LCA Report
Cisco Public

ISO-Aligned Life Cycle Assessment Report

N9324C-SE1U

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N9300 Series, 24p 100G Smart Switch

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Abbreviations

ADP	abiotic depletion potential
ASIC	Application-Specific Integrated Circuit
BOM	bill of materials
BWC	blue water consumption
Cisco	Cisco Systems, Inc.
CO_2	carbon dioxide
CO_2e	carbon dioxide equivalent
CPU	Central Processing Unit
CTUe	Comparative Toxic Units equivalent (ecotoxicity)
CTUh	Comparative Toxic Units equivalent (human toxicity)
EOL	end-of-life
GB	gigabyte
GHG	greenhouse gas
GWP	global warming potential
IPCC	Intergovernmental Panel on Climate Change
IC	integrated circuit
ISO	International Organization for Standardization
kg	kilogram
kWh	kilowatt-hour
L	liter
LCA	life cycle assessment
LCI	life cycle inventory
LCIA	life cycle impact assessment
MJ	megajoule
PCB	printed circuit board
PED	primary energy demand
SSD	Solid-State Drive
Sb	antimony
W	watt
WSP	WSP USA Inc.

Version History

Version & Date	Developed by	Changes Made	Version of Cisco Scalable LCA Model used
V 1.0 2025-08-04	WSP Team	Initial version created	Version 3.0

Disclaimer on comparability and model updates

As the Scalable LCA Model is continuously updated, both in terms of the foreground model (such as data from Cisco) and the background model (such as electricity grid mixes), it is important to note which version of the model has been used for the specific study. This LCA data is not intended to be compared to LCAs of other Cisco products or any third-party products.

Primary data has been used when possible. Secondary data along with estimates and assumptions has been used for the background system and to fill data gaps. The following LCI databases were used in Version 3.0 of the Scalable LCA Model.

- LCA For Experts service pack 2024001000
    - “Professional 2024” database
    - “XI: electronics 2024” extension database
- ecoinvent version 3.10

Results in this report are estimates and indicative only, based on assumptions and approximations, for particular products and points in time. They are neither predictions, commitments or guarantees of actual outcomes nor intended for purposes other than identifying opportunities to improve the environmental performance of products at various points in their life cycle. Cisco and WSP continue to refine the methodology, modeling, and assumptions. Data and other information are therefore subject to change and uncertainties that are difficult to predict.

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Further information on Cisco’s approach to Life Cycle Assessments (LCAs) is available at Cisco's Purpose Reporting Hub at https://www.cisco.com/c/m/en_us/about/csr/esg-hub.html

1 Goal of the Study

This report is based on a study performed for Cisco using a Scalable Life Cycle Assessment Model developed by WSP USA Inc. (WSP). It is a parameterized model in the LCA for Experts[1] (formerly GaBi®) software that, when combined with an Excel spreadsheet template called the "Parameterizer," streamlines life cycle assessments (LCAs) of Cisco products. The Parameterizer automatically reads bills of materials (BOMs) to inform parameters for electrical components, which, together with manual data entries and assumptions for data gaps, inform the model's parameters.

Cisco commissioned WSP to develop an LCA using the Scalable LCA Model to calculate the global warming potential (GWP) (excluding biogenic carbon), non-renewable primary energy demand (PED), and blue water consumption (BWC) of Cisco's N9324C-SE1U smart switch (from here on referred to as "the product"). GWP is also referred to as greenhouse gas (GHG) emissions and the GWP results (excluding biogenic carbon) of the product life cycle are characterized by the Intergovernmental Panel on Climate Change (IPCC) AR6 characterization factors for GWP100. The PED from the non-renewable resources impact category represents the amount of fossil energy demanded from the ecosystem. BWC is the volume of surface and groundwater consumed (or otherwise made unavailable by evaporation or fouling) as a result of the production of a good or service. In addition, abiotic depletion potential (ADP), ecotoxicity, and human toxicity (cancer and non-cancer) were also considered. ADP assesses the depletion of non-living resources, such as metals and minerals, and evaluates the potential for resource scarcity. Ecotoxicity assesses the potential toxicity of emissions to ecosystems and aquatic life and evaluates the potential harm to the environment due to the release of toxic substances. Human toxicity assesses the potential harm to human health due to exposure to substances that have cancerous and non-cancerous (toxic) effects.

This LCA covers the life cycle of the product from cradle-to-grave. The Cisco N9324C-SE1U smart switch is a 1-rack unit, top of rack switch with fixed ports designed for deployment in data centers. Therefore, the goal of this study is to determine the GHG emissions, PED, BWC, ADP, ecotoxicity, and human toxicity (cancer and non-cancer) impacts of Cisco's N9324C-SE1U from cradle-to-grave.

1.1 Reasons for Carrying Out the Study

This study is meant to inform product development and internal decision making by identifying the environmental impact of N9324C-SE1U. Cisco recognizes that the environmental impacts depend greatly on the specifics of the inputs, production method, location, transportation, and disposal of the product.

This study was conducted to determine the GHG emissions, PED, BWC, ADP, ecotoxicity, and human toxicity (cancer and non-cancer) impacts associated with the production, transport, use phase, and end-of-life (EOL) of the product according to International Organization for Standardization (ISO) Standards 14040 and 14044 on LCA (ISO, 2006). The GHG emissions, PED, BWC, ADP, ecotoxicity, and human toxicity (cancer and non-cancer) impacts were selected based on potential business value, data availability, requests from stakeholders, and commonly included metrics for electronic products. While the results of the Scalable LCA model are in alignment with ISO Standards 14040 and 14044 for LCA, there currently is no ISO standard that applies to LCA models or tools. The ISO standards only apply to reports and their contents. Therefore, the Scalable LCA model itself cannot be considered "ISO-conformant" and the Scalable LCA model's results can only be considered ISO-conformant if documented in an ISO-

[1] Modeling for all systems in this study was conducted in the LCA software LCA for Experts (formerly GaBi), developed by thinkstep, now Sphera (https://sphera.com/product-sustainability-software/).

conformant LCA report that undergoes critical review. In summary, instead of performing critical review of each individual LCA report, the Scalable LCA Model itself has been reviewed.

1.2 Intended Applications

The study is intended to provide actionable environmental impact information about the GHG, PED, BWC, ADP, ecotoxicity, and human toxicity (cancer and non-cancer) impacts from all cradle-to-grave life cycle phases of the Cisco product.

1.3 Target Audience

The study results are prepared for Cisco's internal use and external reference in alignment with ISO Standards 14040 and 14044. Specific audiences may include the company's employees (e.g., leadership, product designers and engineers, communications, and sustainability professionals).

1.4 Critical Review

This report is intended to be aligned with the requirements of ISO Standards 14040 and 14044, which set forth the requirements for public disclosures and documentation for LCAs. This report has not been critically reviewed and is therefore not ISO-conformant.

2 Scope of the Study

The study is a cradle-to-grave LCA of a Cisco electronic product. This section outlines the function of the product, its declared unit, system boundary, and other scope specific information.

2.1 Product and Function

The Cisco N9324C-SE1U (Figure 1) is engineered for high-performance networking with robust capabilities designed to meet the demands of modern data centers. With a 480 gigabytes solid state drive (SSD), this switch ensures rapid data access and reliability while managing high data throughput of 800 Gbps. Its non-blocking architecture and advanced Layer 4 switching enable seamless communication across multiple devices, facilitating efficient data flows in complex environments. With 24 ports of 100 gigabit ethernet, connectivity is versatile. A brief overview of the technical specifications of the product is provided in Table 1.

Table 1: Technical Specifications of the Product

Technical Data	N9324C-SE1U
Product weight	16.7 kg
Modeled product power[2]	780 W
Dimensions (H * W * D)	17.2 in x 17.3 in x 29.9 in
Market release date	2025
Product Configuration	**Quantity**
N9324C-SE1U	1
NXA-PAC-1400W-PI	2
NXA-SFAN-35CFM-PI	6
CAB-AC-10A-NA	2
NXK-ACC-KIT-1RU	1

[2] Modeled product power is estimated based on product function and assumed product use.

Figure 1: Image of the product – N9324C-SE1U

Source: Cisco

2.2 Functional Unit

The Scalable LCA Model does not generate results per a functional unit, which is typically done in LCA to allow for comparison. A functional unit is a quantified description of the function of the product or process and is used as the reference quantity throughout analysis. This uniform functional unit allows for comparisons across different products. Instead, this study presents results per a declared unit of one device across its life cycle from cradle-to-grave, including the use phase. This is in alignment with PCR 2024:06 on electronic and electrical equipment from The International EPD System (2024) and the International Electrotechnical Commission standard 63366 for LCA of electrical and electronic products and systems (IEC, 2024).

2.3 System Boundary

The Scalable LCA model's system boundary (Figure 2) is from cradle-to-grave for the life cycle inventory (LCI) and impact assessment and includes raw material extraction and refinement, material transport, component manufacturing, assembly, testing, delivery, use phase, and EOL. Infrastructure and capital goods (e.g., buildings and machines used for production) are not included due to their assumed small contribution to the overall impact of the electronics products balanced with the challenges of collecting granular and specific data on the depreciable capital involved in electronics production. Production of infrastructure has been excluded also for background generic processes in order to ensure consistency between the foreground and background datasets.

