The Geography of Green Skills: Measuring Workforce Readiness for the Green Transition across EU Regions

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Abstract

We propose a novel bottom-up methodology to construct a continuous Green Skill Intensity index for NUTS2 regions and sectors in Europe, combining the ESCO skill-occupation matrix, Labour Force Survey microdata, and an official list of 385 green skills. We use natural language models to assess the green relevance of each skill in the ESCO taxonomy, derive occupation-level green scores, and aggregate these into employment-weighted regional indicators at the NUTS2 × sector level. Comparing scores between 2014–2018 and 2019–2023, we document persistent spatial heterogeneity in the workforce's green readiness. Findings have significant implications for place-sensitive, long-term active labour market policies.

Keywords: green transition, green skills, regional labour markets, spatial heterogeneity, green policies

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Introduction

The European Green Deal represents the most ambitious attempt in recent history to reconfigure the productive structure of an entire continent. Its ambition is clear: to achieve climate neutrality by 2050, to reduce net greenhouse gas emissions by at least 55 per cent by 2030, and to do so in a way that is, in the language of the Commission, 'just and inclusive'. The underlying logic is one of managed structural change — an economy-wide transition that simultaneously creates new opportunities while phasing out carbon-intensive activities. This should not entail new winners and losers, leaving no socio-economic group or region behind (Benner, Grünenwald, and Kastrup 2026).

Yet the gap between the rhetoric of a smooth, inevitable transformation and the reality on the ground is becoming increasingly difficult to ignore. The green transition is, at its core, a massive reallocation problem. Capital, labour, and knowledge must shift from brown to green activities (Rodríguez-Pose and Bartalucci 2024; Vandeplas et al. 2022). For capital and technology, this shift can, in principle, be accelerated by investment frameworks, regulation, and price signals. For labour, the adjustment is inherently more complex, more spatially constrained, and more socially fraught, requiring adjustment to new skills to carry out changing tasks. Workers do not have the fluidity of financial capital. They are embedded in specific places, sectors, and occupational categories, and their ability to adapt depends critically on the skills they already possess. Indeed, the impact of the green transition varies significantly across industries and regional productive structures (Tyros, Andrews, and Serres 2023; Vona et al. 2018). This underscores the need to identify and assess green skills and their allocation across sectors and regional labour markets to improve readiness for the economy's green transformation. Green skills are defined as capabilities related to an occupation that contribute widely to the economy 's shift away from fossil fuels and towards a low-carbon model (Green 2023).

Studies on green skills are a work in progress, with scholarship on them growing. However, a systematic, detailed analysis of green skills is lacking (Fuchs 2024). Østergaard et al. (2021) proposed indicators for examining green skills and human capital at the national level across the four Nordic countries. Consoli et al. (2016) compared green and non-green occupations in the USA to identify skill differences using O*NET task data. Vona et al. (2018) explored specific skill demands of green jobs, again focusing on the USA, and constructed a 'greenness' index to measure the intensity of environmental tasks within occupations. All in all, the preparedness of regional labour markets for the transition to a greener economy in terms of skills has been relatively under-explored.

This paper contributes to the academic and policy discourse on regions' readiness to green their economies and highlights the importance of the labour market dimension of the green transition by examining the preparedness of regional labour markets for green transformation. It does so by addressing the following research question: to what extent does the existing EU workforce already possess the skills that the green economy demands, and how is this capacity distributed across industries and regions? With Europe being an area of extreme regional economic variety (Content, Frenken, and Jordaan 2019), there is little reason to expect that green skill endowments should be more evenly distributed than any other form of economic capability. If green-ready workforce segments are concentrated in urban, high-income regions while manufacturing peripheries lag, thereby reproducing historical regional development trajectories and divisions (Rosés and Wolf 2018), then the transition will generate a geography of winners and losers with profound implications for its political viability. Therefore, from a policy perspective, insights about the regional labour market readiness for the green transition could be useful to support green skills through place-based, long-term labour market policies to, first, further facilitate the greening of the economy, and second, to prevent further divergence between green-ready and transition-exposed regional labour markets, towards a fair transition.

In terms of methods, the challenge in quantifying green skills intensity is that no direct, comparable measure exists for EU regions. On the one hand, the Eurostat Labour Force Survey (LFS) does not include questions about whether workers' skills are green. On the other hand, existing attempts to measure green employment typically rely on industry-level classifications of 'green jobs', which are too coarse to capture the skill heterogeneity within sectors and too static to track changes over time. We address this gap by developing a novel bottom-up index of Green Skill Intensity (GSI) that operates at the level of individual occupations and aggregates up to the NUTS2 region using actual employment shares from LFS microdata.

This paper contributes to the methodological approaches to studying green skills and their geographical variation in three ways. First, we use the European Skills, Competences, Qualifications and Occupations (ESCO) taxonomy to characterise the skill content of 40 two-digit ISCO-08 occupational groups. Second, we use natural language processing (NLP) models to assess, for each of the 296 skills in the ESCO occupation matrix, its semantic similarity to an official list of 385 green skills, producing an aggregate green relevance weight for each ESCO skill. Third, we combine these weights with the ESCO skill-occupation profiles to derive occupation level green scores, which are then integrated with regional LFS employment shares to produce employment-weighted green skill intensity scores at the NUTS2 × sector level. By repeating this exercise for two five-year periods (2014–2018 and 2019–2023), we can analyse the spatial evolution of green workforce

readiness across the EU. Although the 'beginning' of the green transition cannot be precisely captured and national and regional economies have different time points of departure, the context of the post-2014 period is characterised by the emblematic Paris Agreement (2015) and the European Green Deal (2019).

The paper is structured as follows. Section 2 situates our contribution within the literature on green jobs, green skills, and regional labour market adjustment. Section 3 describes the data and methodological framework in detail. Section 4 presents preliminary empirical results, which are expanded and detailed in Section 5 before discussing them, focusing on the policy implications in Section 6. Section 7 concludes.

Green Skills, Regional Labour Markets, and the Delivery Gap

The field of economics of the green transition has been growing rapidly. Early contributions focused primarily on the aggregate employment effects of environmental policy, debating whether green investment would create more jobs than it destroyed (Bezdek, Wendling, and Diperna 2007; Bowen, Kuralbayeva, and Tipoe 2018). Indeed, macro drivers of change, including technological change, globalisation, and the green transition, have important implications for the labour markets, leading to changing patterns of job creation and destruction (Kapetaki 2021), as well as job reallocation across branches within the same industry and regions (Walker 2011). These impacts are by and large industry-specific, thus frequently affecting employment distribution rather than causing overall job losses (Laubinger, Lanzi, and Chateau 2020). The emerging consensus is that the aggregate effect is likely to be positive but modest, with the critical issue being the sectoral and occupational composition of net job creation rather than its headline size (International Labour Organization 2018; OECD 2017). However, vulnerable socio-economic groups, such as low-skilled workers who have lost their jobs, face challenges in re-employment due to limited competences and financial capacity (Cardenas Rubio, Warhurst, and Anderson 2022). Skills are the capabilities that enable competent performance of occupational tasks (Zierahn, Gregory, and Arntz 2016).

Here, the important point is to note the process of occupational change. Many professions and jobs evolve, requiring new skills to adapt to the green transition rather than being entirely eliminated (Van der Ree 2019). The study of the process of job change requires examining the entire spectrum of the labour market, including skills, occupations and industries. However, few studies provide in-depth analyses of skills before labelling jobs

as green, while also considering occupational change and evolution (Botta 2019; Causa, Nguyen, and Soldani 2024; Consoli et al. 2016; Vona et al. 2018; Zierahn, Gregory, and Arntz 2016).

Indeed, more recent work has shifted attention to the skill dimension of the transition. Vona et al. (2018) show, using US data, that workers in pollution-intensive industries possess skills that are significantly less transferable to green occupations than those in other sectors, and that the transition therefore generates substantial skill mismatches that standard active labour market policies are poorly designed to address. Consoli et al. (2016), again focusing on the USA, document that green jobs require significantly higher levels of cognitive and analytical skills, and that these requirements are growing faster than in non-green occupations. Botta (2019) extends this analysis to the European context, finding that the skill premium associated with green employment is particularly pronounced in countries with weak vocational training systems.

