the forest sector increased by approximately 10 percent in 2022, largely driven by employment growth in Asia and the Americas. Of the three subsectors, wood manufacturing employed the highest number of women. In the same year, over 2 million women

Table 3. Estimates of female employment (thousands) by subsector and region

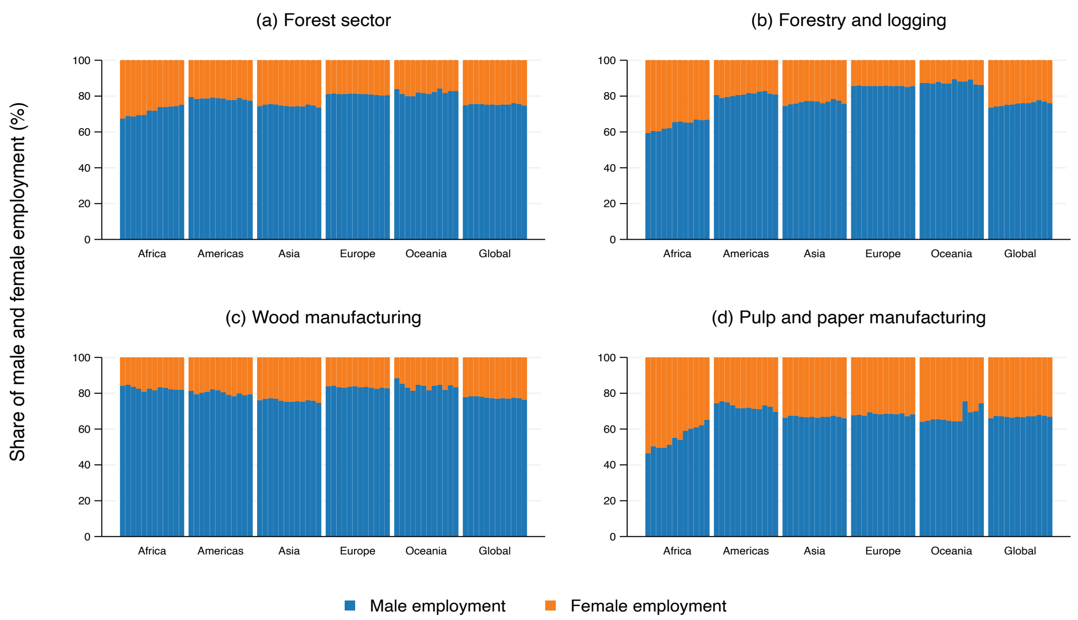
REGION	FOREST SECTOR FEMALE EMPLOYMENT (THOUSANDS)				
	2011	2014	2017	2020	2022
Africa	1430.4	1456.9	1519.3	1274.3	1234.6
Americas	723.5	754.4	764.7	660.5	824.7
Asia	6552.8	6606.0	6975.9	6738.0	7662.0
Europe	837.3	793.8	770.3	813.1	812.3
Oceania	26.8	32.8	30.7	30.1	27.8
Global	9570.8	9643.9	10060.9	9516	10561.4
	FOREST AND LOGGING FEMALE EMPLOYMENT (THOUSANDS)				
	2011	2014	2017	2020	2022
Africa	888.0	843.3	863.2	643.5	599.5
Americas	186.9	207.9	201.0	156.3	206.6
Asia	1480.9	1342.7	1320.4	1169.6	1569.9
Europe	215.1	210.0	203.5	208.6	193.4
Oceania	4.4	5.2	4.6	4.5	5.8
Global	2775.3	2609.1	2592.7	2182.5	2575.2
	WOOD MANUFACTURING FEMALE EMPLOYMENT (THOUSANDS)				
	2011	2014	2017	2020	2022
Africa	269.6	355.1	440.1	454.7	498.3
Americas	310.8	302.6	307.1	282.0	341.0
Asia	3892.2	3986.7	4260.5	4217.4	4567.1
Europe	322.7	316.0	296.1	323.9	328.7
Oceania	12.1	16.1	17.8	17.3	16.0
Global	4807.4	4976.5	5321.6	5295.3	5751.1
	PULP AND PAPER MANUFACTURING FEMALE EMPLOYMENT (THOUSANDS)				
	2011	2014	2017	2020	2022
Africa	272.8	258.5	216.0	176.1	136.8
Americas	225.8	243.9	256.6	222.1	277.2
Asia	1179.8	1276.7	1395.1	1351.0	1525.0
Europe	299.5	267.8	270.7	280.5	290.2
Oceania	10.3	11.5	8.3	8.3	6.1
Global	1988.2	2058.4	2146.7	2038.0	2235.3

Note: Estimates of all years between 2011 and 2022 are provided in Annex 8. Geographical domains are based on FAO. 2025a. FAOSTAT: Country/Region. [Accessed on 1 February 2025]. https://faostat.fao.org/en/#definitions. Licence: CC-BY-4.0.
Source: Authors' own elaboration.

were employed in forestry and logging worldwide, despite a 7 percent decline over the past decade. Another 2.2 million women were working in the pulp and paper manufacturing, with Asia and the Americas experiencing the largest absolute and relative increase in this subsector over the last decade.

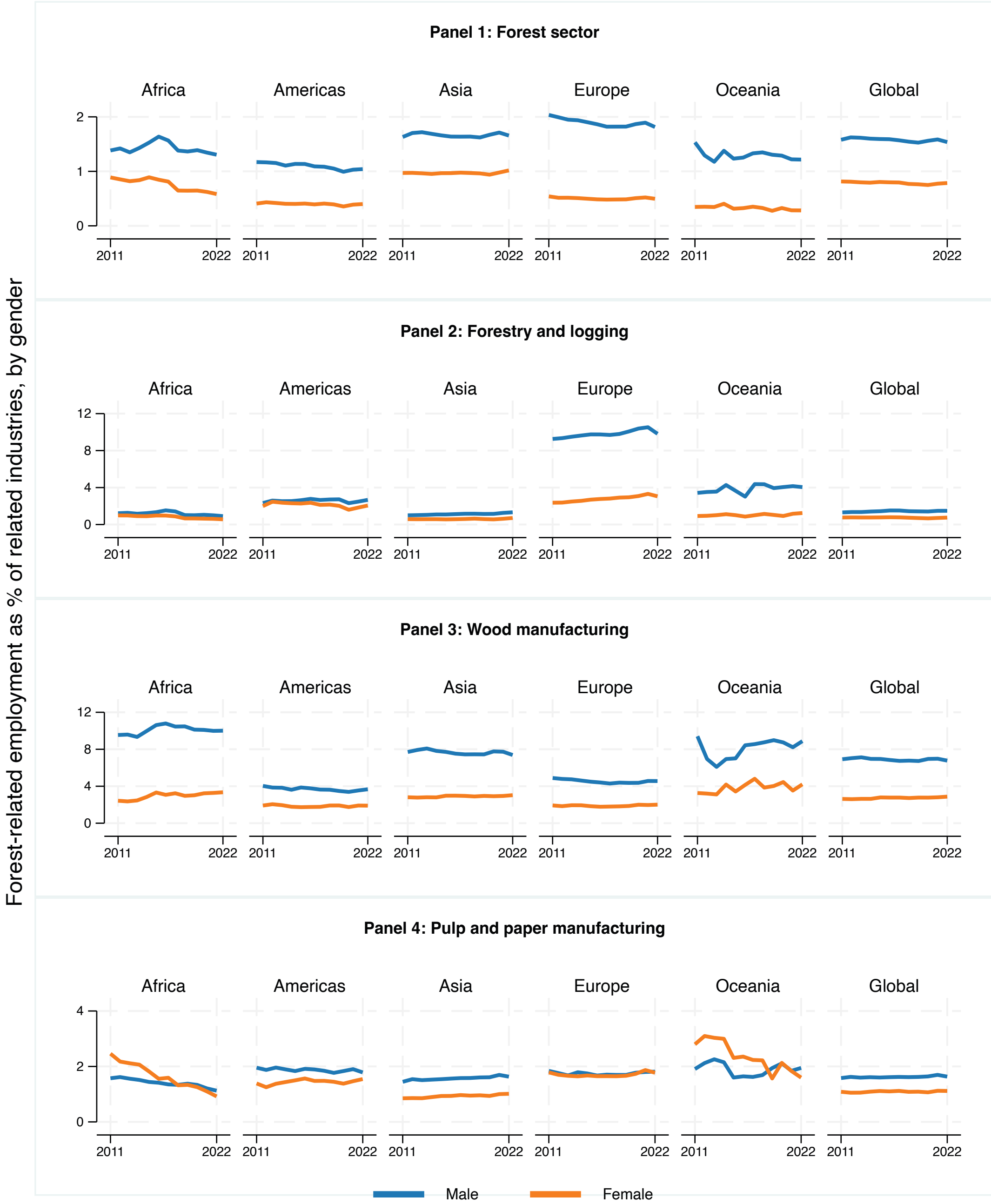
The share of women in the forest sector was lower than that of men across all regions between 2011 and 2022, ranging from 17 percent to 29 percent of total forest-sector employment in 2022 (Figure 8a). Globally, the share of women in forest-sector employment remained relatively stable over the period. However, Africa experienced a significant decline, with women's share in the forest-sector employment decreasing from about 32.5 percent in 2011 to 24.8 percent in 2022. This decline was particularly pronounced in forestry and logging (Figure 8b) and the manufacturing of paper and paper products (Figure 8d). In contrast, women's participation in Africa slightly increased in the wood manufacturing subsector (Figure 8c). The Americas and Asia witnessed an increase in the share of female employment in wood manufacturing and pulp and paper manufacturing. Meanwhile, in Europe, women's share in total employment remained stable across all subsectors.