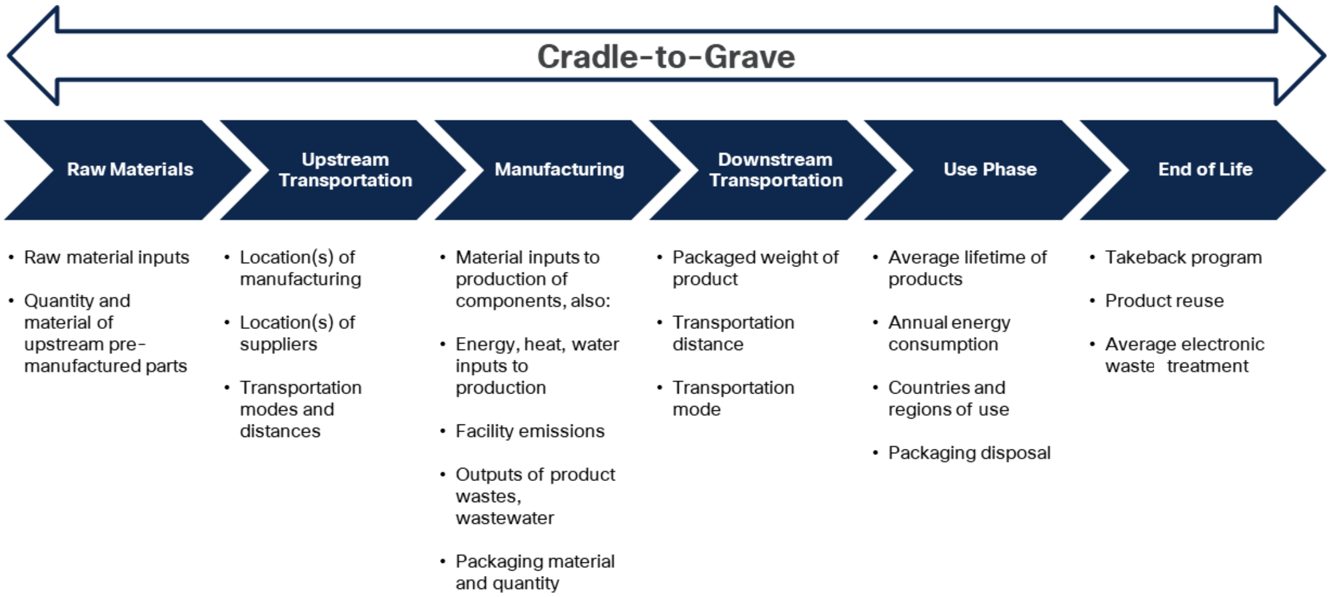


Figure 2: The system boundaries of the Cisco Scalable LCA model

Manufacturing boundaries will vary depending on the product and the selected source of secondary data for production burdens. The system boundaries are set by the secondary data sources used. The tool categorizes manufacturing into two steps: assembly and testing. Assembly entails producing the final product through combining components and materials. Testing is done to ensure the functionality and reliability of the product through hardware and software testing. Excluded are the peak conditions tests, which involve extreme temperatures and altitude testing, as this is not performed on every single product produced. Rather, testing in this context is the nominal testing that is performed on all products produced to ensure functionality before shipping.

Packaging materials for the raw materials and semi-finished goods are also excluded for the same reason as infrastructure and capital goods. However, the weights of packaging can be added to the transportation burdens through simple assumptions. Recovery in EOL is excluded from the system boundaries due to recycled waste stream methodology, the “cut-off” approach (also called the recycled content approach), applied in this tool. The recovery includes the material flows intended for reuse, recycling, and energy recovery, and includes waste processing for recycling and energy recovery (e.g., shredding).

2.4 Temporal and Geographical Boundary

All material, transportation, manufacturing, and use data inputs are from 2023 and 2024. The data that are matched to the material inputs are valid for 2024, with some valid through 2025 and 2026. The product is disposed of at its EOL, modeled as five years after production. All the datasets used to model EOL are for 2022.

The study assumes most electronics production occurs in Asia. All material inputs are matched to datasets that are either global averages or Chinese datasets. Manufacturing is modeled specifically for China as the manufacturing country in terms of energy consumption. The use phase is assumed to take place in the United States. EOL is assumed as a global average.

2.5 Cut-off Criteria and Limitations

LCA for Experts (formerly GaBi) databases were used, including the LCA for Experts implementation of the ecoinvent v3.10 database. Any cut-off criteria implemented in the ecoinvent or LCA for Experts databases are included in this assessment according to the LCA for Experts Modeling Principles (Sphera, 2023). Where applicable, cut-off criteria would only be applied for components that contribute to 1 percent or less of total mass or energy of the system and 5 percent or less of the total environmental impacts. Cut-off criteria were applied within the electronic components.

In addition, no mass was excluded within non-electricals, plastic, or product packaging. One exclusion was made in packaging materials for raw materials and semi-finished components. No other primary data or mass and energy flows were knowingly excluded. However, there are several limitations.

The primary limitations of the Scalable LCA Model are the assumptions related to electronic and electrical components and the use of secondary data for these as well as for the manufacturing burdens. In terms of materials burdens, a special focus was placed on key electricals that are known to have a disproportionately high environmental impact compared to other components such as housing or packaging. Several proxies needed to be made using scaling factors, as direct dataset matches were not available.

Manufacturing burdens for both assembly and testing were proxied using secondary datasets from ecoinvent, which represent different levels of complexity in the assembly and testing processes. This is a significant limitation that should be addressed in future iterations of the Scalable LCA model through additional data collection (e.g., representative Cisco manufacturing sites).

2.6 Allocation

No co-products during manufacturing were identified for the studied product. Therefore, this study did not perform allocation. Allocation of environmental burdens to material and energy co-products throughout the upstream supply chain is embedded in the LCI data used in this study and described in the documentation of these datasets.

3 Life Cycle Inventory Analysis

3.1 N9324C-SE1U Life Cycle Inventory

This section outlines the inventory compiled to assess the life cycle impacts of the N9324C-SE1U. The smart switch includes 1 metal chassis housing, 2 hot-swappable 1,400 W power supplies, 6 fan modules, 2 cables, and 1 accessory kit. Its internal composition includes complex electronic subsystems such as a Silicon One E100 Application Specific Integrated Circuits (ASIC), a 16-core Intel Central Processing Unit (CPU), 96 gigabytes of system memory, and 480 GB of SSD storage. It has 24 QSFP28 ports used for 40/100G operation on the front panel. The modeling of all these components is described in section 3.1.1. The components are assembled into a finished product before undergoing testing and being distributed to customers. The product then consumes electricity throughout the use phase as it delivers secure network connectivity. Finally, the products reach EOL and are recycled, landfilled, or returned to Cisco for recycling.

3.1.1 Component Manufacturing

The components utilized in manufacturing Cisco products fall into four main categories: key electronic, electrical, electro-mechanical, and mechanical components. The key electricals category is defined as printed circuit boards (PCBs), integrated circuits (ICs), and memory modules, such as solid state drives (SSDs) and dual in-line memory modules (DIMMs). Electrical components are capacitors, inductors, resistors, diodes, and transistors. Electro-mechanical components include cables, fans, connectors, batteries, disks, video equipment, power supplies, etc. The mechanicals category is defined as all other materials, such as housing materials (plastics, metals), heatsinks, nuts, spacers, screws, solder paste, and the like. Based on WSP's experience on similar projects and readily available literature, electrical components (through manufacturing, but potentially also at EOL incineration) and the use phase typically are the most significant contributors to environmental impacts for information technology (IT) products (Gonzalez, et al., 2012). Therefore, emphasis has been placed on the modeling of electrical components specifically, as outlined in the following subsection.

It is important to acknowledge that there will be manufacturing waste generated during processes such as grinding and sawing. Therefore, a 2 percent waste rate has been incorporated to represent the percentage of material that is discarded or lost in the manufacturing process, a common assumption when the waste flows are unknown.

Modeling of Electronic and Electrical Components

The list of electrical components includes ICs, PCBs, capacitors, resistors, transistors, and inductors. Furthermore, ICs, PCBs, and memory modules are considered key electricals. For each category, key variables were identified based on environmental impacts and internal categorization at Cisco. The most commonly used parts by Cisco were identified and categorized around the key variables. For example, for PCBs, the number of layers were identified as a key driver of environmental impacts from PCBs, and as such the number of layers were identified by Cisco.

As part of the Parameterizer, WSP integrated the functionality to read the BOM for the electrical components based on the part descriptions in the BOM. Compared to the non-electricals, for which the user must enter values manually, this enables an automatic extraction of electrical components into the desired format of the model. In essence, this means that the electricals of the BOM were easily summarized into the inputs specified in the confidential appendix. If the BOM reading failed to identify the specific type of electrical component (such as a specific IC), it defaulted to the highest impact option as a conservative assumption. Due to the sensitive nature of the data, it is placed in a confidential appendix not included in the public version of this report.

In some of the passive component dataset descriptions, there is a distinction between base metals and precious metals. Base metals typically include commonly used metals such as copper, zinc, and nickel, while precious metals typically include more rare and expensive metals such as gold, silver, and platinum. This is a critical distinction in some datasets because impacts associated with the extraction and refinement of base and precious metals can vary drastically due to differences in their mining and processing practices. Free online documentation of the LCA for Experts Extension database “XI: electronics” 2024, as well as all other databases, can be found here.

Electronic and Electrical components modeling assumptions

A central aspect of the BOM read is the connection between the components that are being read and what dataset they are matched to. As previously mentioned, the most common electrical components that Cisco used were identified in collaboration with an internal Cisco team and were included in the BOM read. However, several of these components do not have direct dataset matches. As such, several proxies needed to be made. For those components that do not have a direct match, scaling factors were applied to the most suitable match. For example, linear ICs of the TSSOP packaging type are matched to a dataset for the SSOP packaging type (based on IC type and dimensions) with a scaling factor of 0.69.

As the BOM read does not cover all of the components that Cisco uses, there was a need for a solution for “unidentified components.” The BOM read summarizes all unidentified components for each component type and conservatively assumes that they are the dataset with the highest environmental impact. For ICs, this solution has more proxy options than the other components. IC unidentified proxies are made based on IC type and packaging type to the degree possible. The other components have a singular assumption each, as presented in Table 2.

Table 2: Assumptions for Unidentified Electrical Components

Component	Unidentified Component Assignment
Resistors	Resistor flat chip 1206 (9.2mg)
Capacitors	Capacitor ceramic MLCC 0603
Inductors	Coil multilayer chip 1812 (108mg) 4.5x3.2x1.5
Transistors	Transistor signal SOT223 8 leads (180mg) 3.8x7.65x3
Diodes	Diode power DO214/219 (93mg) 4.3×3.6×2.3
Linear IC	IC SSOP 24 (123mg) 8.2x5.3 mm
Logic IC	IC SSOP 24 (123mg) 8.2x5.3 mm
Communication IC	IC BGA 48 (72mg) 8x6 mm
Microprocessor IC	IC BGA 256 (4g) 27x27 mm
Memory IC	IC TSOP 32 (373mg) 8x20 nm flash

Other IC	IC BGA 144 (360mg) 13X13mm

Modeling of Electromechanical Components

The electro-mechanical components category consists of audio and video equipment (e.g., microphones and displays), cables, switches, connectors, batteries, power supplies, and fans. As Cisco BOMs do not always contain information necessary to convert into the unit of measure used by the LCA dataset, assumptions were also needed for electro-mechanical components (regardless of whether being read from the BOM or entered manually). The assumptions made for those components that do not have quantities as a unit of measure in the LCA datasets are presented in the confidential appendix. The assumptions are made based on the weights of the components in the dataset.