The changing skill requirements in the context of the green transition and the subsequent policy shifts (carbon taxes adoption, restrictions in the production and use of conventional vehicles), business changing strategies (divestment from activities that are high-emission), consumer demand shifts (a growing demand for green commodities), and shifts in industrial growth, imply that certain groups of skills are expected to face the greatest demand. These include skills related to engineering, construction, operational management, monitoring and compliance, physics and biology, as well as equipment installation and maintenance (Tyros, Andrews, and Serres 2023; Vona et al. 2018). Finally, soft skills, such as project management, organising green projects and production, and managing sustainability systems, could also record growing demand (Fuchs 2024).

The economic sector is of great importance for the effects and implementation of the green transition. While the green transition creates new employment opportunities in emerging occupations and novel skills, it also disrupts traditional sectors (García-García, Carpintero, and Buendía 2020). Indeed, achieving the climate goal of a carbon-neutral economy demands significant socio-economic transformations, particularly in fossil-fuel-dependent industries (Vandeplas et al. 2022). Fossil fuel-reliant industries have undergone extensive labour-market transformation and experienced changes in the skills demanded, with the automotive, construction and energy sectors particularly affected (Greenspon and Raimi 2024). Indeed, skills related to fossil fuel extraction and processing, the operation of coal-fired power plants, refinery operations, conventional automotive mechanics, and nuclear plant maintenance have been significantly impacted by the green transition (Vona et al. 2018).

Beyond industry, geography is also crucial. Given the importance of the industrial structure for the evolution of the regional labour market, the effects of the green transition on employment also vary across space (Rodríguez-Pose and Bartalucci 2024; While and Eadson 2022). Regional labour markets with a high specialisation in industries most affected by the green transition face greater disruption and greater potential for transformation in their skill composition (Froy et al. 2022; Langguth 2025). Important here is that regional labour markets with a high level of skill transferability across sectors, i.e., skill-relatedness, are anticipated to achieve more effective labour reallocation across sectors (Laubinger, Lanzi, and Chateau 2020). These insights highlight the need to study the evolution of green skills across regions.

However, the spatial dimension of green skill distribution has received comparatively less attention, with this paper enriching our knowledge about the geography of green skills. From a geographical perspective, the largest body of existing literature focuses on the national level, thereby not accounting for the regionally specific socio-economic context, which is largely important for understanding the variegation of socio-economic practices across space (Koster and Kapitsinis 2015). That is, most studies do not highlight regional labour market change and thus fail to provide a comprehensive understanding of the geographically uneven implications of the green transition (García-García, Carpintero, and Buendía 2020). Muro, Maxim, and Whiton (2019) provide an important exception, documenting the concentration of clean energy employment in a small number of metropolitan areas in the USA and the limited geographic mobility of affected workers. For Europe, Froy, Pyne, et al. (2011) show that local institutional capacity is a critical determinant of the ability of regional labour markets to adjust to structural economic change, but do not specifically focus on the green transition. Bijnens, Konings, and Vanormelingen (2022) examine the regional distribution of green employment in Belgium and find substantial subnational variation, but their analysis is limited to a single country and relies on industry rather than skill-based classifications. Fernández-Vázquez (2022) examined how coal-dependent local labour markets evolve once mining support policies are withdrawn, although again focusing on a single country (Spain).

This paper also makes a modest contribution to the broader literature on the political economy of the green transition. Several recent studies have documented a 'green backlash' in regions most exposed to the costs of decarbonization (Colantone and Stanig 2018; Mildenberger 2020; Rodrik 2021). This evolving 'green discontent' reflects a tendency for places experiencing significant contraction in employment and economic dynamism due to the decarbonization of the production model to be more likely to express their discontent (Rodríguez-Pose and Bartalucci 2024). If low green skill intensity is a reliable predictor of political resistance to environmental policy, then the geography of green skills

is not merely an academic concern but a central input into the political viability of the European Green Deal itself.

Data and Methodology

The measurement of green skills specifically is a more nascent field. Existing approaches broadly fall into two categories. The first uses administrative or survey data on job postings and vacancies to identify green-skill requirements from employers (Lassébie et al. 2021). This approach has the advantage of being forward-looking and capturing demand-side dynamics, but is limited by coverage, comparability across countries, and the absence of historical data. The second approach, which we follow, is supply-side: it uses information on the skill content of existing occupations and the occupational composition of employment to infer the green skill endowment of the current workforce. This approach is better suited to cross-country, longitudinal analysis at the regional level.

Within the supply-side tradition, the most closely related work is Vona, Marin, and Consoli (2019), who use the O*NET occupational skill database and the US BLS Occupational Employment Statistics to construct region-level measures of green skill intensity. Our paper contributes to this literature in three ways. First, we develop a comparable methodology for the European context, using the ESCO taxonomy and EU Labour Force Survey data, which allows cross-country comparability across all EU member states. Second, we employ NLP-based semantic similarity methods to link the ESCO skill taxonomy to an official EU list of green skills, providing a more granular and methodologically transparent mapping than previous approaches based on expert coding or keyword matching. Third, we exploit the longitudinal dimension of the LFS to track changes in green workforce readiness over time, providing evidence on whether the EU's green skill gap is narrowing or widening.

Our methodology constructs a Green Skill Intensity (GSI) index for each NUTS2 region r and NACE two-digit sector j through a three-stage pipeline. The first stage derives green relevance weights for each skill in the ESCO taxonomy using NLP-based semantic similarity. The second stage combines these weights with the ESCO skill-occupation matrix to compute a green score for each occupation. The third stage integrates occupation-level scores with regional employment shares from the LFS to produce NUTS2-level indicators.

The ESCO Skill-Occupation Matrix and Natural Language Processing

The European Skills, Competences, Qualifications and Occupations (ESCO) framework provides a hierarchical taxonomy of skills and occupations conceptually aligned with the ISCO-08 international standard. We use ESCO Matrix 3.2, which characterizes 40 two-digit ISCO-08 occupational groups in terms of 296 skills[1]. The matrix entry s_{ok} gives the share of skill k in the skill profile of occupation o, with each row summing to unity:

$$\hat{s} = \{s_{ok}\}, \qquad \text{where} \qquad \sum_k s_{ok} = 1 \quad \forall o. \tag{1}$$

The 296 skills in the ESCO occupation matrix must be evaluated for their relevance to the green economy. We use as our benchmark an official list of 385 green skills compiled within the EU skills policy framework. We employ a sentence-transformer NLP model (all-mpnetbase-v2) to embed both the ESCO skill labels and the green skill descriptions in a shared vector space and compute cosine similarity between each pair (i,j) of green skill i and ESCO skill j:

$$\text{sim}(i,j) = \cos(e^I, e_j) = \frac{e^I \cdot e_j}{\|e^I\| \, \|e_j\|} \tag{2}$$

This produces a raw similarity matrix of dimension 385 × 296. Before row-normalising, we apply a domain-mismatch penalty that down-weights spurious high-similarity matches arising from incidental lexical overlap rather than genuine occupational relevance.[2] We then apply a ReLU transformation (setting negative similarities to zero) and row-normalise so that each green skill's weights sum to unity across the 296 ESCO skills:

$$W_{ij} = \frac{\max(\text{sim}(i,j), 0)}{\sum_k \max(\text{sim}(i,k), 0)} \tag{3}$$

The entry W_j^i captures the share of green skill i's semantic content captured by ESCO skill j. We aggregate over the green skill dimension to obtain a scalar green relevance weight for each ESCO skill:

[1] . The three ESCO sub-groups for armed forces (C01, C02, C03) are aggregated into a single armed forces category (C00) by taking the row mean of their skill-share vectors, which preserves the unit-sum property

[2] . Similarity cells for ESCO skills whose own label contains no vocabulary from either the energy-transition or primary/environmental keyword groups defined in Section 5 are scaled down to 5% of their raw cosine value prior to row-normalisation. This reduces spurious matches driven by incidental shared vocabulary (e.g., a foodpreparation skill matching a heat-pump installation skill because both mention ”heat” and ”water”) without discarding genuine but weakly worded matches outright. Appendix A explains the details followed to avoid “false positives” when measuring semantic similarity based on these descriptions.

$$g_j = \sum_i W_{ij} \tag{4}$$

A high value of g_j indicates that ESCO skill j is semantically proximate to many green skills across the official taxonomy.