Figure 8. Distribution of male and female employment by subsector and region, 2011-2022



Notes:
Panel 8a illustrates the share of male and female forest-sector employment in total forest-sector employment.
Panel 8b illustrates the share of male and female employment in total employment within the forestry and logging subsector.
Panel 8c illustrates the share of male and female employment in total employment within the wood manufacturing subsector.
Panel 8d illustrates the share of male and female employment in total employment within the pulp and paper manufacturing subsector.
In each bar, the share of male and female employment covers the 2011–2022 period.
Geographical domains are based on FAO. 2025a. FAOSTAT: Country/Region. [Accessed on 01 February 2025]. https://faostat.fao.org/en/#definitions. Licence: CC-BY-4.0.
All data used in this figure are based on 182 countries and areas.
The distribution by subregion for 2011 and 2022 can be found in Annex 9.
Source: Authors' own elaboration

Figure 9. Employment trends by subsectors and related industries, by gender, 2011-2022



Notes:

Panel 1 refers to the share of male and female forest-sector employment (FEM modelled estimates) in total male and female employment (ILO modelled estimates) across all economic activities.

Panel 2 refers to the share of male and female forestry and logging employment (FEM modelled estimates) in total male and female employment in the agriculture sector (ILO modelled estimates).

Panel 3 refers to the share of male and female wood manufacturing employment (FEM modelled estimates) in total male and female manufacturing employment (ILO modelled estimates).

Panel 4 refers to the share of male and female pulp and paper manufacturing employment (FEM modelled estimates) in total male and female manufacturing employment (ILO modelled estimates).

Forest-sector employment, by gender and subregion, is outlined in Annex 10.

Geographical domains are based on FAO. 2025a. FAOSTAT: Country/Region. [Accessed on 01 February 2025. https://faostat.fao.org/en/#definitions. Licence: CC-BY-4.0.

4.4 Female employment trends in the forest sector and related industries

The trends in male and female employment within the forest sector are presented as the relative share of total employment in the broader economic activity. Between 2011 and 2022, approximately 0.8 percent of women and 1.5 percent of men were employed in the global forest sector. Despite some regional variations, the gender employment gap[8] in the sector persisted over time and in all regions. In Europe, for example, about 1.8 percent of the total male workforce was employed in the forest sector in 2022, which amounted to four times the female employment rate, making it the region with the widest gap. In contrast, the employment gap in the forest sector was relatively lower in Africa, the Americas and Asia, ranging from 0.6 to 0.7 percentage points. That said, Africa experienced a slight decline in forest-sector employment rates for both men and women between 2016 and 2022. Although the forest sector remained male-dominated, there was an increase in female participation. Particularly, in South and Southeast Asia, the female employment rate in the forest sector gradually increased after the pandemic, from 1.1 percent in 2019 to 1.3 percent in 2022. Consistent with this trend, the gender employment gap in the subregion steadily narrowed, declining from 0.36 in 2011 to 0.15 percentage points in 2022 (Annex 10).

The trend of female employment and employment gaps appears more pronounced between subsectors. In 2022, forestry and logging accounted for about 0.8 percent of the global agricultural employment, with a gender employment gap of 0.7 percentage points. Africa saw a steady decline over time in female employment, while the Americas and Asia experienced a temporary drop during the pandemic, followed by a post-pandemic recovery, with female employment reaching 2.1 percent and 0.7 percent in 2022, respectively. Despite these shifts, the gender gap in these regions remains narrow. In contrast, Europe's female employment in forestry and logging has remained stable, yet it has the widest gender employment gap, at 6.8 percentage points.

Of the three subsectors, wood manufacturing has the highest female employment levels, although the gender employment gap persists even there. However, the gender employment gap in this subsector has narrowed by 9 percent between 2011 and 2022. Africa experienced notable growth, with female employment reaching 3.4 percent of total female employment in manufacturing. Despite this growth, Africa still has the widest gender employment gap in this subsector, reaching 6.7 percentage points. Asia and the Americas saw gradual increases, reaching 3 percent and 1.9 percent of total female employment in manufacturing, respectively, which suggests that the industry is more accessible to women. Oceania showed some fluctuations, but maintained relatively stable female employment in wood manufacturing compared to other regions.

Women's participation in pulp and paper manufacturing remains low around the world, even though, of all subsectors, it is the one with the smallest gender gap. Africa and Oceania showed a sharp decline, with female employment dropping to 0.9 percent and 1.6 percent of the regional manufacturing employment in 2022. The opposite trend, however, can be observed in the Americas and Asia, where pulp and paper manufacturing employment reached 1.5 percent and 1 percent in the same period. Europe exhibited more stable participation rates for women, which slightly increased during the COVID-19 pandemic but returned to pre-pandemic levels by 2022. It is worth noting that Europe also has a relatively small gender employment gap in this subsector.

8 The gender employment gap refers to the difference between the male and female employment rates, expressed in percentage points.

5. METHODOLOGICAL ADVANTAGES AND LIMITATIONS

This chapter evaluates the FEM model, discussing its advantages and limitations both on its own and in comparison with the wave-based method (WBM) introduced by Lippe *et al*., 2022. Both the FEM model and the WBM have significantly improved global forest-sector employment estimates by adhering to the employment definitions established in the ICLS guidelines and resolutions. Both methods rely on harmonized microdata processing from the ILO, a comprehensive and standardized data source derived from the LFS and similar household surveys. Specifically designed for the collection of labour statistics, the LFS features a structured survey that asks probing questions to improve data accuracy and ensure a comprehensive assessment of employment-related topics (ILO, 2018). As a result, both the FEM model and the WBM contribute to align employment data and promote harmonized reporting at the global and regional levels.