Modeling of Mechanical Parts and Packaging

The mechanical components category consists of plastic and metals, commonly used as housing material and for smaller components such as screws, gaskets, spacers, and heatsinks. The complete list of inputs, values, and data sources is provided in the confidential appendix.

3.1.2 Transportation of Materials and Components to Factory

The packaging for raw materials and components was not included in this study. Upstream transportation between supplier and manufacturing facility assumes a mix of truck, sea freight, and air freight (Table 3). Distances were assumed based on regional sourcing with an average transportation distance of 3,000 miles, distributed as 39 percent truck transport, 60 percent sea freight, and 1 percent air freight. Exact distances between supplier and manufacturing facility were not calculated. A simplified approach to transportation was taken in the Scalable LCA Model because early iterations showed that transport was not a significant contributor to environmental impacts and generic distance options for different kinds of geographical sourcing was deemed sufficient. For example, 3,000 miles is approximately equivalent to transportation within East Asia.

Table 3: Generic Data Used for Upstream Transportation

Dataset	Value (tkm)	Data Source	Last Update Date	Geographical Coverage
transport, freight, lorry 16-32 metric ton, EURO6	42.8	ecoinvent 3.10	2024	Rest of the World
transport, freight, sea, container ship	65.9	ecoinvent 3.10	2024	Global
transport, freight, aircraft, dedicated freight, long haul	1.1	ecoinvent 3.10	2024	Global

3.1.3 Assembly

As primary data were not available on assembly burdens, a proxy was used. As the product under study is a smart switch, it was deemed that the smartphone dataset from ecoinvent was a suitable proxy for assembly burdens (details in Table 4). Both smartphones and smart switches involve intricate technological systems, requiring the assembly of various electronic components to create a functional end product. The complexity and diversity of components in a smartphone make it a representative model for understanding the assembly burdens of the smart switch.

Table 4: Proxy Data for Assembly Burdens

ecoinvent process	consumer electronics production, mobile device, smartphone
Literature source the ecoinvent process is based on[1]	Güvendik (2014)
Water use (liter) per kilogram of product	513
Electricity (kilowatt-hour) per kg of product	2.78
Wastewater output (cubic meter) per kilogram of product	0.48

Note: [1] As identified by WSP as the underlying data informing the ecoinvent process.

Electricity consumption, water use, and wastewater output were extracted from the proxy and included in the modeling of assembly by scaling based on the weight of the studied product. Activity values and datasets used are provided in Table 5. Manufacturing was assumed to take place in China. Water use and electricity consumption were modeled using a country-specific dataset, while wastewater uses a regional average dataset.

Table 5: Assumptions for Assembly

Activity	Value	Dataset	Data Source	Geographical Coverage
Electricity (kWh)	46.4	Sphera	Electricity grid mix	China
Water use (liter)	8,563.1	Sphera	Tap water from ground water	China
Wastewater output (cubic meter)	8.01	ecoinvent	Market for wastewater, unpolluted	Rest of World

3.1.4 Testing

For testing, an approach similar to assembly was used, as no primary data was available. The power consumption of the device, in combination with an assumption on testing extent, was used to calculate energy consumption inputs for testing. For example, some testing requires both heat and electricity, while some testing is more manual and uses lower amounts of electricity. The maximum power consumption was used as a conservative assumption since this is the most amount of energy the device can use (Table 6). The approach is meant to represent average nominal testing before shipping, not peak testing in extreme conditions.

Table 6: Assumptions for Testing

Activity	Value (kWh)	Dataset	Data Source	Geographical Coverage
Electricity	83.46	Electricity grid mix	Sphera	China
Heat	33.38	Market for heat, district or industrial, other than natural gas	ecoinvent 3.10	Rest of World

Note: Testing was assumed to take place in China.

3.1.5 Distribution

Distribution entails transportation from the manufacturing location to the consumer. Burdens from storage in warehouses were not considered. Downstream transportation between the manufacturing facility and the customer assumes a mix of truck and air freight (Table 7). Distances were assumed based on international distribution with an average transportation distance of 7,000 miles, distributed as 2 percent truck transport and 98 percent air freight. Exact distances between manufacturing facility and consumer were not calculated for the reasons provided in Section 3.1.2 on upstream transportation. The distance of 7,000 miles is approximately equivalent to transportation between China and the United States.

Table 7: Generic Data Used for Downstream Transportation

Dataset	Value (tkm)	Data Source	Last Update Date	Geographical Coverage
transport, freight, lorry 16-32 metric ton, EURO6	5.02	ecoinvent 3.10	2024	Rest of the world
transport, freight, aircraft, dedicated freight, long haul	246	ecoinvent 3.10	2024	Global

3.1.6 Use

The use phase comprises the electricity needed during the device's lifetime operation, including the electricity needed for processing and routing data packets across network connections, thus ensuring continuous and efficient communication between various interconnected devices. The product was modeled as being used in the United States. The use phase has been modeled around energy consumption with the following parameters:

- Country of use: United States
- Modeled power consumption: 780 Watts
- Modeled annual energy consumption: 6,832.8 kWh
- Lifespan of product: 5 years

The modeled power and energy consumption and lifespan of the product were provided by Cisco. The annual energy consumption is multiplied by the lifespan of the product for the complete use phase electricity consumption, which is provided in Table 8 alongside the dataset used for the grid mix.

Table 8: Generic Data Used for Use Phase

Dataset	Value (kwh)	Data Source	Last Update Date	Geographical Coverage
Electricity grid mix	34,164	Sphera	2024	United States

Note: Information on the grid mix composition can be found in the dataset documentation: https://sphera.com/2023/xml-data/processes/6b6fc994-8476-44a3-81cc-9829f2dfe992.xml

3.1.7 End-Of-Life

The EOL stage was modeled as a split between the United States national average treatment of electronic products and the Cisco takeback program. The United States average treatment of electronics waste is assumed to be 75 percent landfill and 25 percent recycling, in line with previous work conducted by WSP and readily available statistics (EPA, 2022), although the range of recycling of electronics varies between 15 to 30 percent depending on the source. Basing the EOL on data specific to the United States assumes the most responsible and burdensome waste management, a conservative approach in which all products are properly disposed. Adding regional options for the average waste treatment of electronics could be considered in future improvements of the Scalable LCA model.

Electronics that are sent to landfill or recycling facilities are typically first shredded. For recycling, default processes for metal recycling and plastic recycling are used. Metal recycling is used for electronics, while plastic recycling is used for non-electricals.

Besides recycling and landfilling, Cisco also has a takeback program. The specifics of how this influences EOL flows is detailed in the confidential appendix, along with a table summary of all EOL flows. In the takeback flow, all of the products are assumed to go to recycling. The confidential appendix presents the complete statistics for EOL as outlined in this subsection.

In summary, the EOL phase consists of transportation, landfill, recycling, and takeback. The confidential appendix contains the complete list of activities and values applied in the EOL stage of this study.

3.2 Limitations

There are a few key data limitations associated with electrical components and the use of secondary data for assembly and testing. Within the BOM, electrical components were matched to the components available in the LCA for Experts (formerly GaBi) and ecoinvent databases, which were not always an exact match. The matching was done using packaging type and dimensions to match the electrical parts in the product to that of electricals components available in the databases. Proxied components were scaled by length and width or mass to reflect the number and type of components in the product under study.

Manufacturing burdens of the assembly and testing of the product were proxied using secondary datasets from ecoinvent, as these operations involve energy consumption and water use and the proxies include all these flows. A limitation of the proxies is that they do not track operations improvements or changes over time.

3.3 Cut-Off Criteria

All secondary data are considered to be internally consistent as they have been modeled according to the LCA for Experts Modeling Principles and guidelines. According to these principles, cut-off rules for each unit process require coverage of at least 95 percent mass and energy of the input and output flows and 98 percent of their environmental relevance (according to expert judgement). Where applicable, cut-off criteria would only be applied for components that contribute to 1 percent or less of total mass or energy of the system and 5 percent or less of the total environmental impacts. The cut-off criteria were applied to packaging of upstream materials and components as well as warehouse burdens due to data availability.

3.4 Allocation Procedures

There are no co-products associated with the studied product. Therefore, this study did not perform allocation. Allocation of environmental burdens to material and energy co-products throughout the upstream supply chain is embedded in the LCI data used in this study and described in the documentation of these datasets.

4 Life Cycle Impact Assessment

4.1 Life Cycle Impact Assessment Procedures and Calculation

LCA for Experts can generate results for many impact categories. Below is a list of impact categories that were assessed as part of the development of the Scalable LCA model and were assessed in this study. These impact categories were identified as being of key interest to Cisco and its stakeholders while also being common categories for assessment of electronics. Attached to each impact category is the method implemented in LCA for Experts to generate results for the stated impact category.

- Abiotic Depletion (ADP Elements) (kilogram [kg] antimony [Sb] equivalent) - CML 2001 (Aug. 2016)
  - Assesses the depletion of non-living resources, such as metals and minerals, and evaluates the potential for resource scarcity.
  - The impact is expressed in terms of the environmental damage equivalent to the depletion of a certain amount of Sb.
- GHG emission (GWP 100, excluding biogenic carbon dioxide [CO_2]) (kg CO_2 equivalent [CO_2e]) - IPCC AR6 (excluding biogenic)
  - Assesses the emission of GHGs into the atmosphere and evaluates the contribution to GWP over a 100-year period and excludes emissions from biological sources.
  - The impact is expressed in terms of carbon dioxide equivalents. As each greenhouse gas has a different warming effect depending on the chosen timeframe, this unit represents all greenhouse gases converted into equivalents of carbon dioxide over a 100-year period.
- PED (from non-renewable energy sources) (megajoules [MJ]) – LCA for Experts Energy Indicators, non-renewable energy
  - The low heating value (or net calorific value) approach was used to determine the primary energy from non-renewable resources and is measured in MJ.
- BWC (kg) – LCA for Experts Water Indicators, BWC
  - Assesses the consumption of freshwater resources from surface and groundwater bodies.
  - The BWC results are presented in kilograms in LCA for Experts; however, since 1 kg of water is equal to 1 liter of water in the metric system, results are presented in liters.
- Ecotoxicity (Comparative Toxic Units ecotoxicity [CTUe]) - USEtox 2.12
  - Assesses the potential toxicity of emissions to ecosystems and aquatic life and evaluates the potential harm to the environment due to the release of toxic substances.
  - This impact is expressed as comparative toxic units (CTUe) where each chemical is converted to CTU based on the estimated fraction of species affected over time per mass of chemical emitted.
- Human toxicity, cancer (Comparative Toxic Units human toxicity [CTUh]) - USEtox 2.12
  - Assesses the potential harm to human health due to exposure to substances known to cause cancer.
  - This impact is expressed as comparative toxic units (CTUh), where each chemical is converted to CTU based on the estimated increase in morbidity in the total human population per mass of a chemical emitted.