Green Occupation Scores

For each two-digit ISCO-08 occupation o, the green occupation score γ_o is defined as the dot product of the occupation's skill-share vector with the green relevance weight vector g:

$$\gamma_o = \sum_k s_{ok}\, g_k \tag{5}$$

This score is a weighted average of the green relevance of all skills used in that occupation, with weights reflecting each skill's share of the occupation's profile. Occupations relying heavily on green-relevant skills receive higher γ_o scores.

Computing a Green Skills Intensity score across regions, industries and occupations

WeexploitemploymentdatafromtheEULabourForceSurvey(LFS)microdatapanel, covering the period 2014–2023. The LFS provides employment counts disaggregated by NUTS2 region of work, two-digit NACE sector, and two-digit ISCO occupation.[3]

For each NUTS2 region r and NACE sector j, the occupation share of occupation o is:

$$\hat{e}_{orj} = \frac{L_{orj}}{\sum_o L_{orj}} \tag{6}$$

[3] . We harmonise regional codes to NUTS 2021 boundaries using a three-step procedure: observations already coded to valid NUTS 2021 codes are retained as-is; observations coded to older NUTS revision codes are converted using population-weighted crosswalk tables from the R nuts package, which appropriately splits employment for one-to-many regional boundary changes; and observations coded to non-NUTS custom national codes are dropped. Cells with fewer than five underlying LFS observations are imputed using national (country × sector) occupation shares as a fallback.

where L_{orj} denotes employment of occupation o in region r and sector j. The industry region Green Skill Intensity score G_{rj} is defined as $G_{rj} = \sum_0 \hat{e}_{orj} \times \gamma_o$ which allows for defining the region-level green score G_r as the employment-weighted average of G_{rj} across sectors:

$$G_r = \sum_j \left(\frac{L_{rj}}{L_r} \right) G_{rj} \tag{7}$$

where L_{rj} is total employment in node (r,j) and L_r is the total regional employment. The score G_r therefore captures the average green skill intensity of a region's workforce, accounting for both sectoral composition and occupational mix within sectors. We also consider a time l dimension, and for the temporal analysis, we construct two five-year period averages: 2014–2018 and 2019–2023. Employment is summed across all years within each period before computing occupation shares, stabilizing cells with small observation counts.

Empirical Results

Green Scores at the Occupation Level

We begin by examining the distribution of green scores across the 40 two-digit ISCO occupational groups. The relationship between green skills and occupations is significant, as the demand for green competences varies across professions, with the latter exhibiting different task and skill composition related to the transformation of the economy towards a low-carbon production model (Van der Ree 2019; Vona et al. 2018). Figure 1 reports the full ranking of occupations by their γ_o score in 2021.

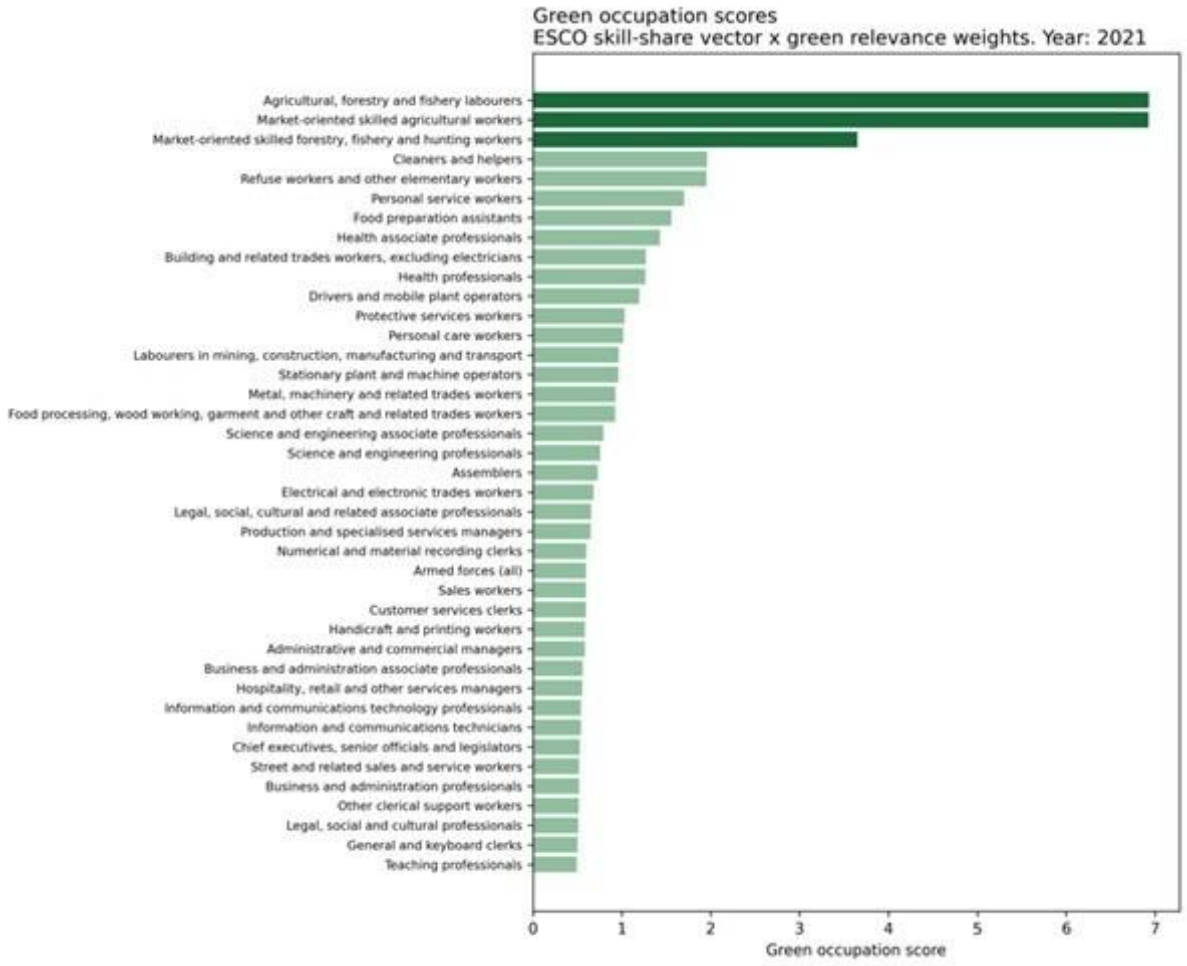


Figure 1: Green occupation scores (γ_0) for all ISCO-08 two-digit occupational groups. Scores derived from ESCO Matrix 3.2 and NLP-based green skill weights. Year: 2021.

The occupation-level results present a pattern that is both informative and, in some respects, counterintuitive. Agricultural, forestry and fishery labourers and market-oriented skilled agricultural workers occupy the top two positions by a wide margin, scoring roughly twice as high as the third-ranked occupation and more than four times the score of the broad cluster of elementary and personal-service occupations — cleaners and helpers, refuse workers, personal service workers, and food preparation assistants — that follows. This reflects the fact that the official EU green skills list is strongly anchored in natural resource management, environmental stewardship, and physical resource handling — competences that are prominent in low- and medium-skilled occupations directly engaged with natural environments and physical production processes (Tyros, Andrews, and Serres 2023).

Health associate professionals and health professionals are a notable exception to this pattern, ranking eighth and tenth, respectively — above every craft, trade, and manufacturing occupation except building trades — which suggests that health-related ESCO skill labels carry more environmental and safety-related vocabulary than is usually assumed. Science and engineering professionals and associate professionals, by contrast, occupy a middling position, well below the elementary and personal-service occupations. At the bottom of the distribution sit teaching professionals, general and keyboard clerks, legal, social and cultural professionals, and ICT professionals and technicians, indicating limited green intensity and a limited contribution to decarbonization efforts, mainly due to their small carbon footprint (Vandeplas et al. 2022). This confirms that green skill intensity is a distinct dimension of occupational skill profiles that cannot be approximated by standard proxies for educational attainment or skill level (Cardenas Rubio, Warhurst, and Anderson 2022). The variation across occupations is substantial: the ratio of the highest to the lowest score exceeds 14, indicating that the occupational composition of regional workforces will be a primary driver of spatial differences in green skill intensity.