Although the WBM already provided a solid overview of the global forest-sector employment, the FEM model presents several additional advantages when it comes to addressing data gaps:

1. Yearly estimates for better trend monitoring: the FEM model generates yearly employment estimates rather than three years intervals, enabling more detailed tracking of employment trends in the forest sector.
2. Country-specific predictions instead of regional averages: unlike the WBM, which relies on regional employment ratios to fill data gaps, the FEM model uses specific country-level information, including socioeconomic, demographic and forest sector characteristics, to predict the missing values.
3. Retention of country-specific relationships: unlike the WBM and other methods (e.g. mean and hot deck imputations), the FEM model maintains relationships between country-level attributes through panel regression techniques. By preserving the individual and joint distribution of all covariates, the FEM model ensures that imputed values align with actual patterns, resulting in more accurate and realistic estimates (Rubin, 1987).

In addition, the predictive accuracy between the WBM and FEM modelling approaches is compared using cross-validation. This simulation technique allows the data to determine the most effective imputation method, measured by the out-of-sample root mean squared error (RMSE). Cross-validation was performed separately for reporting and non-reporting countries as well as at least two subsectors: forestry and logging and wood manufacturing.[9] The results, shown in Annex 11, indicate that the FEM modelling approach outperforms the WBM in predictive accuracy, as evidenced by the lower out-of-sample RMSE values. This finding supports the FEM model's effectiveness in addressing employment data gaps in the forest sector. Integrating cross-validation into the FEM modelling process further improves the imputation of plausible values (Denk and Weber, 2011).

[9] To be more efficient, cross-validation (CV) should be run on the largest subsector or the one with the most complete data. In this context, CV was performed in forestry and logging as well as in wood manufacturing. Running CV separately for all subsectors may raise potential complications: different models may be selected for different subsectors (e.g. the WBM for one but not for others), resulting in inconsistencies within the imputation framework. Such divergence could undermine the comparability of estimates across subsectors and complicate interpretation. Balancing methodological rigour with consistency and practical constraints is therefore essential when selecting and applying models across subsectors.

The weighted FEM estimation results (Annex 12 to Annex 17) reveal that the coefficients of determination in all model specifications for reporting countries are remarkable, with an overall R-squared of around 80 percent. However, it is somewhat lower for models of non-reporting countries. The employment share strongly correlates with key predictors, including GDP per capita, apparent wood consumption and the labour dependency ratio. Similarly, female labour force participation and fertility rates serve as useful predictors in the FEM models estimating female employment shares in all three subsectors. The percentage of individuals using the internet as a proportion of the population further influences the total employment share in the pulp and paper manufacturing subsector. A high correlation between predictors and the missing variable ensures accurate imputation and better preservation of data structure (Pasteels, 2013).

Despite improvements made to the new FEM model, there are still some limitations. First of all, the FEM model predicts missing values using a function of explanatory variables at the country level, which makes the exercise more complex. The same countries often lack data for macroeconomic and forest-related indicators. Linear interpolation is used to fill in missing values of each covariate for countries for which such a procedure is possible. However, a significant challenge arises for countries that lack data on some covariates across all years. This limitation either restricts the range of predictors used or requires that these countries be excluded from the analysis.

Second, many covariates – including GDP per capita, apparent consumption of wood products and labour-related indicators – consist of both actual data and imputed values for a substantial number of countries. Although the use of imputed data is often unavoidable, it must be acknowledged that estimated forest-sector employment for missing data points relies on layered imputations, which can potentially compound uncertainties.

The third uncertainty has to do with the availability of data on forest products used in the FEM model, which varies by subsector. In the case of forestry and logging, the employment share for missing data points is predicted using forest rents as a percentage of GDP and the apparent consumption of wood fuel, along with other macroeconomic indicators. However, the forestry and logging subsector also includes the gathering of non-wood forest products (NWFPs), for which neither production nor consumption data at the country level were available during the study period. A similar challenge arises in the wood manufacturing subsector, where apparent consumption of sawn wood and wood-based panels serves as a proxy indicator. Yet country-level data on products of wood and cork, which are an integral part of the wood manufacturing subsector, remain unavailable. Thus, the absence of comprehensive data on NWFPs and products of wood could also contribute to underestimation in some countries.

Lastly, a significant proportion of missing data, particularly for female employment, poses a further challenge for the FEM model, which relies on relationships between observed data to fill in missing values. A small number of real data points may reduce statistical power. Moreover, a model trained on a small subset of countries may not apply well to others, especially for non-reporting countries whose imputed values are solely based on data from the reporting country. Estimated data for countries without actual values should thus be interpreted and used with caution.

6. CONCLUSIONS AND WAYS FORWARD

Sector-specific employment data, disaggregated by gender, are essential for understanding the social and economic importance of the sector and its development. Forest-sector employment data play a vital role in achieving sustainability by providing insights into workforce status, transformation and management practices. However, the reliability and completeness of data continue to be a major challenge in many countries, making it difficult to gain an overview of the forest sector's contribution to the global labour force. The FEM model employed in this study is an updated methodology designed to close data gaps in cross-country time series. The model provides annual estimates of forest-sector employment between 2011 and 2022 for 182 countries, enabling the estimation of employment figures broken down by gender. Notably, it offers the first global estimates of women employed in the traditional forest sector.

Despite these valuable contributions, the following recommendations are made to ensure the quality and accuracy of forest-sector employment data:

- Expanding actual employment data to the ISIC two-digit divisions would help to refine the FEM model estimates for those employed in the forest sector. This is particularly crucial for those countries that do not have any available data yet in the ILOSTAT database.
- Examining the employment FEM modelled estimates in relation to social, economic and environmental indicators at the subregional and national levels would improve data validation. Such in-depth analysis would shed further light on the transformation of forest-sector employment, occupational segregation, the growing role of women in the forest-related market and how employment relates to other dimensions of the forest sector.
- Data on the production and economic value of NWFPs are vital as they are likely to contribute to higher employment estimates, especially in the informal economy. To capture this, specific modules on NWFP-related activities should be integrated into the LFS or similar household surveys.
- Associated sectors that encompass forests and forest product-related activities should be identified, along with a suitable method for quantifying sound employment figures within these sectors. Examples include employment in economic sectors such as wood furniture manufacturing, transportation and ecotourism.
- Efforts should focus on further improving the availability of internationally comparable data on job quality in the forest sector. In particular, greater emphasis is needed on improving data related to the number of green jobs, fatal and non-fatal accidents, social security coverage (contributory and non-contributory), as well as actual working hours and remuneration. These indicators are essential for understanding the forest-sector workforce beyond employment counts alone, and they capture key dimensions of job quality. Furthermore, they could be incorporated into future extensions of the modelling framework or used to strengthen model validation.

Implementing these recommendations requires long-term cooperation and dialogue among international organizations, national statistical offices and research institutes. It also depends on collaboration and policy coherence at the country level between all the relevant stakeholders, including statistical offices, forest sector actors including relevant ministries, and representatives from the world of work, such as Ministries of Labour and employers' and workers' organizations.[10] Strengthening the national capacity to conduct the LFS or similar household surveys will improve the availability of reliable, gender-disaggregated labour statistics across economic sectors.

10 This recommendation is confirmed by recent workshops in Canada, Türkiye and the United Republic of Tanzania (FAO, 2025b, 2025c, 2025d).