- Human toxicity, non-cancer (CTUh) - USEtox 2.12
    - Assesses the potential harm to human health due to exposure to substances that do not cause cancer but can still have toxic effects.
    - This impact is expressed as comparative toxic units (CTUh), where each chemical is converted to CTU based on the estimated increase in morbidity in the total human population per mass of a chemical emitted.

The results of the abiotic depletion, ecotoxicity, and human toxicity (cancer and non-cancer) environmental impact indicators are not intended for comparison due to high uncertainty associated with the indicators. For the toxicity impact categories, a difference of 1,000 percent is not significant.[3] For abiotic resource depletion, the results shall be used with care as the uncertainties of the results are high due to high variability depending on calculation approach and uncertainties in the material reserves data.

4.2 Life Cycle Impact Assessment Results

The LCA for Experts software calculates life cycle impact assessment (LCIA) results in its balance function and computes the environmental impact results according to predefined characterization methods in the selected LCIA methodology.

4.2.1 Global Warming Potential

The GHG emissions (excluding biogenic carbon) per N9324C-SE1U were 16,638 kg CO_2e. As shown in Figure 3, the GHG emissions were categorized into different life cycle stages covering manufacturing, transport, use phase, and disposal.

The use phase significantly influences the overall impact, contributing 94 percent of GHG emissions. All other life cycle stages accounted for approximately 6 percent of GHG emissions combined. As stated above, the product was modeled as being used in the United States. The United States electric grid is heavily dependent on fossil fuels, with 34 percent of electricity from natural gas and 29 percent of electricity from coal (Sphera, 2023a). The dependence on fossil fuels such as coal and natural gas is known to be large contributors to GHG emissions from the United States electric grid.

[3] The USEtox documentation provides further insights on uncertainty in toxicity impact metrics: https://usetox.org/model/documentation

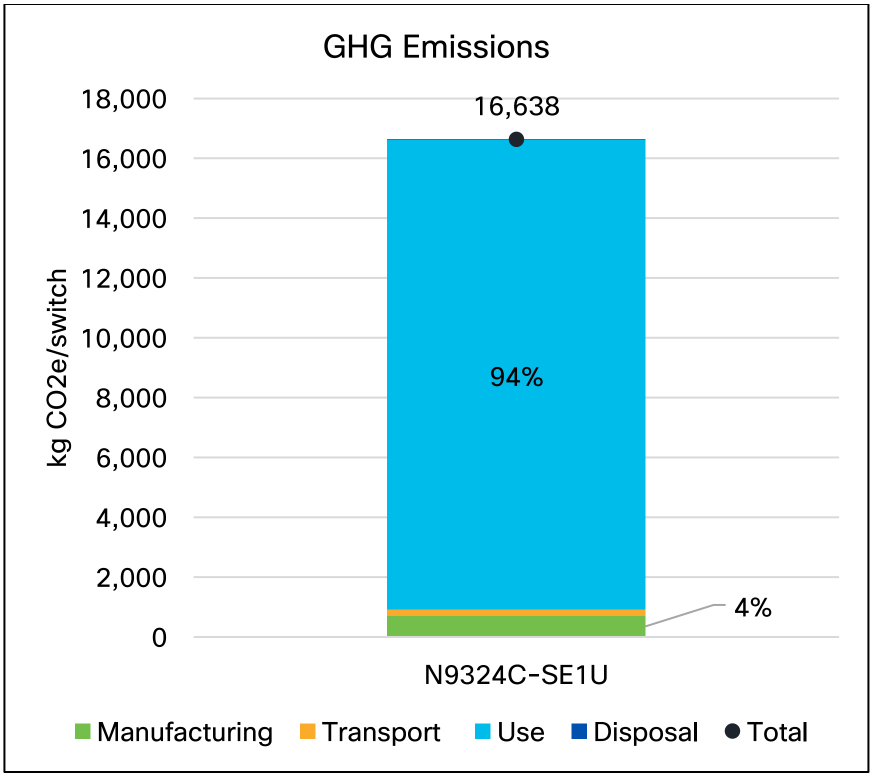


Figure 3: Global Warming Potential per Switch by Life Cycle Stage

The manufacturing phase was the second-largest contributor to GHG emissions, accounting for 4 percent of total GHG emissions per switch. This device often includes printed circuit boards and integrated circuits, all of which require energy-intensive manufacturing processes.

As shown in Figure 3, excluding the energy consumed during assembly and testing, as well as the treatment of manufacturing waste and packaging, and focusing solely on the components processed within the upstream supply chain, key electricals, such as the PCBs and ICs, contributed 77 percent of the manufacturing impacts. The second major contributor is the electro-mechanical components, such as power supplies, which account for 12 percent of the manufacturing impacts. Electro-mechanical and key electricals are major drivers of environmental impact due to their energy-intensive manufacturing processes.

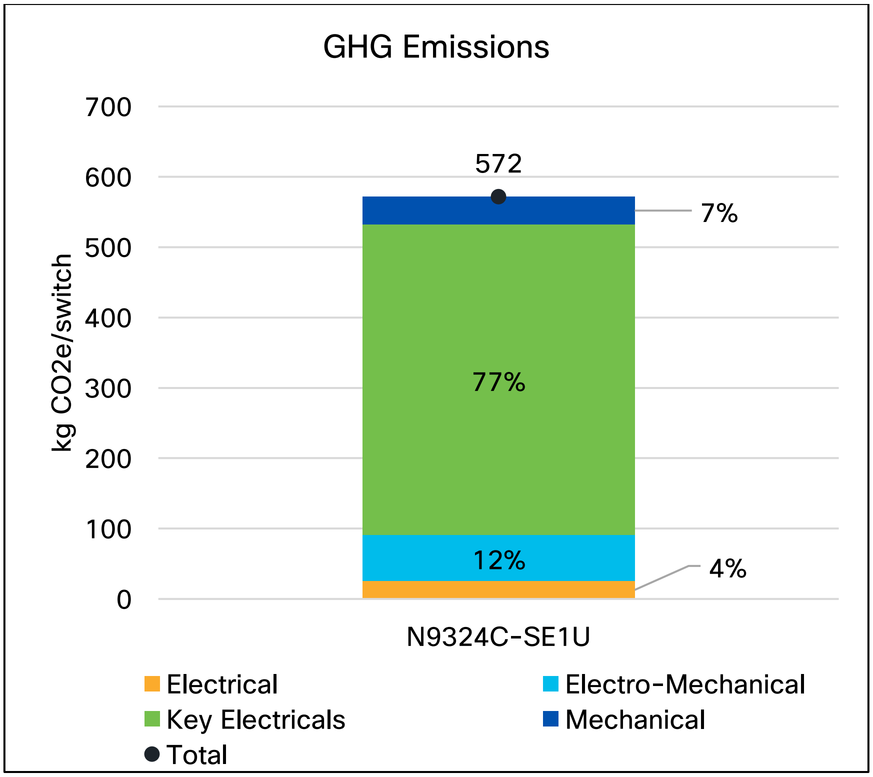


Figure 4: Global Warming Potential per Switch from Manufacturing Components Across the Upstream Supply Chain

4.2.2 Primary Energy Demand

The PED from non-renewable sources reflects the amount of energy demanded from the ecosystem. As shown in Figure 5, the total PED, characterized by fossil-based energy demand, was 294,439 MJ per switch. The use phase dominates the overall impact, contributing 96 percent to the total non-renewable energy consumption, due to annual energy consumption of 6,832.8 kWh over a 5-year lifetime, driven by direct and indirect energy. Direct energy is the operation of electricity itself, while indirect energy is the energy required to produce electricity. Indirect electricity includes the mining, transportation, and processing of resources required to produce electricity. Manufacturing is the second-largest contributor to PED at 3 percent. These impacts are due to the electricity required to produce electronic components within the switch. Within this phase, key electricals are the primary drivers contributing 64 percent of the manufacturing impacts. Among key electrical components, the ICs and PCBs are the highest drivers, all of which require high energy due to the energy-intensive processes involved, such as semiconductor fabrication and metal refining.