Green Skill Intensity across Sectors

Figure 2 shows the distribution of node-level green scores G_{rj} across NACE sectors for both time periods, with box plots ordered by the median score pooled across the two periods. Coloured dots identify NUTS2 regional outliers lying below the first quartile minus 1.5 times the interquartile range, coded by EU macro-region. These scores are crucial when considering the important variation in green skills across industries and, more broadly, the variegated implications of the green transition across sectors of economic activity (García-García, Carpintero, and Buendía 2020; Vandeplas et al. 2022).

Agriculture and fishing (SEC_A) consistently ranks at the top of the sectoral distribution, followed by households as employers (SEC_T) and administrative services (SEC_N). This pattern reflects the high green scores of the agricultural and low-skilled service occupations that dominate employment in these sectors (García-García, Carpintero, and Buendía 2020). Mining and quarrying (SEC_B) occupies a middling position, close to the pooled median, reflecting a mixed occupational base of craft, trade, and plant-operator occupations alongside lower-scoring managerial and technical roles, which carry above-average green scores due to their proximity to physical resource extraction and management.

At the bottom of the distribution, finance and insurance (SEC_K), ICT (SEC_J), professional and scientific activities (SEC_M), and education (SEC_P) consistently score lowest. These are

sectors dominated by professional, managerial, and clerical occupations , which are precisely

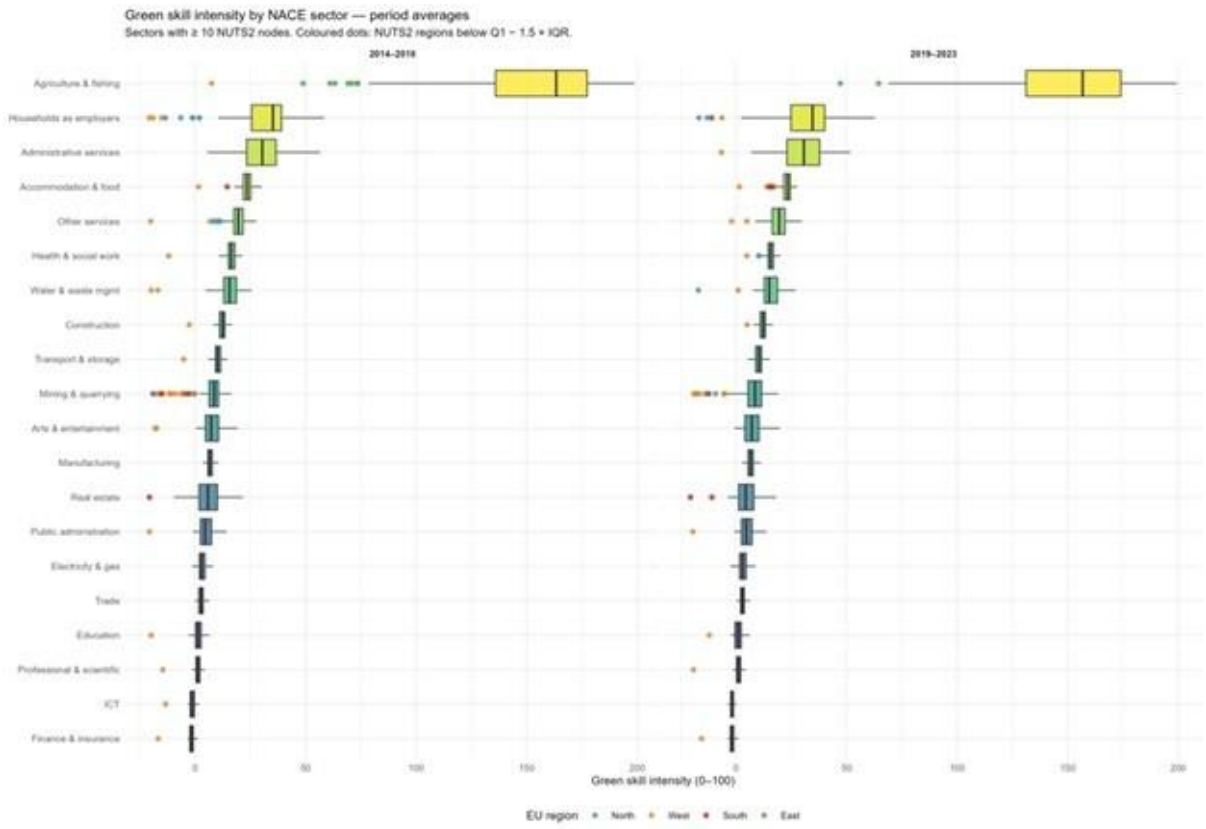


Figure 2: Distribution of Green Skill Intensity scores (G_{rj}) by NACE sector, 2014–2018 and 2019–2023. Box plots ordered by pooled median. Coloured dots: NUTS2 regions below Q1 1.5 × IQR by EU macro-region.

the groups that score lowest on the γ_o scale, indicating a tight link between profession and industry in terms of green skills (Cardenas Rubio, Warhurst, and Anderson 2022). The implication is that the greening of these sectors, although exhibiting low margins due to their small carbon footprint (Vona, Marin, and Consoli 2019), will require a more fundamental transformation of the skill content of professional work, rather than a simple reallocation of existing workers.

The between-period comparison reveals that the sectoral ordering is highly stable, but there is modest evidence of an upward shift in scores across most sectors in the 2019–2023 period. This shows that most industries change and evolve in terms of competences, with a greater green intensity of their skill composition. The spread of scores within sectors, however, remains wide, indicating persistent regional heterogeneity even within narrowly defined industries.

Disentangling the Green Transition: Primary-Sector versus Energy-Transition Green Skills

The results presented in Section 4 show that agricultural, forestry and fishery occupations score four to fourteen times higher than the rest of the occupational distribution, so any employment weighted regional index built directly from the aggregate γ_o scores would be dominated by each region's share of agricultural employment rather than by anything specific to the energy transition. For that reason, we move a step further and, in this section, we distinguish the 385 ESCO green skills into primary-sector/environmental and energy-transition categories, and then construct two distinct regional geographies based on these two dimensions of the green transition.

Constructing a Sub-Classification of Green Skills

ESCO's own green-skill label is binary. This means that a skill is either flagged as green or not, following the definition of green skills as "the knowledge, abilities, values and attitudes needed to live in, develop and support a society which reduces the impact of human activity on the environment" (Cedefop 2012; European Commission 2022). Therefore, it does not distinguish between different environmental domains. To construct a sub-classification on a documented and reproducible basis rather than through subjective judgement, we drew the classification vocabulary from the EU Taxonomy for Sustainable Activities (Regulation (EU) 2020/852), which the European Commission (2022) itself cites as one of the reference sources used to train the ESCO green-skills labelling model.

The Taxonomy defines six environmental objectives in its Article 9 and specifies, through two Delegated Acts, the named economic sectors and activities that substantially contribute to each. Skills whose text matched sector or activity terms associated with the climate change mitigation objective (energy, manufacturing, transport, construction and real estate, and information and communication) were assigned to the energy-transition category.[4] Skills matching terms from the water and marine resources, circular economy, pollution prevention, and biodiversity and ecosystems objectives, together with the forestry-related activities recognised under the mitigation objective, were assigned to the primary-sector/environmental category.[5]Skills matching terms from both categories, or

[4] . See the Commission Delegated Regulation (EU) 2021/2139, Annex I.

[5] . See Commission Delegated Regulation (EU) 2023/2486, Annex I; Commission Delegated Regulation (EU) 2021/2139, Annex I, Section 1.

from neither, were retained as a residual "general/mixed" group and excluded from both sub-category scores, so that each category remains internally coherent.