7. ANNEXES

Annex 1. Share of countries with imputed employment estimates by subsector and region over the period of 2011–2022

YEAR	FORESTRY AND LOGGING (SHARE OF COUNTRIES WITH IMPUTED EMPLOYMENT ESTIMATES, %)									
	AFRICA		AMERICAS		ASIA		EUROPE		OCEANIA	
	TE	FE	TE	FE	TE	FE	TE	FE	TE	FE
2011	88.7	94.3	45.2	64.5	75.0	83.3	28.2	53.8	81.8	100.0
2012	84.9	90.6	45.2	64.5	68.8	77.1	25.6	53.8	81.8	100.0
2013	86.8	92.5	48.4	61.3	62.5	70.8	23.1	48.7	81.8	90.9
2014	84.9	92.5	48.4	64.5	62.5	72.9	25.6	46.2	90.9	100.0
2015	86.8	90.6	54.8	61.3	62.5	72.9	28.2	41.0	90.9	100.0
2016	86.8	92.5	54.8	67.7	66.7	77.1	20.5	46.2	81.8	100.0
2017	84.9	90.6	48.4	61.3	60.4	70.8	20.5	43.6	81.8	100.0
2018	81.1	84.9	51.6	61.3	62.5	77.1	23.1	41.0	90.9	90.9
2019	64.2	77.4	51.6	64.5	54.2	72.9	23.1	43.6	81.8	90.9
2020	84.9	94.3	54.8	71.0	62.5	77.1	30.8	51.3	81.8	81.8
2021	83.0	84.9	58.1	64.5	62.5	79.2	25.6	48.7	90.9	90.9
2022	75.5	79.2	51.6	61.3	68.8	77.1	25.6	53.8	81.8	81.8
YEAR	WOOD MANUFACTURING (SHARE OF COUNTRIES WITH IMPUTED EMPLOYMENT ESTIMATES, %)									
	AFRICA		AMERICAS		ASIA		EUROPE		OCEANIA	
	TE	FE	TE	FE	TE	FE	TE	FE	TE	FE
2011	86.8	88.7	48.4	54.8	72.9	85.4	20.5	30.8	81.8	81.8
2012	84.9	86.8	48.4	58.1	68.8	77.1	20.5	30.8	90.9	100.0
2013	84.9	90.6	51.6	58.1	60.4	68.8	20.5	28.2	81.8	90.9
2014	84.9	90.6	48.4	54.8	58.3	66.7	20.5	33.3	90.9	90.9
2015	84.9	90.6	51.6	58.1	60.4	68.8	20.5	33.3	90.9	90.9
2016	84.9	88.7	48.4	54.8	62.5	70.8	17.9	30.8	90.9	90.9
2017	83.0	88.7	45.2	45.2	52.1	66.7	17.9	38.5	90.9	90.9
2018	79.2	83.0	48.4	54.8	56.3	70.8	15.4	30.8	90.9	90.9
2019	71.7	84.9	48.4	58.1	52.1	68.8	17.9	28.2	90.9	90.9
2020	84.9	88.7	54.8	61.3	56.3	72.9	25.6	35.9	81.8	81.8
2021	77.4	90.6	58.1	58.1	54.2	68.8	23.1	35.9	81.8	90.9
2022	67.9	75.5	51.6	58.1	62.5	70.8	25.6	33.3	72.7	90.9

YEAR	PULP AND PAPER MANUFACTURING (SHARE OF COUNTRIES WITH IMPUTED EMPLOYMENT ESTIMATES, %)									
	AFRICA		AMERICAS		ASIA		EUROPE		OCEANIA	
	TE	FE	TE	FE	TE	FE	TE	FE	TE	FE
2011	92.5	94.3	48.4	54.8	81.3	85.4	30.8	43.6	81.8	90.9
2012	88.7	90.6	48.4	67.7	75.0	83.3	25.6	38.5	90.9	100.0
2013	90.6	94.3	51.6	67.7	70.8	75.0	23.1	43.6	90.9	100.0
2014	92.5	96.2	48.4	61.3	68.8	72.9	23.1	38.5	90.9	100.0
2015	90.6	94.3	61.3	64.5	72.9	77.1	23.1	38.5	90.9	100.0
2016	94.3	96.2	58.1	61.3	68.8	77.1	20.5	35.9	90.9	100.0
2017	90.6	90.6	48.4	54.8	58.3	75.0	20.5	38.5	90.9	100.0
2018	92.5	92.5	54.8	64.5	62.5	75.0	20.5	35.9	81.8	81.8
2019	83.0	84.9	54.8	58.1	60.4	70.8	23.1	38.5	90.9	90.9
2020	90.6	94.3	54.8	67.7	62.5	77.1	30.8	41.0	81.8	81.8
2021	88.7	94.3	58.1	61.3	62.5	75.0	28.2	35.9	90.9	90.9
2022	86.8	94.3	51.6	58.1	68.8	79.2	30.8	41.0	90.9	90.9

Note: TE and FE denote total employment and female employment, respectively.
Source: Authors' own elaboration

Annex 2: The overview of employment data imputation

STEP	PROCEDURE
1 Preparation of the dependent variables	• Normalizing the dependent variables: forest employment share in the broad economic sector employment
2 Preparation of explanatory variables (covariates)	• Country socioeconomics, demographics, forest resources, and the supply of and demand for forest products
3 Calculating response-probabilistic weights	• Identifying the type of missing data • Performing logit regression and calculating response-probabilistic weights
4 Weighted FEM model	• Performing FEM model by subsector, gender, reporting and non-reporting countries, using weighted panel regression
5 Selecting the best model specification	• Leave-P-Out cross-validation
6 Reconciliation with actual data	• Adjusting FEM modelled estimates to their observed values, if available • Scaling the remaining estimates to ensure a smooth transition over time
7 Calculating employment in headcount	• Multiplying the FEM modelled estimates by ILO employment modelled estimates for the broad economic sector

Source: Authors' own elaboration.

Annex 3. Logit regression estimates for the probability of reporting total employment data by subsector

DEPENDENT VARIABLE: REPORTING TOTAL EMPLOYMENT DATA (YES = 1, OTHERWISE ZERO)	FORESTRY AND LOGGING	WOOD MANUFACTURING	PULP AND PAPER MANUFACTURING
GDP per capita, PPP constant 2017 international USD (log)	-0.094	0.059	0.149 +
Total populations (log)	0.416 ***	0.372 ***	0.556 ***
Labour force survey (availability score over 10 years)	1.806 ***	1.768 ***	2.355 ***
Regional fixed effects			
Americas	1.371 ***	1.086 ***	1.685 ***
Asia	0.450 **	0.400 *	0.562 **
Europe	0.912 **	0.852 **	1.149 **
Oceania	-0.006	-0.434	-0.154
Country classification # total population (log)			
Developing country (dummy)	-0.162 ***	-0.146 ***	-0.164 ***
Intercept	-4.211 ***	-5.070 ***	-8.670 ***
Number of observations	2126	2126	2120
χ^2	738.21	763.11	1002.12

Notes: + significant at the 10% level; *significant at the 5% level; **significant at the 1% level; ***significant at the 0.1% level; # denotes the interaction between two covariates. Standard errors are not presented because of the table's length.

Source: Authors' own elaboration.