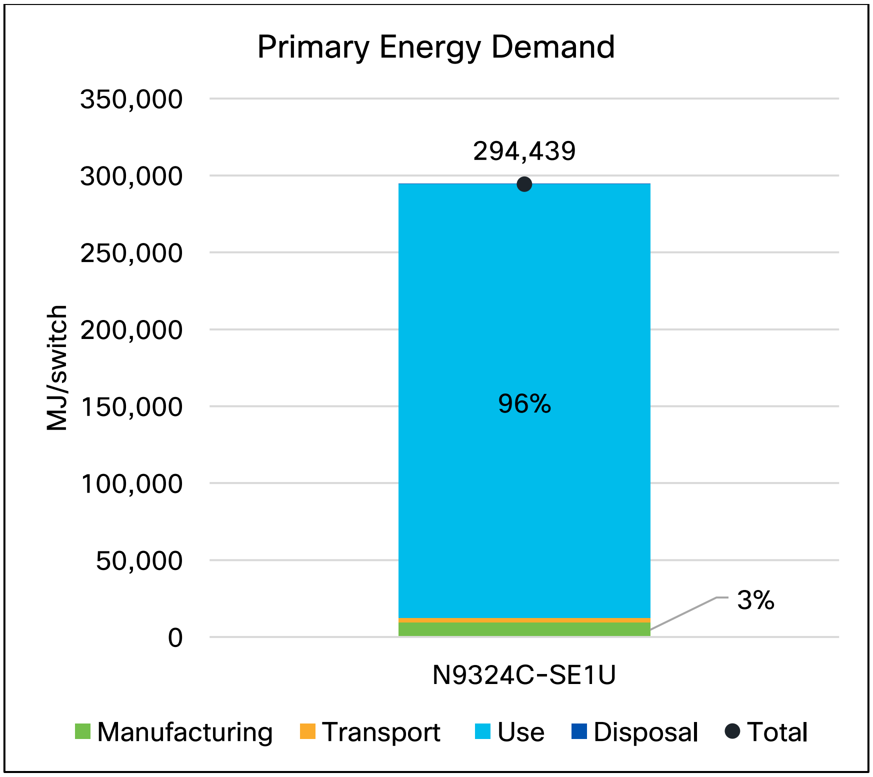


Figure 5: Primary Energy Demand per Switch by Life Cycle Stage

4.2.3 Blue Water Consumption

BWC represents the net difference between water extracted from the ecosystem and water returned to the ecosystem in a usable form. As shown in Figure 6, the BWC results are 120,426 liters per N9324C-SE1U. Use phase accounts for 92 percent of BWC impacts due to water required for electricity production.

Manufacturing is the second largest contributor at 8 percent of the total BWC impact. Mechanical components and key electrical components are the main contributors to BWC in the manufacturing phase, accounting for 44 and 37 percent, respectively. Mechanical components like aluminum housing and steel plates contribute significantly to water consumption, since their production often involves water-intensive industrial process for material extraction, refining, forming, and finishing. These steps require substantial water usage, especially for cooling, cleaning, and chemical processing, thus collectively driving the high BWC impact for the switch.

As previously mentioned, the United States electric grid mix is primarily dependent on fossil fuels such as coal and natural gas. Both these sources require water for their extraction and electricity generation, where water is converted to steam post-resource combustion (Union of Concerned Scientists, 2010; WRI, 2020).

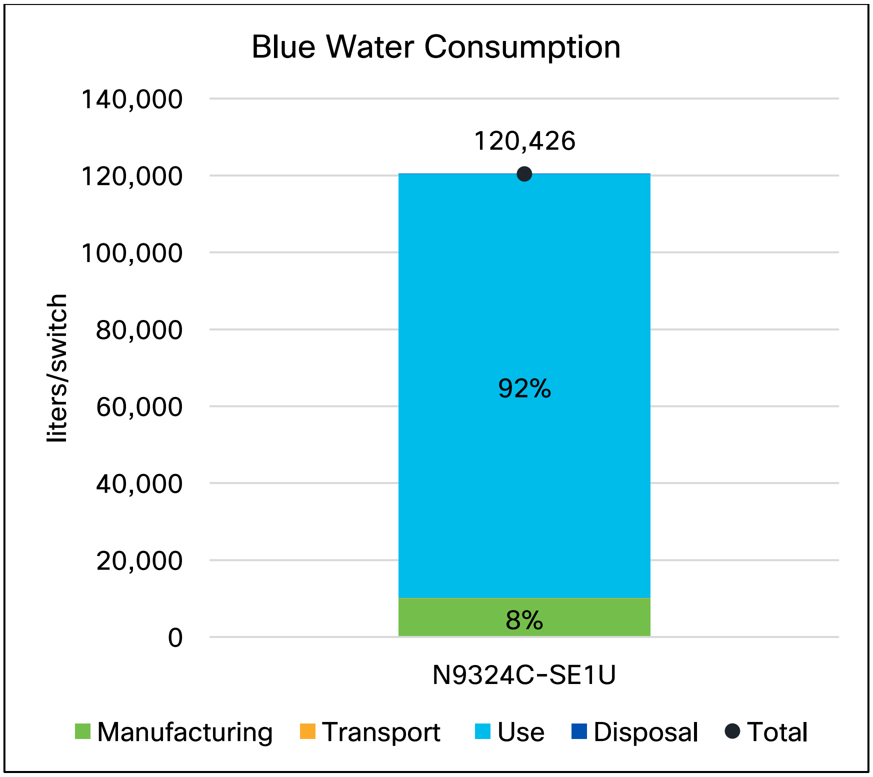


Figure 6: Blue Water Consumption per Switch by Life Cycle Stage

4.2.4 Abiotic Depletion Potential

ADP assesses the depletion of non-living resources, such as metals and minerals (not energy), and evaluates the potential for resource scarcity. The impact is expressed in terms of the environmental damage equivalent to the depletion of a certain amount of antimony (Sb). As shown in Figure 7, the ADP result is characterized as 0.07 kg Sb-equivalent per switch. The manufacturing phase is the largest driver of ADP, contributing 97 percent of the impact. This prominence is largely attributed to the use of materials and energy in the production processes, particularly in the extraction and processing of raw materials, such as metals and minerals, which significantly contribute to ADP. Key electrical components contribute 76 percent to manufacturing impacts, primarily driven by the metal and mineral extraction and processing of raw materials. PCBs and ICs contribute significantly to ADP due to their use of resource-intensive materials, production complexity, water generation, and technological complexity.

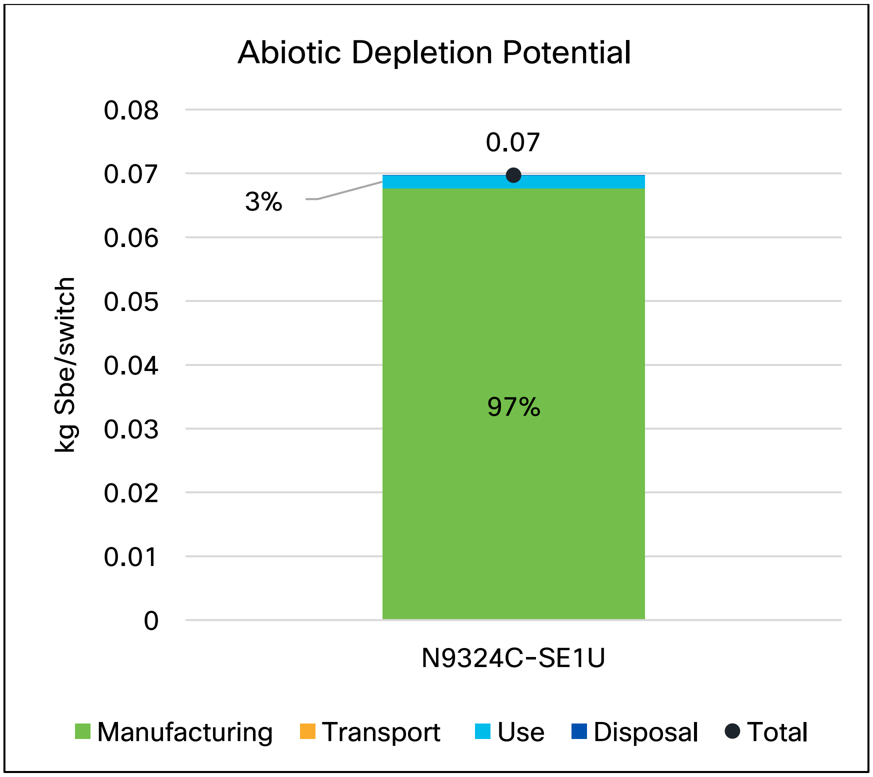


Figure 7: Abiotic Depletion Potential per Switch by Life Cycle Stage

4.2.5 Ecotoxicity

Ecotoxicity assesses the potential toxicity of emissions to ecosystems and aquatic life and evaluates the potential harm to the environment due to the release of toxic substances. As shown in Figure 8, ecotoxicity result is quantified as 43 CTUe per switch. Within the switch, manufacturing and transport phases are the largest contributors, each accounting for 39 percent of the total impact. The manufacturing phase involves the extraction and processing of raw materials, as well as the production of complex components such as PCBs and PSUs. These processes often involve the use of heavy metals, solvents, and other hazardous chemicals, which can result in toxic emissions to air, water, and soil if not properly managed. Air freight emits higher levels of toxic substances, including heavy metals and particulate matter, which contribute significantly to ecotoxicity through atmospheric deposition and runoff into aquatic systems. As a result, the transportation phase also accounts for a large share of the total ecotoxicity associated with the switch. The use phase is the third contributor, accounting for 22 percent of the total impact. The N9324C-SE1U consumes 6,832.8 kWh of electricity to operate each year. Since the United States electric grid is heavily reliant on fossil fuels, electricity generation results in a significant number of toxic metals and pollutants in the ecosystem.

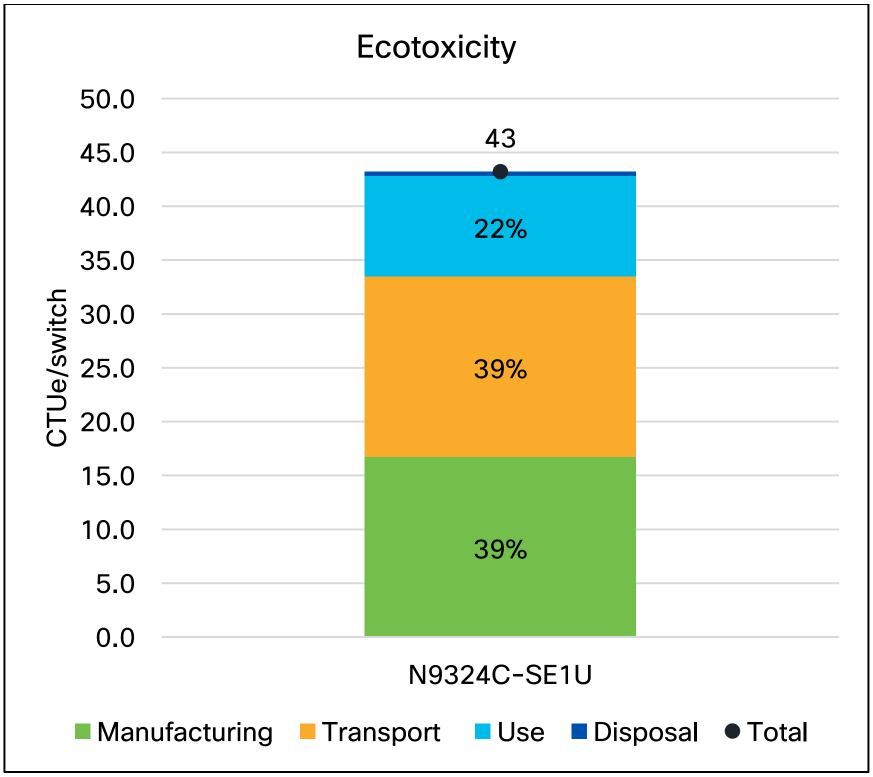


Figure 8: Ecotoxicity per Switch by Life Cycle Stage

4.2.6 Human Toxicity, Cancer

Human toxicity (cancer) assesses the potential harm to human health due to exposure to substances known to be carcinogenic to humans. As shown in Figure 9, human toxicity (cancer) result is characterized as 5.1E-03 CTUh per N9324C-SE1U. The human toxicity (cancer) impact is dominated by the aluminum sheet manufactured during the manufacturing phase, accounting for almost 100% of the total. This dominance is primarily due to the resource- and energy-intensive processes involved in aluminum production, including bauxite mining, and alumina refining, which will release toxic air pollutants. These activities release toxic air pollutants that significantly contribute to human toxicity (cancer) during the manufacturing phase.