This procedure classified 166 skills (43.1%) as primary-sector/environmental, 79 (20.5%) as energy-transition, and 140 (36.4%) as general/mixed. This indicates that the compositional skew toward primary-sector/environment-related green skills (more than twice as many skills fall into that category as into the energy-transition category) is a structural feature of the official green skills list itself, which should be taken into account.

The Occupational Mapping and the Regional Geography of Primary Sector versus Energy-Transition Green Skills

Recomputingtheindicatorseparatelyfortheprimary-sector/environmentalandenergy-transition skill sets, and re-aggregating to the occupation and NUTS2 level exactly as in the previous section, shows why a single undifferentiated map would have masked some interesting heterogeneity.[6] Figure 3 (with the occupational scores γ_o) and Figures 4 and 5 (with the green skill indicators G_r calculated for both sub-categories) show how the energy-transition dimension of the green transition has its own distinct geography, although it contributes only moderately to the aggregate index reported in Section 4.

The occupations that lead the energy-transition ranking are, substantively, a different workforce from the one that leads the aggregate index. Building and related trades workers, electrical and electronic trades workers, science and engineering associate professionals and professionals, and metal, machinery, and assembly occupations are leading. Thus, a construction-, engineering-, and manufacturing-based profile is at the forefront of the green skill intensity index, corresponding far more closely to conventional understandings

[6] . For comparison, we also computed the naive aggregate indicator that pools all 385 green skills without distinguishing between categories. At the regional level (n =223 NUTS2 units), this naive aggregate index and the primary-sector sub-score correlate at r =0.9998 (Pearson) and ρ =0.999 (Spearman); the top 20 and bottom 20 NUTS2 regions under the two specifications are identical, region for region. The naive aggregate correlates far weaker with the energy-transition sub-score (r = 0.232, ρ = 0.434), and only 2 of the 20 highest-scoring regions under the energy-transition specification also appear in the naive aggregate top 20. In other words, an undifferentiated green-skill-intensity map would have reproduced the primary-sector map in Figure 4 below and told us essentially nothing about the energy transition specifically. The same pattern holds at the occupation level. Across the 40 ISCO-08 two-digit occupational groups, the aggregate score correlates with the primary-sector score at r =0.999 (ρ =0.980), and with the energy-transition score at r =0.014 – statistically indistinguishable from zero (p =0.93; ρ =0.483). In other words, once the domain-mismatch correction described above is applied, the aggregate index no longer represents a blend of primary-sector and energy-transition green skills in any meaningful sense.

of the green-technology workforce (Vona et al. 2018) than the agricultural and elementary occupations that dominate the aggregate score.

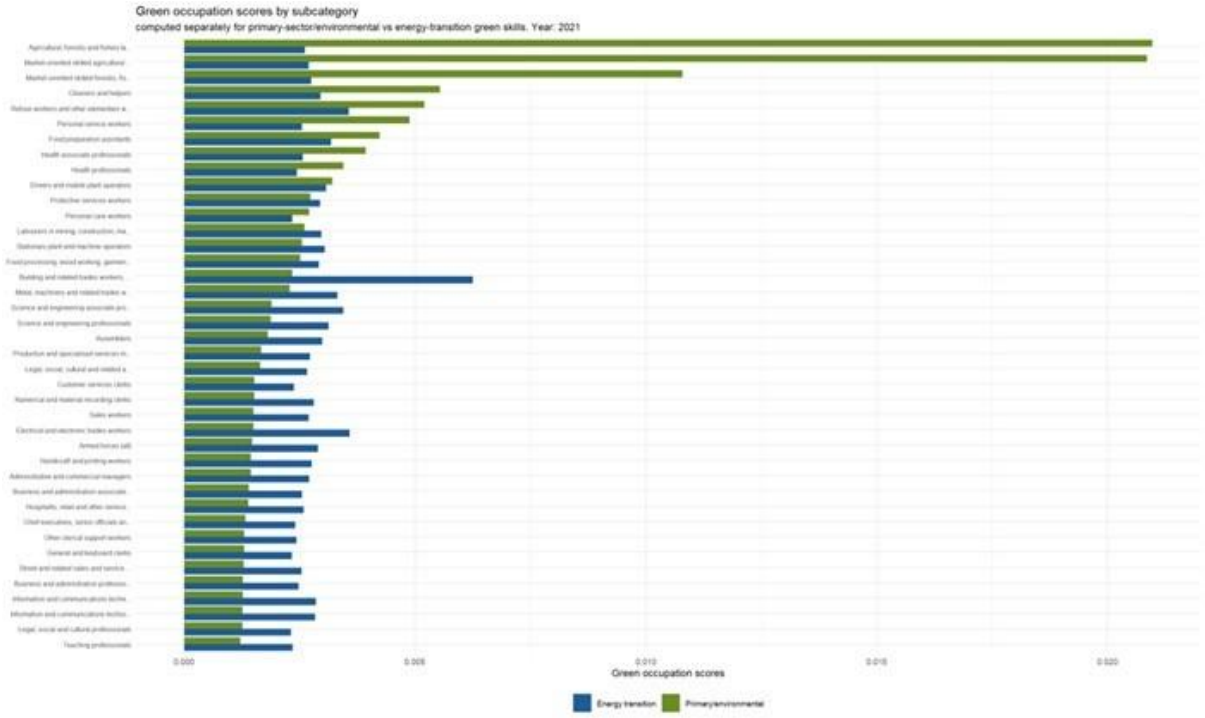


Figure 3: Green occupation scores computed separately from primary-sector/environmental and energy-transition green skills, ISCO-08 two-digit groups.

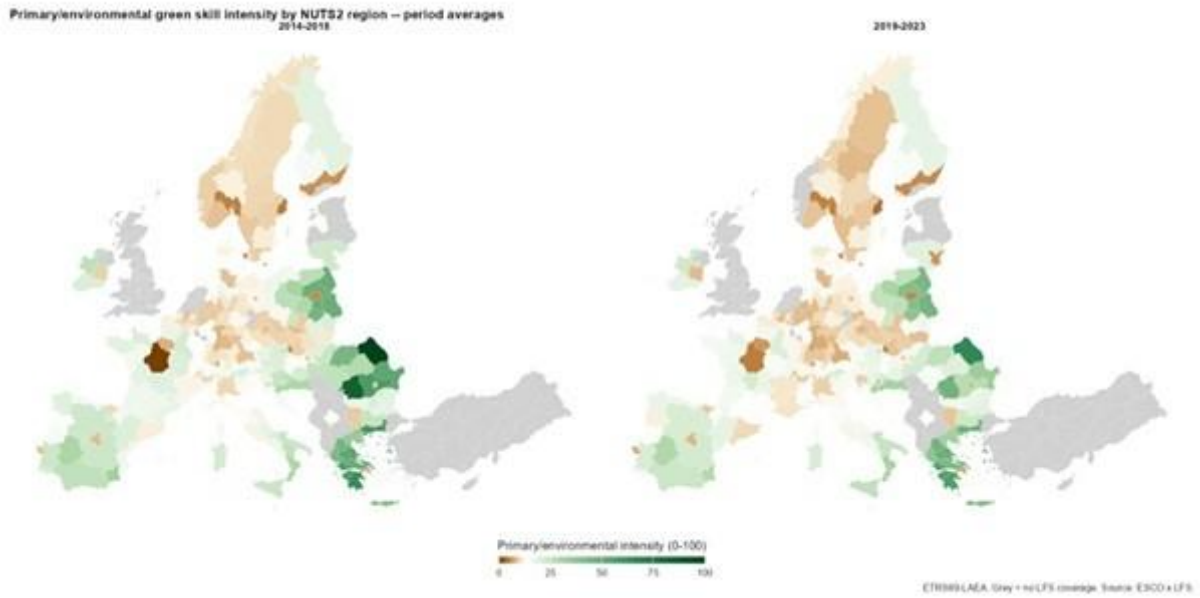


Figure 4: Primary-sector/environmental green skill intensity by NUTS2 region, period averages 2014–2018 and 2019–2023.