Annex 4. Logit regression estimates for the probability of reporting female employment data by subsector

DEPENDENT VARIABLE: REPORTING FEMALE EMPLOYMENT DATA (YES = 1, OTHERWISE ZERO)	FORESTRY AND LOGGING	WOOD MANUFACTURING	PULP AND PAPER MANUFACTURING
GDP per capita, PPP constant 2017 international USD (log)	-0.270 **	0.072	0.360 ***
Total populations (log)	0.474 ***	0.504 ***	0.639 ***
Labour force survey (availability score over 10 years)	1.802 ***	1.934 ***	1.943 ***
Regional fixed effects			
Americas	1.546 ***	1.345 ***	1.494 ***
Asia	0.560 **	0.199	0.185
Europe	1.087 ***	0.824 *	0.689 +
Oceania	-0.205	-0.374	-1.070 +
Country classification # Total populations (log)			
Developing country (dummy)	-0.136 ***	-0.140 ***	-0.155 ***
Intercept	-4.139 ***	-7.129 ***	-11.469 ***
Number of observations	2120	2126	2120
χ^2	558.8	777.02	871.72

Notes: + significant at the 10% level; *significant at the 5% level; **significant at the 1% level; ***significant at the 0.1% level; # denotes the interaction between two covariates. Standard errors are not presented on account of the table's length.

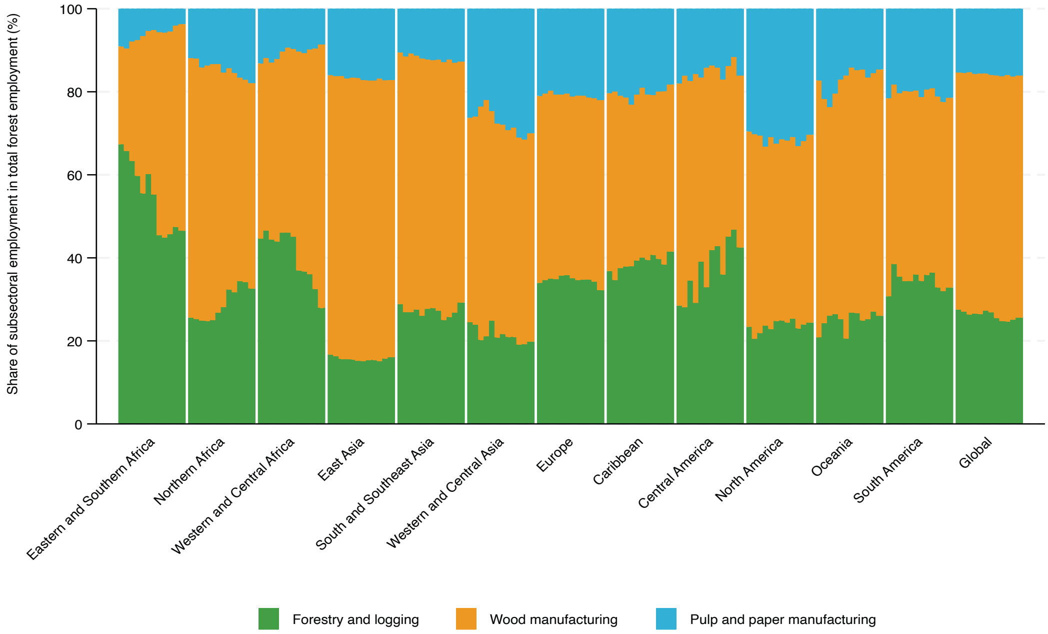
Source: Authors' own elaboration.

Annex 5. Estimates of employment (millions) by subsector and region over the period of 2011–2022

REGIONS	FOREST-SECTOR EMPLOYMENT (MILLIONS)											
	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Africa	4.4	4.5	4.4	4.7	5.2	5.5	5.4	4.8	4.8	5.0	4.9	5.0
Americas	3.5	3.6	3.6	3.5	3.7	3.7	3.6	3.7	3.6	3.1	3.5	3.7
Asia	25.6	26.7	27.0	26.9	26.8	26.8	27.1	27.3	27.3	27.3	28.7	29.0
Europe	4.4	4.3	4.2	4.2	4.2	4.1	4.1	4.1	4.2	4.2	4.3	4.2
Oceania	0.2	0.1	0.1	0.2	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Global	38.1	39.2	39.3	39.5	40.0	40.3	40.4	40.1	40.1	39.8	41.6	42.1
	FORESTRY AND LOGGING EMPLOYMENT (MILLIONS)											
	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Africa	2.2	2.2	2.1	2.2	2.4	2.7	2.5	1.9	1.9	2.0	1.9	1.8
Americas	1.0	1.1	1.1	1.0	1.1	1.1	1.1	1.1	1.1	0.9	1.0	1.1
Asia	5.8	5.7	5.7	5.7	5.6	5.6	5.7	5.7	5.4	5.4	6.0	6.5
Europe	1.5	1.5	1.5	1.5	1.5	1.5	1.4	1.4	1.4	1.5	1.5	1.3
Oceania	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Global	10.5	10.6	10.4	10.5	10.6	11.0	10.8	10.2	9.9	9.8	10.4	10.7
	WOOD MANUFACTURING EMPLOYMENT (MILLIONS)											
	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Africa	1.7	1.8	1.8	2.0	2.3	2.4	2.4	2.5	2.5	2.6	2.6	2.8
Americas	1.7	1.7	1.7	1.6	1.7	1.6	1.6	1.6	1.6	1.4	1.5	1.7
Asia	16.3	17.1	17.6	17.3	17.3	17.2	17.2	17.4	17.6	17.7	18.2	18.1
Europe	2.0	1.9	1.9	1.9	1.8	1.8	1.8	1.8	1.8	1.8	1.9	1.9
Oceania	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Global	21.8	22.6	23.1	22.9	23.2	23.1	23.1	23.4	23.6	23.6	24.3	24.6
	PULP AND PAPER MANUFACTURING EMPLOYMENT (MILLIONS)											
	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Africa	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.4	0.5	0.5	0.4	0.4
Americas	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.8	0.9	0.9
Asia	3.5	3.8	3.7	3.9	3.9	4.0	4.1	4.2	4.3	4.1	4.5	4.5
Europe	0.9	0.9	0.8	0.9	0.9	0.8	0.9	0.9	0.9	0.9	0.9	0.9
Oceania	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Global	5.8	6.1	5.9	6.2	6.2	6.2	6.4	6.4	6.6	6.3	6.7	6.7

Source: Authors' own elaboration.

Annex 6. Distribution of subsectoral employment in total forest-sector employment, by subregion, 2011–2022 (FAO, 2025e)