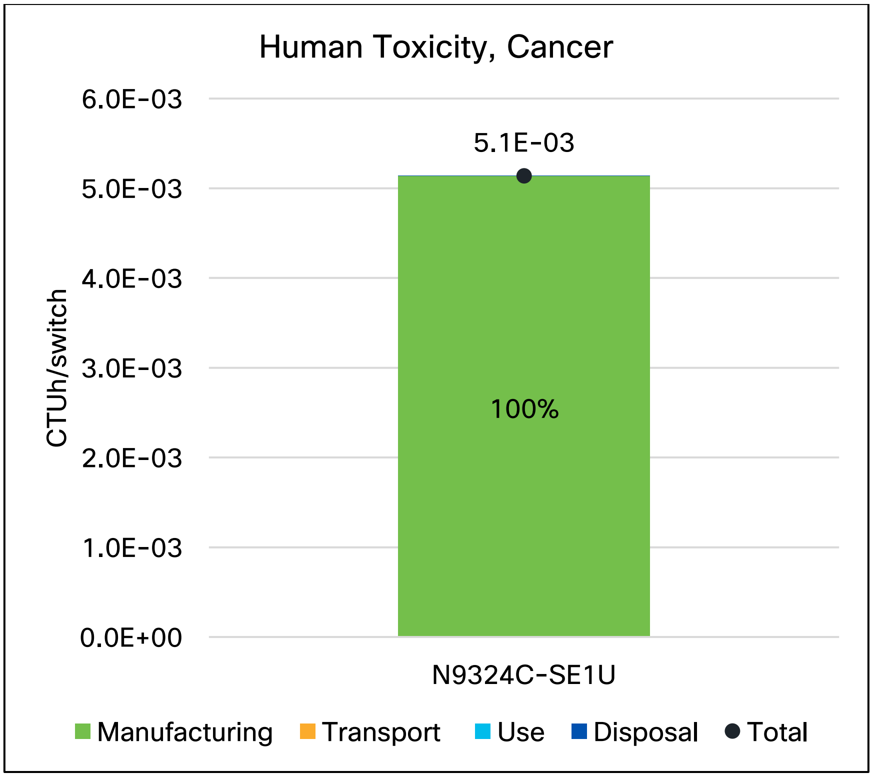


Figure 9: Human Toxicity (Cancer) per Switch by Life Cycle Stage

4.2.7 Human Toxicity, Non-Cancer

Human toxicity (non-cancer) measures the potential harm to human health due to exposure to substances that do not cause cancer but can still have harmful effects on human health. As show in Figure 10, human toxicity (non-cancer result) is quantified as 3.4E-08 CTUh per switch.

Use phase is the largest contributor to human toxicity (non-cancer), accounting for 53 percent of the impact. As noted, a considerable portion of the United States electric grid is generated from coal and natural gas, leading to emissions of pollutants and chemicals during fuel combustion and energy production. These emissions contribute to the potential harm to human health measured by this impact category.

The second largest life cycle stage to human toxicity (non-cancer) is the manufacturing phase, contributing 36 percent to human health (non-cancer) impacts. The material extraction and refinement for the production of key electrical components and electro-mechanicals, such as PCBs and PSUs, can lead to the release of toxic substances into the ecosystem.

The transport phase, constituting 11 percent of impacts, is the third largest driver of human health (non-cancer) impacts. The transportation of goods within a globalized supply chain typically involves long-distance air freight or sea freight, in combination with trucking. Fossil-based fuels used in aircraft, watercrafts and trucks release pollutants as fuel is combusted. Gasoline and diesel generate emissions containing harmful substances such as particulate matter, nitrous oxides, and volatile organic compounds. Exposure to these pollutants generated during transportation can lead to adverse, non-cancer, health impacts.

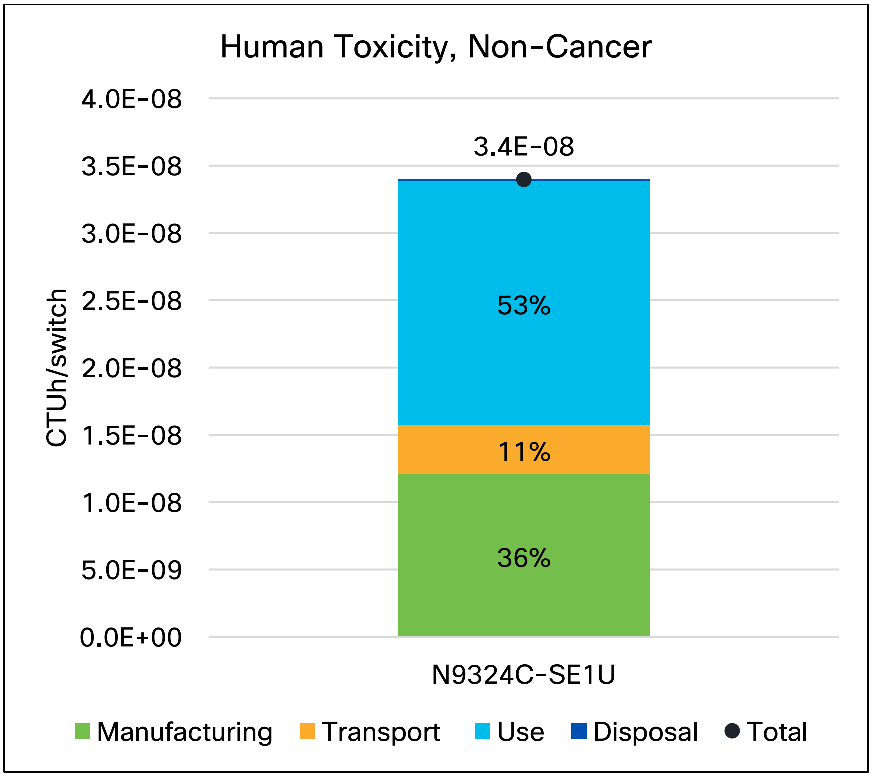


Figure 10: Human Toxicity (Non-Cancer) per Switch by Life Cycle Stage

4.3 Limitations

The primary limitations of the Scalable LCA Model are the assumptions related to electrical components and the use of secondary data for manufacturing burdens. In terms of materials burdens, a special focus was placed on electrical components that (as outlined in Section 3) are known to have a disproportionately high environmental impact compared to other components such as housing or packaging. The initial intention was to cover the top 10 most-used component types in each component category (ICs, PCBs, etc.), which leads to a limitation for Cisco products that mainly use components not represented in this version of the model. However, throughout the iterations of the Scalable LCA model additional components have been added, and today over 90 electronic components and their dimensions are included in the BOM reader. Furthermore, several proxies needed to be made using scaling factors, as direct dataset matches were not available. The dataset proxies were made based on component attributes such as electrical packaging type or dimensions, but there remains a limitation in the scaling factors being based on linear relationships based on area or volume. Based on the area or volume of the component under study, the proxy dataset was scaled to the equivalent area or volume. It is a known limitation of this approach that environmental impact does not scale linearly in this way.

Manufacturing burdens for both assembly and testing were proxied using secondary datasets from ecoinvent. Other than the circular activities of Cisco, the EOL disposal and manufacturing waste uses average datasets that could benefit from higher resolution, especially in terms of manufacturing waste, which currently only has a metals waste flow and a plastics waste flow.

The Scalable LCA Model applies the recycled content approach to modeling materials reuse and recycling (also called the cut-off approach), which in this context means that the burdens from processing wastes into recycled materials are included as part of the materials burdens for manufacturing Cisco products, while any emissions or credits of reused materials are “cut off” at transport to recycling facilities. As such, no credit is given, and no system expansion is conducted to align with the system boundaries of the approach.

Beyond the limitations and assumptions associated with the modeling and tool, there are further considerations that need to be made for the underlying data. As identified by the data quality assessment, the data have an average representative score of 2 to 3, with large variations between the life cycle stages and several instances of low representativeness. Identifying these limitations will help inform stakeholders on how the Scalable LCA model can be improved to be more representative in future iterations.

4.4 Description of Practitioner Value Choices

The practitioner value choices have been limited to the selected LCIA and the allocations procedures described in the relevant sections of this report. All results are presented on a midpoint basis using the methods noted in Section 4.1; normalization and weighting are not used. Other impact categories have been excluded from the results because they do not answer the questions defined as the goal and scope for the intended audience in Section 1 of this report.

4.5 Statement of Relativity

LCIA results are relative expressions and do not predict impacts on category endpoints, the exceeding of thresholds, safety margins, or risks. No grouping of impact categories has been performed; all impacts are presented at the midpoint level. LCIA impacts presented in this report are based on midpoint characterization factors (e.g., kg CO_2e for GWP), and this study does not refer to the ultimate damage to human health and the environment. For example, GWP and water consumption may have a negative or a positive environmental impact depending on the conditions in locations where emissions or resource consumption occur. Since this study does not present end-point results, it does not draw any conclusions about the relative impact (positive or negative) for the categories considered by the study.