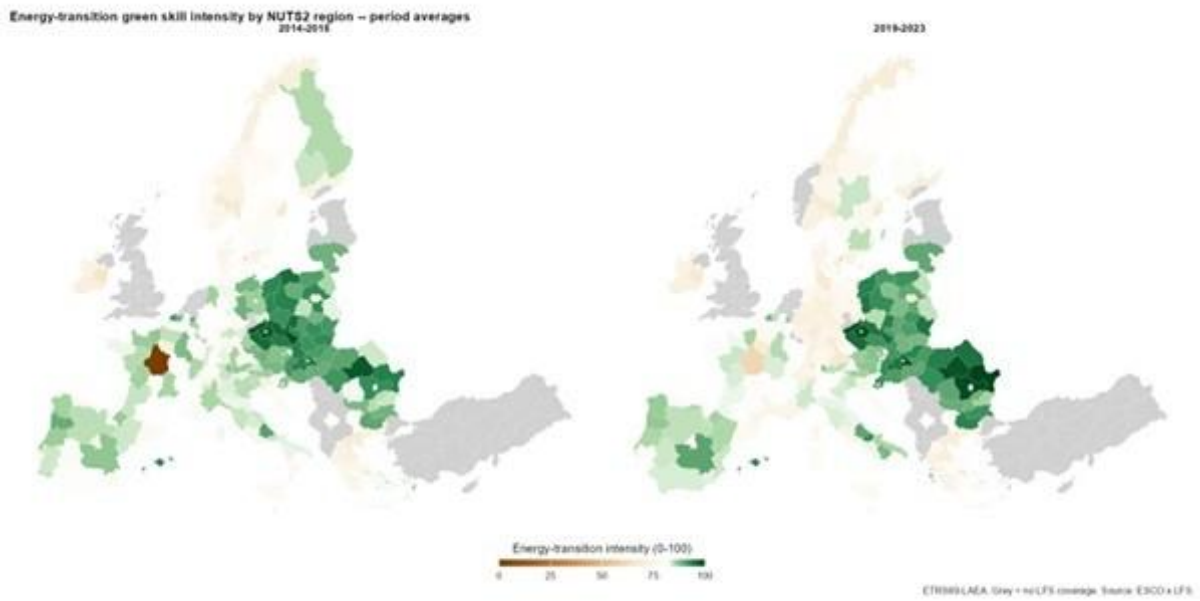


Figure 5: Energy-transition green skill intensity by NUTS2 region, period averages 2014–2018 and 2019–2023.

The regional maps make the divergence concrete. The primary-sector map (Figure 4) shows Greece, together with agricultural regions of Poland and Romania, forming a high-scoring periphery: this is, as shown above, essentially what an undifferentiated map would also show. These regions are among the poorest regions with a large share of agricultural and manual occupations in their employment base. These occupations have a high score of green skill intensity, reflecting the importance of occupational and industrial structure for the green transformation of a regional labour market (Rodríguez-Pose and Bartalucci 2024; While and Eadson 2022). The energy-transition map (Figure 5) identifies a different periphery altogether: Polish, Czech, and eastern German regions with a stronger manufacturing, construction, and engineering employment base, alongside parts of Romania. Note the shift in the high-scoring periphery toward Central European regions (Poland, Czech Republic, eastern Germany, Romania) relative to Figure 4.

By contrast, core, highly urbanised and service-intensive regions, including capital city regions across Northern and Western Europe, score comparatively low in both indexes, despite their overall economic dynamism. EU core regions are defined as those included in the 'Blue Banana' (Faludi 2015) and the capital regions of southern, eastern, and central EU countries. This result reflects the dominance of employment in finance and insurance, ICT, professional and scientific activities, and education, sectors that, as shown in Figure 2, have the lowest green occupation scores and the smallest carbon footprint (Vandeplas et al. 2022). Nevertheless, these relatively low scores should not be interpreted as evidence that core regions lack the broader capacity to contribute to the green transition. Their concentration of financial, scientific, professional, and educational activities may provide complementary capabilities for financing, designing, coordinating, and implementing green investments, even though these occupations contain fewer directly green tasks in the ESCO-based measure.

Persistence of Regional Rankings by Sub-Category

A further question is whether the two dimensions of the green transition are equally locked in spatially and over time. We compare the top 20 and bottom 20 NUTS2 regions under each subcategory between 2014–2018 and 2019–2023 (Figures 6 and 7). The primary-sector geography is highly persistent: 17 of the 20 top-scoring regions and 18 of the 20 bottom-scoring regions are the same in both periods, consistent with a geography anchored in slow-moving agricultural employment shares.

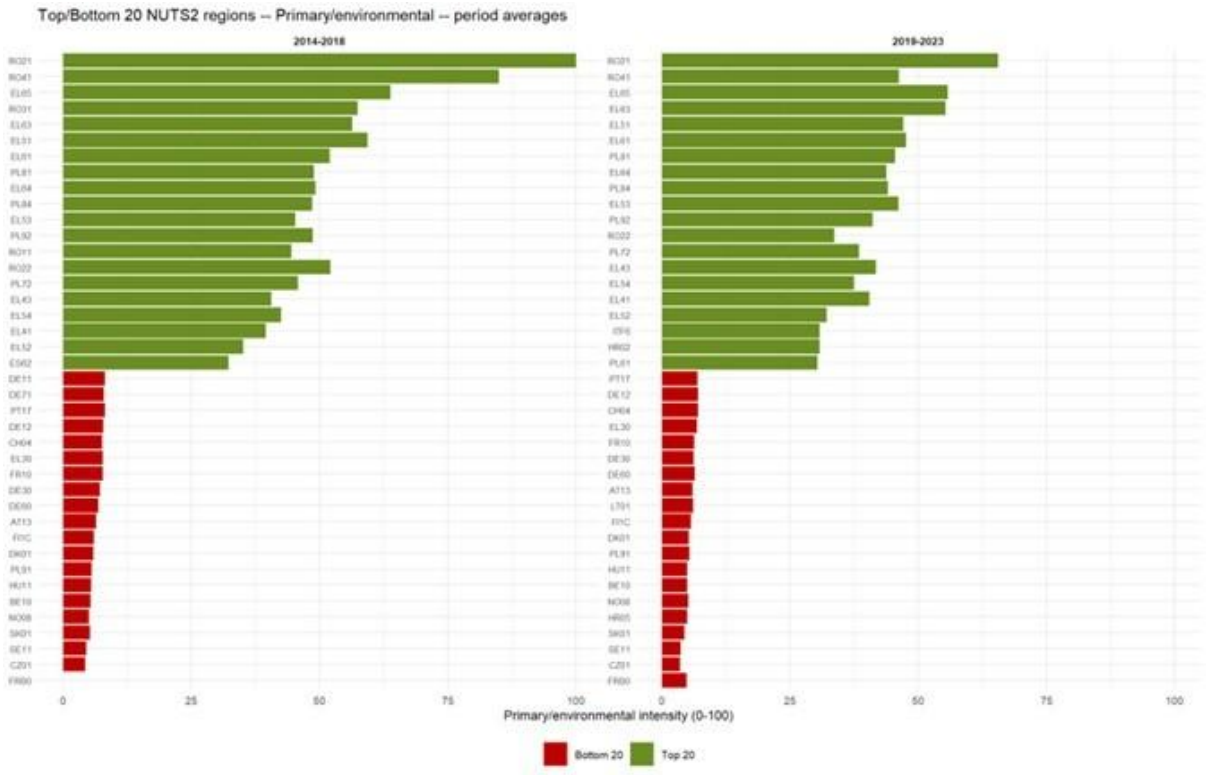


Figure 6: Top/Bottom NUTS2 region by primary sector related green skills, period averages 2014–2018 and 2019–2023.

The energy-transition geography is less rigid, with 13 of 20 top-scoring regions and 12 of 20 bottom-scoring regions persisting across the two periods. Moreover, several Central and Eastern European industrial regions entered the top 20 only in 2019–2023. These regions include Yuzhen Tsentralen in Bulgaria (BG42), Észak-Magyarország in Hungary (HU31), and Podkarpackie Voivodeship in Poland (PL82).