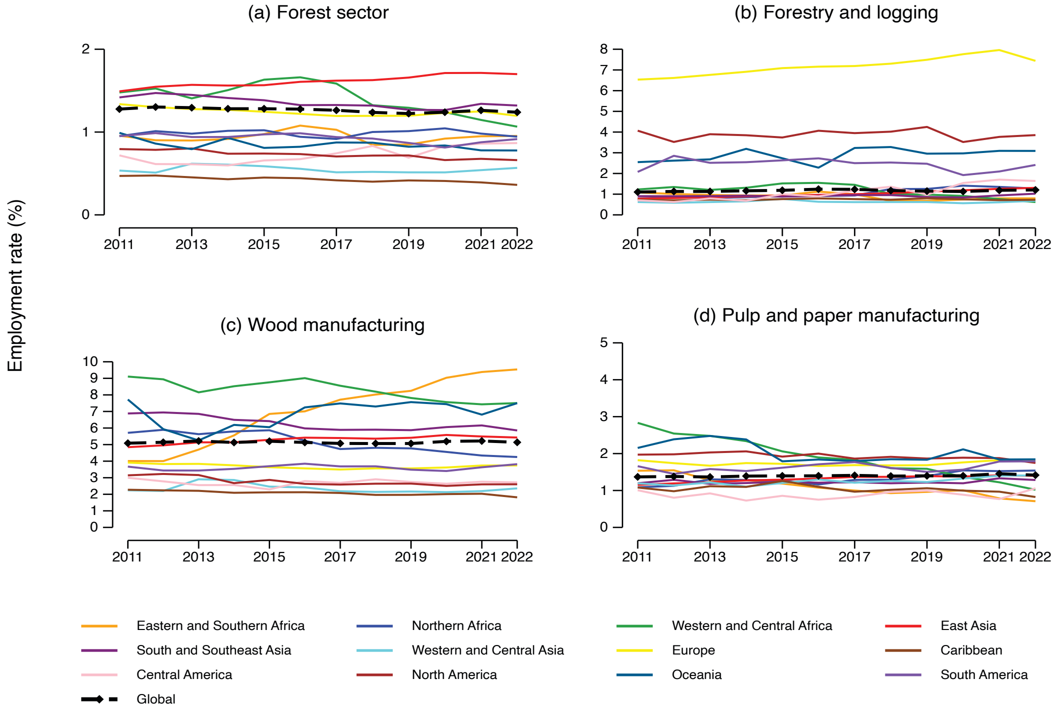


Notes:

The Y-axis refers to the percentage of subsectoral employment in total forest-sector employment in a given geographical domain. In each bar, the share of subsectoral employment in total forest-sector employment covers the 2011–2022 period. Based on data for 182 countries and areas.

Source: FAO, 2025e

Annex 7. Employment trends in the forest sector, by subregion and subsector, 2011–2022 (FAO, 2025e)



Notes:

Employment rate in (a) refers to the share of total forest-based employment using the Forest Employment (FEM) model and estimates for total employment of all economic activities based on International Labour Organization (ILO) modelled estimates.

Employment rate in (b) refers to the share of employment in forestry and logging using the FEM model and estimates of total agricultural employment based on ILO modelled estimates.

Employment rate in (c) refers to the share of employment in manufacturing of wood and products of wood using the FEM model and estimates of total manufacturing employment based on ILO modelled estimates.

Employment rate in (d) refers to the weighted share of employment in manufacturing of pulp and paper using the FEM model and estimates of total manufacturing employment based on ILO modelled estimates.

ILO modelled estimates used in this study refer to estimates for November 2023.

Geographical domains are based on the subregions used in FAO's Global Forest Resources Assessments.

All data used in this figure are based on 182 countries and areas.

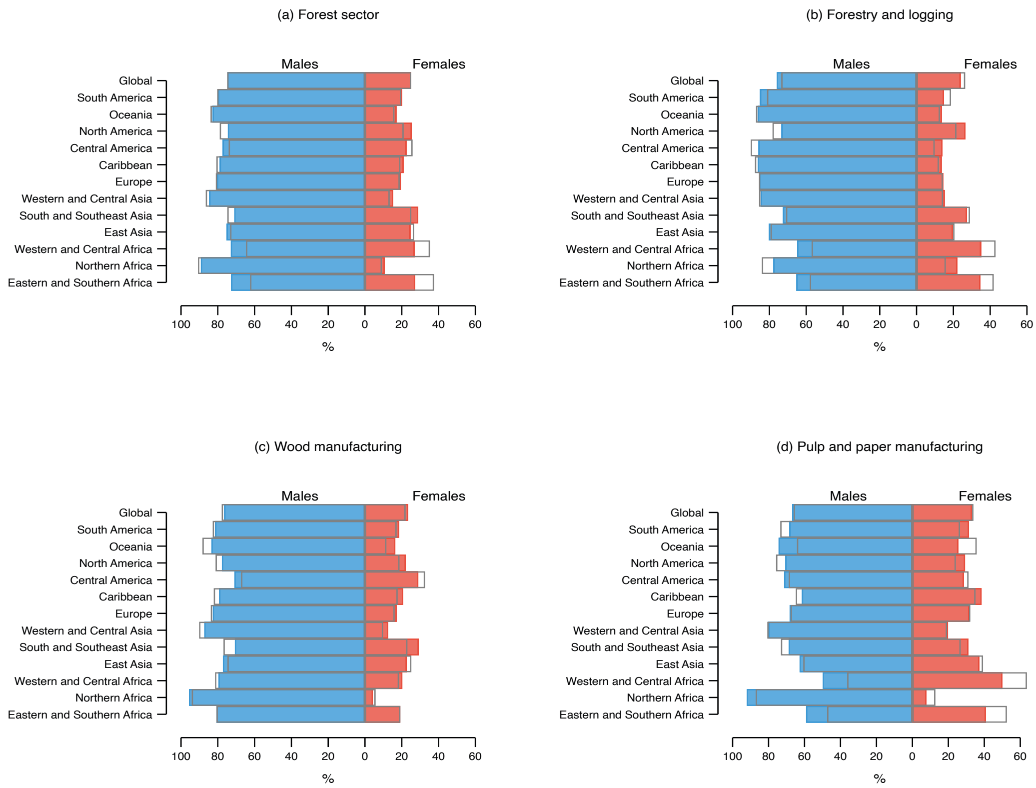
Source: FAO, 2025e

Annex 8. Estimates of female employment (millions) by subsector and region for the 2011–2022 period

REGIONS	FOREST SECTOR FEMALE EMPLOYMENT (MILLIONS)											
	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Africa	1.4	1.4	1.4	1.5	1.6	1.5	1.5	1.2	1.3	1.3	1.3	1.2
Americas	0.7	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.7	0.8	0.8
Asia	6.6	6.6	6.6	6.6	6.8	6.8	7.0	7.0	7.0	6.7	7.2	7.7
Europe	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8
Oceania	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Global	9.5	9.6	9.6	9.7	10.0	9.9	10.1	9.8	9.9	9.5	10.1	10.5
	FORESTRY AND LOGGING FEMALE EMPLOYMENT (MILLIONS)											
	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Africa	0.9	0.9	0.8	0.8	0.9	0.9	0.9	0.6	0.7	0.6	0.6	0.6
Americas	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Asia	1.5	1.4	1.4	1.3	1.3	1.3	1.3	1.4	1.3	1.2	1.4	1.6
Europe	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Oceania	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Global	2.8	2.7	2.6	2.5	2.6	2.6	2.6	2.4	2.4	2.2	2.4	2.6
	WOOD MANUFACTURING FEMALE EMPLOYMENT (MILLIONS)											
	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Africa	0.3	0.3	0.3	0.4	0.4	0.4	0.4	0.4	0.4	0.5	0.5	0.5
Americas	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Asia	3.9	4.0	4.0	4.0	4.2	4.2	4.3	4.2	4.4	4.2	4.4	4.6
Europe	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Oceania	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Global	4.8	4.9	4.9	5.0	5.2	5.2	5.3	5.2	5.4	5.3	5.5	5.7
	PULP AND PAPER MANUFACTURING FEMALE EMPLOYMENT (MILLIONS)											
	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Africa	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1
Americas	0.2	0.2	0.2	0.2	0.3	0.3	0.3	0.3	0.3	0.2	0.2	0.3
Asia	1.2	1.2	1.2	1.3	1.3	1.3	1.4	1.4	1.4	1.4	1.5	1.5
Europe	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Oceania	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Global	2.0	2.0	2.0	2.1	2.1	2.1	2.2	2.2	2.2	2.1	2.2	2.2