5 Life Cycle Interpretation

5.1 Identification of Relevant Findings

The primary drivers of all impact categories under this study switched between the use and manufacturing phases for the N9324C-SE1U switch. The use phase dominates GHG emissions, PED, human toxicity (non-cancer), and BWC. The generation and consumption of electricity during these phases significantly contributes to these impact categories primarily because a substantial portion of electricity in the grid is derived from coal and natural gas sources. For the remaining environmental impact categories, ADP, ecotoxicity, and human toxicity (cancer), the manufacturing phase is the largest driver. Within manufacturing, materials are a significant contributor. This is primarily due to the environmental impacts associated with the extraction, refinement, and processing of raw materials such as aluminum sheet, steel plate, and plastic used in components like PCBs, PSUs, and housing. The complexity and precision of these components demand sophisticated facilities and equipment for their manufacturing, which often involve energy-intensive processes. Other non-key electrical components and mechanical parts have lower material usage and contribute less to the environmental impacts.

5.2 Sensitivity Analysis

To evaluate the ways in which inputs in this study influence results, two sensitivity analyses were conducted by changing input parameters and assumptions. This analysis involved scaling power supply inputs by watt (W) instead of mass and changing the electricity grid mix for the use phase from country specific to a renewable energy mix. The two environmental impact categories with the most significant relative changes from the base case were selected for detailed evaluation and interpretation.

The first alternative was introduced to explore whether the scaling approach based on operational performance, rather than mass of material use, would affect the environmental impacts, since a power supply unit (PSU) with a higher wattage does not weigh much more than one with a lower wattage. BWC and ADP were found to have the largest relative increases across all the impact categories when this parameter was modified.

Given the necessary role of switch power supplies in converting electrical energy from the grid to the required voltage for the device, the sensitivity analysis was performed to understand the effects of scaling the power supply unit by mass versus wattage. In the base case, to proxy power supply unit production impacts, the power supply unit was scaled by mass to calculate the impact, whereas in the scenario analysis, the power supply unit was scaled by wattage. This change in scaling aims to provide a clearer understanding of the ways in which different attributes of power supply units can influence results. By shifting the scaling metric from weight to watts, the equivalent number of PWR 2100 power supply units adjusted from 0.90 pieces to 0.67 pieces. As shown in Figure 11, this scenario results in a 1.7 percent reduction in total ADP, and a 1.2 percent decrease in total Ecotoxicity impact throughout the lifecycle compared to the base case. It should be noted that since there is high uncertainty associated with the ADP and Ecotoxicity impact categories, changes of 1.7 percent and 1.2 percent are considered on par.

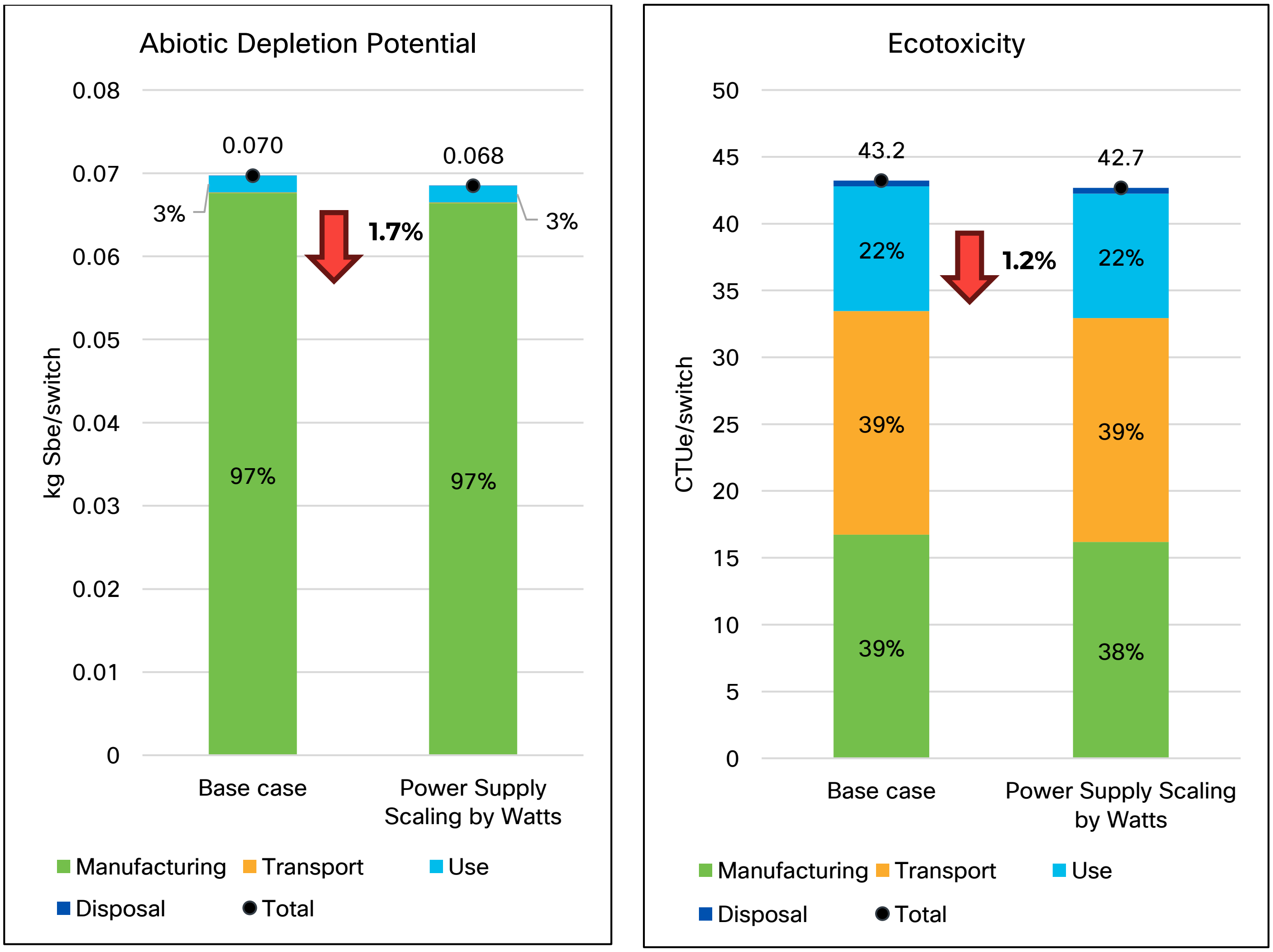
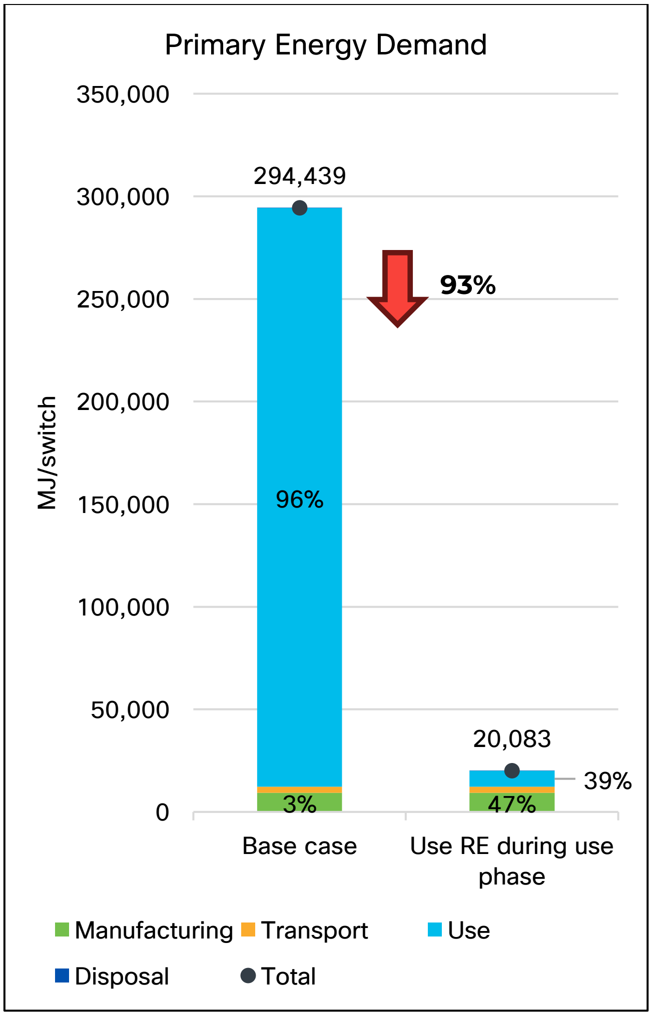


Figure 11: Sensitivity Analysis Results for ADP and Ecotoxicity with the change in the Measurement Base for Power Supply

As shown in Figure 12, substituting use phase energy with a renewable energy mix[4] results in a 93 percent reduction in PED and 90 percent reduction in GHG emissions. These changes in renewable energy mix will have a large impact on the overall environmental results, indicating that reducing a heavy fossil fuel energy mix to more renewables during the use phase will have a large impact on the product's life cycle impacts.

[4] For this analysis, the Sphera dataset "Green electricity grid mix (production mix)" was used. The dataset consists of 76% electricity from solar PV panels, 20% from wind, 3% hydro, and the remaining electricity a mix of biomass, biogas, waste, and geothermal.