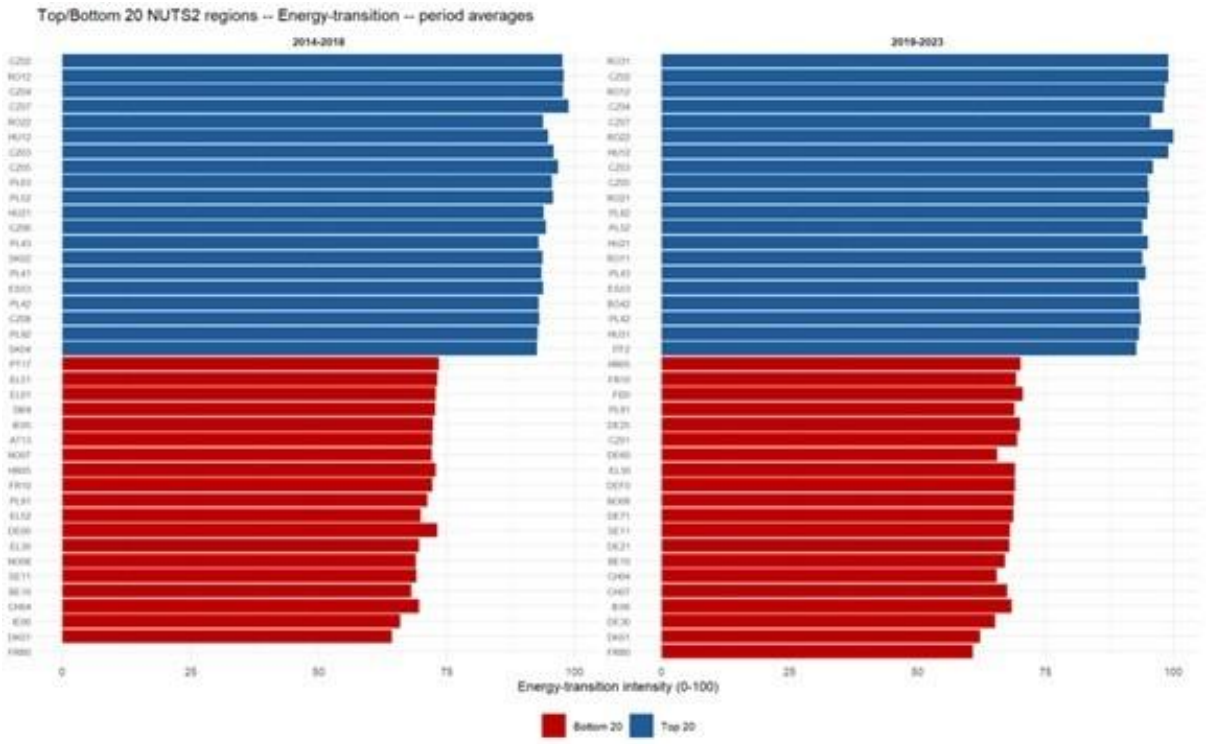


Figure 7: Top/Bottom NUTS2 region by energy transition related green skills, period averages 2014–2018 and 2019–2023.

This gap is informative: the primary-sector green skills geography reflects a deeply structural feature of regional economies connected with the share of employment in agriculture, which changes only slowly. The energy-transition green skills geography, while still concentrated in a set of Central and Eastern European industrial regions, shows greater churn at the margin, consistent with a still-emerging geography of construction-, engineering-, and manufacturing-based green employment. As a consequence, energy-transition workforce readiness may be comparatively more tractable to shift through active policy than the agriculture driven geography of green skills related to agriculture specialization, which has direct implications for how the Just Transition Mechanism and similar instruments should be targeted.

Theseresultssharpenthepaper'scentralcontributionbyfindingthatcore, urbanised, service intensive EU regions possess the least green-relevant workforce is robust across every specification we test (primary-sector and energy-transition alike) and remains the paper's most policy relevant result. Regions in Greece, Romania, and Poland are identified as the EU's most green ready for reasons specific to the dominance of the agricultural industry, rather than to any particular readiness for energy-related decarbonisation. A genuinely distinct energy-transition periphery, however, emerges in Poland, the Czech Republic,

eastern Germany, and parts of Romania, driven by construction, engineering, and manufacturing occupations rather than agricultural ones.

Discussion and Policy Implications

Section 5 established how the green skill index would have been dominated by primary-sector and agricultural employment, and that a distinct, smaller energy-transition geography exists in Central and Eastern European industrial regions. The discussion below applies to both dimensions, given the finding that core, urbanised, service-intensive regions are the least green-skill ready under either specification. Our results have several direct implications for the design of labour market policies intended to support the green transition. We organise these around three themes: the measurement gap, the targeting of place-based active labour market policies, and the long-run challenge of structural transformation and institutional capacity.

The Measurement Gap and the Case for ESCO-Based Monitoring

A fundamental precondition for place-sensitive green transition policy is a reliable monitoring framework capable of identifying, at the sub-national level, where skills gaps are largest and how they are evolving. That is, to strengthen the case for a smooth transition towards a low carbon production model, the regions, industries and occupational groups in which workers or job seekers most frequently lack the specific skills employers require need to be identified. However, there is space for improvement in the current monitoring mechanism across Europe, and particularly at the regional level (ETF, 2023).

Our methodology provides a blueprint for such a framework. The ESCO taxonomy is already the backbone of several EU employment policy initiatives, including the European Skills Agenda and the Pact for Skills, though it lacks a green skill intensity dimension. Extending ESCO-based monitoring to include a green skill intensity dimension would provide policymakers, regional authorities, and employers with actionable intelligence on the green skill landscape at a level of granularity that current instruments do not provide.

We note, however, that our methodology is a supply-side measure: it captures the green relevance of skills that workers currently possess, as inferred from their occupational classification. An integrated monitoring system should ideally combine supply- and demand-side indicators, linking the ESCO-based GSI scores to vacancy data from platforms such as EURES, OVATE or national public employment services. Indeed, a comprehensive examination of the green transformation of the labour market requires

data and information from both the demand (employers) and supply (workers) sides (García-García, Carpintero, and Buendía 2020).

Targeting of Place-Based, Active Labour Market Policies

The spatial heterogeneity we document implies that the green transition will impose adjustment costs that are highly concentrated geographically, and that the specific nature of the exposure differs by dimension. Regions with low energy-transition scores and high employment in fossil fuel-adjacent or heavy-manufacturing sectors face the greatest risk of labour-market disruption as energy-related decarbonisation proceeds (Kapetaki 2021), since it is precisely this workforce that lacks the construction, engineering, and manufacturing-based skill profile identified in Section 5.3. These are also, in many cases, regions with weaker institutional capacity, lower educational attainment, and more limited access to training infrastructure – precisely the conditions that make skill upgrading most difficult (Vandeplas et al. 2022). Regions that are weak on both dimensions — disproportionately the urbanised, knowledge-intensive core identified throughout this paper — face a different but equally real challenge: their existing skill base is not naturally aligned with either the agricultural or the industrial green economy, and building capacity there means starting closer to zero.

In contrast to this empirical evidence, the standard toolkit of active labour market policy operates at the national level with eligibility criteria and programme designs that are uniform across regions (Fuchs 2024). Our findings suggest that this one-size-fits-all approach is ill-suited to the challenge of adjusting to the green transition, particularly from a fairness perspective, where no region, occupation or socio-economic group is left behind. Each regional labour market has particular socio-economic features, such as industrial structure, occupational mix, skill mix, as well as gender, age and ethnic composition, that need to be considered when planning and implementing policies to address the implications of the green transition. For instance, the often core, prosperous regions at the bottom of the green skill intensity distribution require not merely more resources but qualitatively different interventions: longer-duration training programmes, stronger employer engagement, close coordination between regional development agencies, vocational education institutions, and sectoral bodies, as well as accessible training to all regardless of age, gender or ethnicity.

The Just Transition Mechanism (JTM) and its associated Just Transition Fund (JTF) represent a first step toward territorially targeted support, but their current design focuses primarily on regions with high dependence on fossil fuel extraction and heavy manufacturing. While these regional labour markets should be the point of departure and focal point, our results

suggest that the geography of green skill disadvantage is wider than the geography of fossil fuel dependence, and that the JTM's territorial scope may need to be expanded to address the full range of regional vulnerability, always being adjusted to the regional socio-economic specificities.