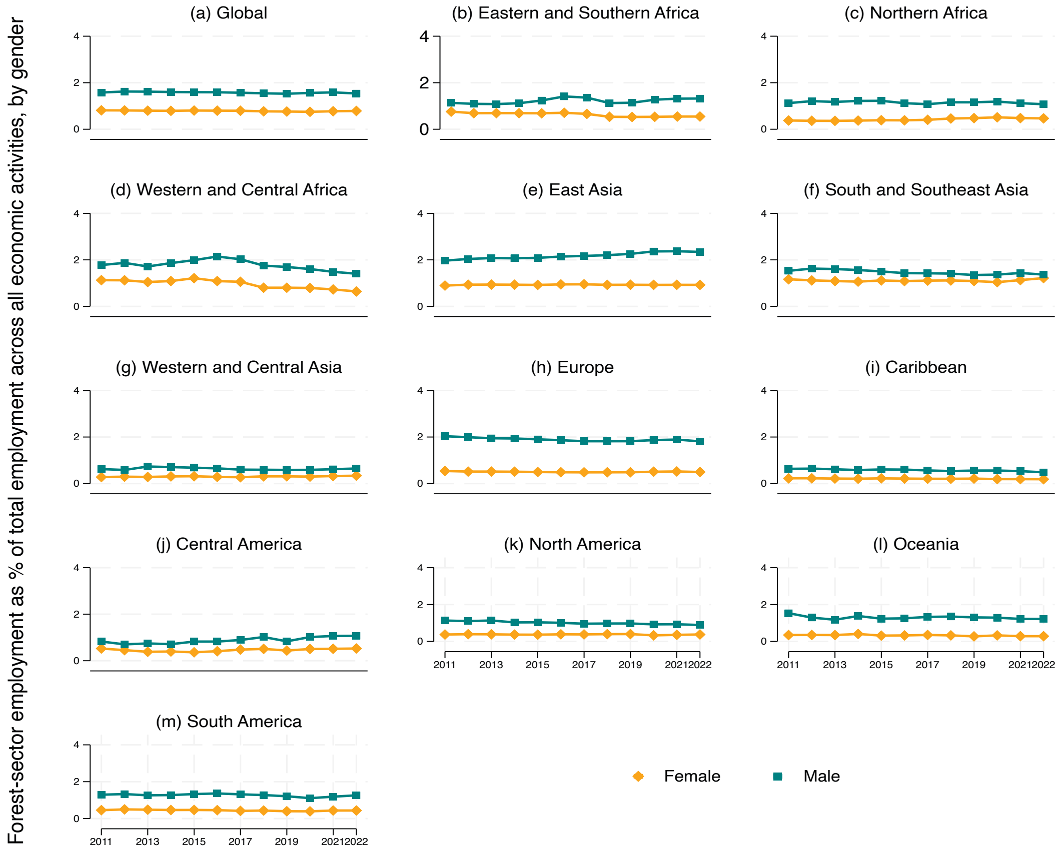
Source: Authors' own elaboration.

Annex 9. Males and females employed in the forest sector as a share of total employment, by subsector and region or subregion, 2011 and 2022 (FAO, 2025e)



Notes:
The blue and red bars refer to the share (%) of male and female forest-sector employment, respectively, in total employment, by subsector and region or subregion, in 2022.
The transparent overlay bar (grey line) indicates the share (%) of male and female employment in total employment, by subsector and region or subregion, in 2011.
Geographical domains are based on the regions/subregions used in FAO's Global Forest Resources Assessments..
All graphs are based on 182 countries and areas.
Source: FAO, 2025e

Annex 10. Forest-sector employment, by gender and subregion, 2011–2022 (FAO, 2025e)



Notes:
a) refers to the share of male and female forest-based employment using the FEM model and to female employment in all economic activities based on International Labour Organization (ILO)-modelled estimates.
(b–m) refers to the share of male and female forest-based employment using the FEM model and to male and female employment in all economic activities based on ILO modelled estimates.
ILO modelled estimates used in this study refer to estimates made in November 2023.
Geographical domains are based on the subregions used in FAO's Global Forest Resources Assessments.
All graphs are based on 182 countries and areas.
Source: FAO, 2025e.

Annex 11. Out-of-sample root mean squared error (RMSE) for wave-based method and Forest EMployment model

SUBSECTOR	WAVE-BASED METHOD (WBM)		FOREST EMPLOYMENT (FEM) MODEL	
	REPORTING COUNTRIES	NON-REPORTING COUNTRIES	REPORTING COUNTRIES	NON-REPORTING COUNTRIES
Forestry and logging (A02)	1.97	7.42	1.36	6.26
Wood manufacturing (C16)	3.4	11.3	2.39	4.69
Pulp and paper manufacturing (C17)	n/a	n/a	0.57	1.26

Source: Authors' own elaboration.

Annex 12. The selected FEM model specifications for total employment share in forestry and logging

DEPENDENT VARIABLE: TOTAL EMPLOYMENT IN FORESTRY AND LOGGING AS A PERCENTAGE OF AGRICULTURE EMPLOYMENT	REPORTING COUNTRIES	NON-REPORTING COUNTRIES
Forest area (% of country land area)	0.082 **	0.009 *
Forest rent (% of GDP)	0.191 +	0.102 *
Urban population (% of total population)	-7.707 *	-0.159
Labour dependency ratio, ILO modelled estimates	-0.646 +	
Unemployment rate (%), ILO modelled estimates	0.022	0.015
Country classification # year		
Developed country (dummy) # year	0.001	
Developing country (dummy) # year	-0.008	
Country classification # labour dependency ratio		
Developing	0.316	
GDP per capita, PPP constant 2017 international USD (log)		0.760 ***
Agriculture, value added (% of GDP)		0.027 *
Population growth (%)		-0.136 *
Subregional fixed effects		
Central and Western Asia		-0.03
Eastern Asia		0.255
Eastern Europe		2.064 ***
Latin America and the Caribbean		0.184
Northern Africa		-0.409
Northern America		1.714 ***
Northern, Southern and Western Europe		1.245 ***
Southeast Asia and the Pacific		0.790 *
Southern Asia		-0.395
Sub-Saharan Africa		0.698 *
Intercept	13.212	-7.860 ***
Number of observations	800	800
R-squared	0.92	0.51

Notes: + significant at the 10% level; *significant at the 5% level; **significant at the 1% level; ***significant at the 0.1% level; # denotes the interaction between two covariates. Country-fixed effects and standard errors are not presented on account of the table's length.
Source: Authors' own elaboration.

Annex 13. The selected FEM model specifications for total employment share in wood manufacturing

DEPENDENT VARIABLE: TOTAL EMPLOYMENT IN WOOD MANUFACTURING AS A PERCENTAGE OF MANUFACTURING EMPLOYMENT	REPORTING COUNTRIES	NON-REPORTING COUNTRIES
Apparent consumption of sawn wood and wood-based panels (m3/capita, log)	1.196 +	-1.274 ***
Labour dependency ratio, ILO modelled estimates	-2.256 **	-0.141
Manufacturing, value added (% of GDP)	-0.028 +	-0.031 **
Apparent consumption of sawn wood and wood-based panels (m3/capita, log) # GDP per capita, PPP constant 2017 international USD (log)	-0.149 *	0.158 ***
Output per worker (GDP constant 2015 USD)	0	0
Labour force participation rate (%) – ILO modelled estimates	-0.085 *	
Unemployment rate (%), ILO modelled estimates	0.044 *	
GDP per capita, PPP constant 2017 international USD (log)		-0.819 ***
Output per worker (GDP constant 2015 USD) # GDP per capita, PPP constant 2017 international USD (log)		0
Subregional fixed effects		
Central and Western Asia		-0.025
Eastern Asia		0.954 ***
Eastern Europe		0.456
Latin America and the Caribbean		0.108
Northern Africa		0.791 **
Northern America		0.564 *
Northern, Southern and Western Europe		0.715 **
Southeast Asia and the Pacific		0.917 **
Southern Asia		0.740 +
Sub-Saharan Africa		0.649 **
Intercept	9.577 *	8.362 ***
Number of observations	852	852
R-squared	0.85	0.32

Notes: + significant at the 10% level; *significant at the 5% level; **significant at the 1% level; ***significant at the 0.1% level; # denotes the interaction between two covariates. Country-fixed effects and standard errors are not presented on account of the table's length.
Source: Authors' own elaboration.