Structural Transformation, Institutional Capacity and the Long Run

Perhaps the most sobering implication of our analysis concerns the persistence of the primary sector green skill geography: as shown in Section 5.3, 85% of the top-20 and 90% of the bottom20 regions under that specification are unchanged between 2014–2018 and 2019–2023. This path-dependent lock-in (Martin et al. 2016) into low and high trajectories of green skill intensity reflects deep-seated structural factors, such as the industrial structure and occupational composition of regional economies, the educational attainment of the workforce, and the quality of vocational training systems that are not easily or quickly changed by short-run policy interventions. The energy-transition geography is comparatively more fluid suggesting that workforce readiness for energy-related decarbonisation specifically is a more tractable policy target than the deep-rooted agricultural-employment geography.

Any process of structural transformation towards a fairer European labour market throughout the green transition requires policies (Altenburg and Rodrik 2017), although with some changes. The green transition might require a long-horizon perspective on regional development policy that moves beyond the usual planning cycles of EU and national programmes. Building genuine green-skill capacity in lagging regions requires sustained investment in education and training infrastructure, an active industrial policy to attract and equitably distribute green-economy employers, and patient institutional development of the kind that cannot be delivered through project-based funding mechanisms in the short run.

There is also a political economy dimension to this argument. The regions with the lowest green skill intensity among the workforce actively employed in green-critical sectors are, in many cases, also the regions where support for green policy is weakest and where anti-green political movements have gained the most traction – see Rodrik (2021), or Colantone and Stanig (2018). If the green transition continues to generate visible losers in these communities without credible prospects of catching up, the political backlash will not remain localised. Addressing the geography of green-skill disadvantage is therefore not merely a matter of labour market justice — it is also a precondition for fairer political development, with fewer socio-economic groups left behind.

Conclusions

This paper has examined the extent to which the existing EU workforce possesses green skills across industries and regions. To do so, it developed a novel, replicable methodology for measuring Green Skill Intensity at the NUTS2 region and sector level across the European Union, combining the ESCO skill-occupation taxonomy, natural language processing, and Labour Force Survey microdata. It contributes to the literature on green transition economics by providing comparable, sub-national evidence on the distribution of green workforce readiness across EU regions, tracked over two five-year periods (2014-2018 and 2019-2023) spanning the run-up to and early implementation of the European Green Deal.

The main findings can be summarised in six points. First, green skill intensity varies considerably across occupations, with results that challenge simple associations between skill level and green relevance: agricultural and manual occupations score far above the rest of the distribution, while many professional and knowledge-intensive groups score low. Second, green skill intensity scores exhibit significant variation across industries, in the wider context of uneven implications of the green transformation of the economy (Vandeplas et al. 2022). Third, this occupational skew is large enough to justify a disentangling of the official green skills list into primary-sector and energy-transition components, which reveals two largely independent geographies rather than one. Fourth, the primary-sector geography concentrated in Greece, Romania, and Poland is highly persistent over time, while the energy-transition geography concentrated instead in Poland, the Czech Republic, and eastern Germany, and carried by construction, engineering, and manufacturing occupations, is smaller in magnitude and comparatively less locked in. Fifth, one finding is robust across every specification: urbanised, service intensive regions in Northern and Western Europe score consistently lowest on green skill intensity, whether measured by the primary-sector or the energy-transition score, indicating a genuine and durable readiness gap in the EU's economic core. Finally, regional rankings are remarkably stable across the two periods examined, suggesting lock-in and path dependence (Martin et al. 2016). The fundamental geography of green workforce readiness is sticky, not self-correcting, and will require active, place-sensitive, long-term, and visionary policy intervention to change.

These findings have direct implications for the EU labour market and cohesion policy. The green transition is not a neutral force that uniformly upgrades the European workforce. It is a spatially uneven process that requires differentiated policy responses calibrated to the specific skill endowments, sectoral structures, and institutional capacities of individual

regions. Addressing this geography of green-skill disadvantage is not merely a matter of equity but also a precondition for fair political development and a just future.

Several avenues for future research are suggested. Our methodology is a supply-side measure and does not capture demand-side green skill requirements from employers. The ESCO taxonomy is a static snapshot and does not track the rapid evolution of green skill requirements as new technologies emerge. Future work should explore the integration of demand-side vacancy data, dynamic skill mapping approaches, and the linkage of green skill intensity scores to outcomes such as regional wage growth, employment resilience, and electoral support for environmental policies.

Disclaimer

Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Research Executive Agency (REA). Neither the European Union nor the granting authority can be held responsible for them

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A Correcting Spurious Matches in the Semantic-Similarity Step

Applied at scale across 385 × 296 skill pairs, the sentence-embedding matching described in Section 3 occasionally produces matches that are lexically plausible but substantively wrong: two skill descriptions can be judged "similar" because they share incidental vocabulary, even when the underlying activities are functionally unrelated. To illustrate this by means of a particular example, consider the case of the skill "preparing food and drinks" scored highly against several energy-transition green skills (including "install heat pump" and "operate solar thermal energy systems for hot water and heating") because both sets of descriptions refer to heating water, not because a cook and a heating technician share any occupational content.

To correct this systematically for the purpose of the sub-category decomposition, we reused the EU Taxonomy-derived vocabulary described in section 5.1 and applied it to the occupational (ESCO) skill descriptions. For each candidate match between a green skill and an occupational skill, we checked whether the occupational skill's own description contains terminology characteristic of the domain the green skill belongs to. Where this domain-specific vocabulary was entirely absent, the estimated relevance of that match was reduced to 5% of its original value rather than removed outright, preserving a graded rather than all-or-nothing distinction. Applied to "preparing food and drinks", this reduced its similarity to the affected energy-transition skills from a range of roughly 0.27–0.54 to approximately 0.01–0.03. The tables below list the seven keyword groups used for each category, together with representative terms and their source within the two Delegated Acts.

Keyword group	Representative terms
Energy generation	Electricity generation, solar, photovoltaic, wind turbine/power/farm/energy, geothermal, hydropower, ocean/tidal/wave energy, biogas
Low-carbon manufacturing	Low-carbon technology, manufacturing of low-carbon technologies
Transport	Electric vehicle/car, e-mobility, zero-emission vehicle/motor, rail transport, charging infrastructure

Buildings and energy efficiency	Renovation of buildings, energy performance of buildings, construction of new buildings, building management systems, energy efficiency, energy saving, energy audits, insulation, heat pumps, NZEB, district heating, heating, cooling, ventilation, HVAC
Grid and storage	Electricity storage, energy storage, smart grid, electricity transmission/distribution, grid, battery
Hydrogen	Hydrogen
ICT and climate data	Data-driven solutions for GHG, greenhouse gas emissions, emissions, carbon, decarbonisation

Table 1: Energy-transition keyword groups. *Source:* Commission Delegated Regulation (EU) 2021/2139, Annex I.

Keyword group	**Representative terms**
Forestry	Afforestation, reforestation, forest management, conservation forestry, forest, timber, silviculture, trees
Environmental protection and restoration	Environmental protection and restoration, restoration, remediation
Water and marine resources	Water supply, wastewater treatment, urban drainage, flood, drought, water quality, marine, fisheries, aquaculture, irrigation, soil
Circular economy and waste	Recycling, reuse, secondary raw materials, waste, composting, landfill, sludge
Biodiversity and ecosystems	Biodiversity, habitats, ecosystems, wild fauna/flora, Natura 2000, invasive alien species, wildlife, species, animals, veterinary
Pollution prevention	Pesticides, pest control, hazardous substances/materials, contamination
Agriculture	Agriculture, farming, crops, tillage, cultivation, pasture, grazing, livestock

Table 2: Primary-sector/environmental keyword groups. *Source:* Forestry terms are based on Commission Delegated Regulation (EU) 2021/2139, Annex I, Section 1. All other terms are based on Commission Delegated Regulation (EU) 2023/2486, Annex I.