Annex 14. The selected FEM model specifications for total employment share in pulp and paper manufacturing

DEPENDENT VARIABLE: TOTAL EMPLOYMENT IN PULP AND PAPER MANUFACTURING AS A PERCENTAGE OF MANUFACTURING EMPLOYMENT	REPORTING COUNTRIES	NON-REPORTING COUNTRIES
Apparent consumption of pulp, paper and paper board (tonne/capita, log)	1.696 +	-1.986 **
Apparent consumption of pulp, paper and paper board (tonne/capita, log) # gross domestic product (GDP) per capita, purchasing power parity (PPP) constant 2017 international USD (log)	-0.186 +	0.224 ***
Individuals using the Internet (% of population)	-0.170 **	0.043
Individuals using the Internet (% of population) # GDP per capita, PPP constant 2017 international USD (log)	0.018 **	-0.005
Manufacturing, value added (% of GDP)	-0.008	0.007
Unemployment rate (youth, adults:15+), ILO modelled estimates (%)	0.001	0.018
Country group # year		
Developed country (dummy) # year	-0.040 *	
Developing country (dummy) # year	0.004	
Output per worker (GDP constant 2015 US $)		-0.000 **
Subregional fixed effects		
Central and Western Asia		0.086
Eastern Asia		0.067
Eastern Europe		-0.061
Latin America and the Caribbean		0.209
Northern Africa		0.352 *
Northern America		0.512 **
Northern, Southern and Western Europe		0.102
Southeast Asia and the Pacific		0.44
Southern Asia		-0.131
Sub-Saharan Africa		-0.02
Intercept	-9.629	-0.361
Number of observations	722	722
R-squared	0.82	0.21

Notes: + significant at the 10% level; *significant at the 5% level; **significant at the 1% level; ***significant at the 0.1% level; # denotes the interaction between two covariates. Country-fixed effects and standard errors are not presented on account of the table's length.
Source: Authors' own elaboration.

Annex 15. The selected FEM model specifications for female employment share in forestry and logging

DEPENDENT VARIABLE: FEMALE EMPLOYMENT IN FORESTRY AND LOGGING AS A PERCENTAGE OF AGRICULTURAL EMPLOYMENT	REPORTING COUNTRIES	NON-REPORTING COUNTRIES
Forest area (% of country land area)	0.052 ***	-0.004 *
Female labour force participation rate (%), ILO modelled estimates	0.053 **	0.007 +
Fertility rate, total (births per woman)	-0.384 *	-0.042
Apparent consumption of wood fuel (log, m3 per capita)	-0.005	0.095 ***
Urban population (% of total population)	3.728 +	0.177
Unemployment rate (%), ILO modelled estimates	-0.012	-0.019 **
Forest rent (% of GDP)		-0.075 **
Subregional fixed effects		
Central and Western Asia		-0.736 ***
Eastern Asia		-0.773 ***
Eastern Europe		-0.985 ***
Latin America and the Caribbean		-1.203 ***
Northern Africa		-0.849 *
Northern America		-0.778 ***
Northern, Southern and Western Europe		-0.906 ***
Southeast Asia and the Pacific		-0.408 +
Southern Asia		-0.818 ***
Sub-Saharan Africa		0.121
Intercept	-2.476	3.742 ***
Number of observations	555	555
R-squared	0.84	0.5

Notes: + significant at the 10% level; *significant at the 5% level; **significant at the 1% level; ***significant at the 0.1% level; # denotes the interaction between two covariates. Country-fixed effects and standard errors are not presented on account of the table's length.
Source: Authors' own elaboration.

Annex 16. The selected FEM model specifications for female employment share in wood manufacturing

DEPENDENT VARIABLE: FEMALE EMPLOYMENT IN WOOD MANUFACTURING AS A PERCENTAGE OF AGRICULTURAL EMPLOYMENT	REPORTING COUNTRIES	NON-REPORTING COUNTRIES
Apparent consumption of sawn wood and wood-based panel (m3/capita, log)	0.012	0.031
Female labour force participation rate (%), ILO modelled estimates	0.048 **	-0.022 *
Fertility rate, total (births per woman)	-0.363 *	0.124
Urban population (% of total population)	2.157	0.287
Labour dependency ratio, ILO modelled estimates	0.653	-0.919 *
Country classification # year		
Developed country (dummy) # year	0.018 +	
Developing country (dummy) # year	-0.003	
Unemployment rate (%), ILO modelled estimates		0.016
Subregional fixed effects		
Central and Western Asia		-0.662
Eastern Asia		0.145
Eastern Europe		-0.2
Latin America and the Caribbean		0.178
Northern Africa		-1.138 +
Northern America		-0.138
Northern, Southern and Western Europe		-0.05
Southeast Asia and the Pacific		0.269
Southern Asia		-0.223
Sub-Saharan Africa		0.28
Intercept	2.952	4.646 **
Number of observations	680	680
R-squared	0.86	0.27

Notes: + significant at the 10% level; *significant at the 5% level; **significant at the 1% level; ***significant at the 0.1% level; # denotes the interaction between two covariates. Country-fixed effects and standard errors are not presented on account of the table's length.
Source: Authors' own elaboration.

Annex 17. The selected FEM model specifications for female employment share in pulp and paper manufacturing

DEPENDENT VARIABLE: FEMALE EMPLOYMENT IN PULP AND PAPER MANUFACTURING AS A PERCENTAGE OF MANUFACTURING EMPLOYMENT	REPORTING COUNTRIES	NON-REPORTING COUNTRIES
Apparent consumption pulp, paper and paper board (tonne/capita, log)	0.167	-0.157 ***
Female labour force participation rate (%), ILO modelled estimates	0.054 **	0.022 ***
Individuals using the Internet (% of population)	0.001	-0.005 *
Labour dependency ratio, ILO modelled estimates	1.515 **	
Unemployment rate (%), ILO modelled estimates	-0.038 *	
Output per worker (GDP constant 2015 USD)	0	-0.000 ***
GDP per capita, PPP constant 2017 international USD (log)		0.389 ***
Population growth (%)		-0.052
Subregional fixed effects		
Central and Western Asia		-0.049
Eastern Asia		0.132
Eastern Europe		0.253
Latin America and the Caribbean		-0.129
Northern Africa		-0.559 +
Northern America		-0.169
Northern, Southern and Western Europe		0.152
Southeast Asia and the Pacific		0.131
Southern Asia		0.272
Sub-Saharan Africa		0.202
Intercept	-0.546	-0.412
Number of observations	561	561
R-squared	0.81	0.53

Notes: + significant at the 10% level; *significant at the 5% level; **significant at the 1% level; ***significant at the 0.1% level; # denotes the interaction between two covariates. Country-fixed effects and standard errors are not presented on account of the table's length.
Source: Authors' own elaboration.

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