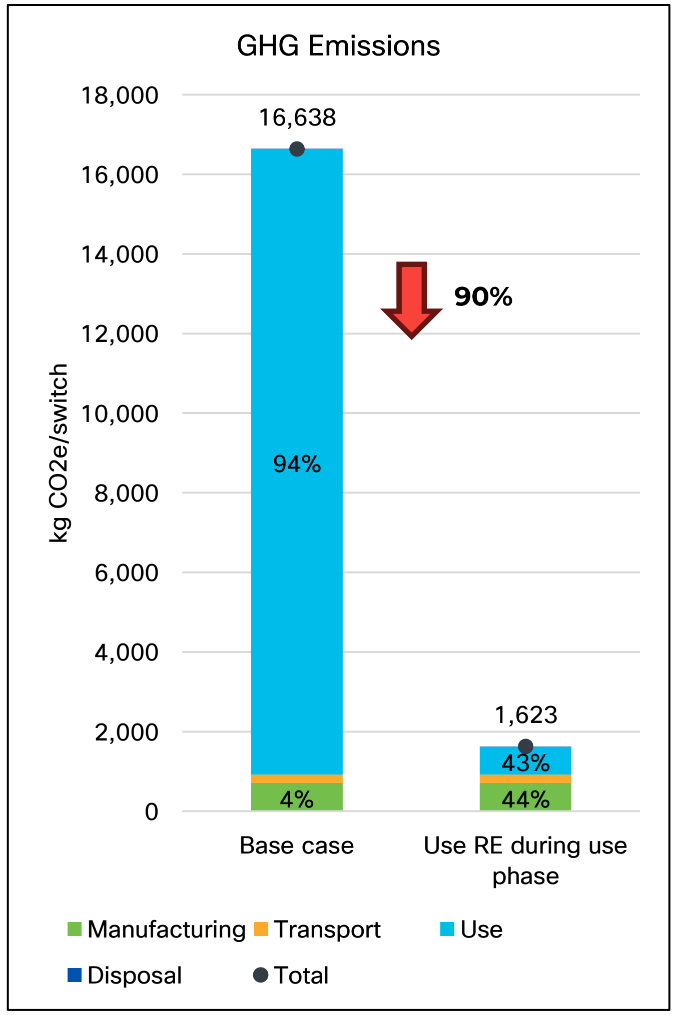


Figure 12: Sensitivity Analysis Results for PED and GHG emissions with the Renewable Energy Mix during Use Phase

5.3 Data Quality Assessment

The quality of fit, or representativeness, of model inputs will be evaluated across five indicator categories: reliability, completeness, temporal correlation, geographical correlation, and technological correlation. For each indicator, a score from 1 to 5 was assigned to each model input, where 1 indicates high representativeness of the product system and 5 indicates low representativeness (Table 9). The assessment was completed across life cycle stages for a final average score (rounded to the nearest whole number) in each indicator (Table 10).

Table 9: Pedigree Matrix Adapted from the United States Environmental Protection Agency

	Highest confidence				Lowest confidence
Data Quality Indicator	**1**	**2**	**3**	**4**	**5**
Reliability	Primary data from Cisco, measured data	Primary data from Cisco, estimated data	Data obtained from literature with an exact proxy match	Data obtained from literature with a proxy match	Data obtained from online sources and not an exact match, limited documentation
Completeness	Representative data from >80% of the relevant market, over an adequate period	Representative data from 60-79% of the relevant market, over an adequate period **or** representative data from >80% of the relevant market, over a shorter period of time	Representative data from 40-59% of the relevant market, over an adequate period **or** representative data from 60-79% of the relevant market, over a shorter period of time	Representative data from <40% of the relevant market, over an adequate period **or** representative data from 40-79% of the relevant market, over a shorter period of time	Unknown **or** data from a small number of sites and from shorter periods
Temporal correlation	Less than 3 years of difference	Less than 6 years of difference	Less than 10 years of difference	Less than 15 years of difference	Age of data unknown or more than 15 years
Geographical correlation	Data from same resolution **and** same area of study	Within one level of resolution **and** a related area of study	Within two levels of resolution **and** a related area of study	Outside of two levels of resolution but related area of study	From a different or unknown area of study
Technological correlation	All technology categories are equivalent	Three of the technology categories are equivalent	Two of the technology categories are equivalent	One of the technology categories is equivalent	None of the technology categories are equivalent

Source: (Edelen & Ingwersen, 2016)

Geographical resolution has seven levels of resolution: global, continental, sub-region, national, province/state/region, county/city, and site-specific (Edelen & Ingwersen, 2016). The sub-region level refers to regional descriptions (e.g., UAE), and the site-specific level, the most granular level, and includes the physical address of the site. The geographical correlation is scored based on the level of the input data and the level of the dataset that is available.

Technological correlation is represented using four categories: process design, operational conditions, material quality, and scalability. Process design refers to the set of conditions in a process that affects the product. Operational conditions refer to variable parameters such as heat, temperature, and pressure that are needed to make the product. Material quality refers to the type and quality of feedstock material. Scale refers to output per unit time or per line needs to be described.

Table 10: Pedigree Matrix Adapted from the United States Environmental Protection Agency

Data Quality Indicator	Data Quality Description by Phase	Average
Reliability	Materials: For electrical components, the tool reads from a BOM and makes the best possible match for components based on area or die volume. Other material inputs are obtained from the user of the tool and is considered primary data. Therefore, the reliability of material data is highly representative of the product being assessed. Even though material and BOM data are primary, they cannot always be matched to exact datasets and proxies with scaling factors are used. Therefore, the reliability score for materials is 2. Manufacturing: Both assembly and testing are proxied as primary data was not available. For assembly, the process was proxied using a dataset that was deemed to have similar assembly complexity. For testing, estimations for energy consumption were made based on the product type, taking the extent of testing and power consumption into account. Therefore, manufacturing has a reliability score of 4. Transport: For upstream and downstream transport, the weight of the product, the distance travelled, and distribution mode are obtained from the user. There are some default values that can be used for distance if exact distances are not known by the user. This is considered primary data and is highly representative. But there are various datasets available for matching and the conservative options were chosen as representative datasets. Therefore, the reliability scores for upstream and downstream transportation are 2. Use: The location of use, the lifespan of the product, and annual energy consumption were obtained from Cisco to calculate total use phase energy. These are primary data that are matched to highly representative grid electricity data, which get updated annually. Therefore, the reliability score for use phase is 1. End-of-Life: The extent of product reuse and recycling was obtained from Cisco. The data are matched to the best available data. Therefore, the reliability score for end-of-life is 1.	**2**
Completeness	Materials: For electrical components, more than 80% of the inputs are accounted for through the BOM read. No BOM item is excluded because a proxy was identified for all BOM items. The processing associated with intermediate products like OEMs are partially covered. The completeness of remaining materials (non-electricals) is deemed high as few exclusions (raw material packaging, component packaging, and warehouse burdens) were made. The completeness score is conservatively assessed as 2.	**2**

Data Quality Indicator	Data Quality Description by Phase	Average
	Manufacturing: Since assembly and testing are proxied, the completeness of the manufacturing inputs and outputs within the model is lower. There is lower confidence in the completeness related to assembly and testing energy amounts, but higher confidence in the location of manufacturing. At least 50% of inputs and outputs are covered. Therefore, the completeness score for manufacturing is 3. Transport: For both upstream and downstream transport, the distance measured for transportation is an approximation based on origin and location, and not on the route. Even though there are some limitations with regards to completeness, there is confidence that there is 70% coverage in all inputs and outputs. Therefore, the completeness score for transport is 2. Use: The use phase of the product is modeled using different locations and corresponding grids. This covers more than 80% of all product use locations. Therefore, the completeness score in the use phase is 1. End-of-Life: Traditional disposal mechanisms (e.g., landfilling and recycling) are considered at end-of-life, along with custom takeback programs that Cisco has deployed. From the end-of-life perspective, the completeness score is 1 because this covers 100% of the product disposal. Overall, from the perspective of the whole system, there are specific processes that are currently excluded. One example is the warehousing of products and the influence of warehousing on the changes in transportation routes. Packaging of raw materials and components before transport is also another stage that is only partially covered by this system boundary, which affects the overall completeness of the model.	
Temporal correlation	Materials: All material data inputs from the user and BOM are from 2024. The data that are matched to the material inputs are valid for 2024, with some valid through 2025 and 2026. The input data used in the model has high representativeness with regards to temporal correlation. Therefore, the score for materials phase is 1. Manufacturing: The datasets to which the input data have been matched are valid for 2024, with some datasets having extended validity through 2025 and 2026. Manufacturing data for the model is highly representative and have a temporal correlation score of 1. Transport: Transport data for the product are provided as an input and are from 2024. The transport datasets used in the model are all valid for the year 2022. Therefore, the transportation model has	**2**

Data Quality Indicator	Data Quality Description by Phase	Average
	a high temporal correlation with a score of 1 for both upstream and downstream transportation. Use: The product is used from 2024 and through end-of-life. The electricity dataset is valid for 2024, and some regional electricity data are valid through 2025 and 2026. Product can consume electricity beyond these time periods, with some products being used up to 2030. Therefore, the temporal correlation of the use phase is scored at 3. End-of-Life: The product will be disposed of at its end-of-life, which will be at least 5 to 10 years after production, depending on the product. All the datasets used to model end-of-life are for 2022. Therefore, at end-of-life, the data are thought to have average representativeness with a score of 3.	
Geographical correlation	Materials: All material inputs are matched to datasets that are either global averages or Chinese datasets. This assumes that most electronics production occurs in Asia. The datasets chosen are within two levels of resolution and within the area of study. It might be known that the activity occurs in a specific country, but the datasets available are global averages. Therefore, the geographical correlation for materials is 3. Manufacturing: Assembly and testing are modeled based on energy use that is specific to a country. The geographical correlation for manufacturing is 2. Transport: A region-specific calculation is not carried out on the tool. The dataset used is a global average for trucks, ship, and air modes. This is a difference of at least two levels of resolution but is still related to the study area. Therefore, the geographical correlation score for transport is 4. Use: Use phase is modeled based on energy use at the country level. The inputs are matched to country-specific datasets. Therefore, the geographical correlation for manufacturing is 1. End-of-Life: There is no regional specificity with regards to the end-of-life location. Even though the processes considered are within the scope of this study, the geographic specification of the dataset is a global average. Therefore, the geographical correlation for end-of-life is 4.	**3**
Technological correlation	Materials: For electrical components, the input data and the chosen datasets represent similar material quality and scalability but are not equivalent for process design and operation conditions. For example, proxy resistors were used when an exact resistor dataset match was not available. For plastic and metal parts, material quality and scalability are equivalent, but there could be deviation	**3**

Data Quality Indicator	Data Quality Description by Phase	Average
	in the process design and operation conditions between the data inputs and datasets used in the model. For example, plastic extrusion can occur at different operating conditions at different locations that are not fully captured within the global average dataset used. There are only two equivalent categories, material quality and scalability, in the materials phase. Therefore, the technological correlation of materials is scored at 3. Manufacturing: The manufacturing process for a product is consistent, regardless of production location. However, manufacturing is modeled using proxy datasets. Therefore, it is not possible to establish process design and operational conditions equivalence between the input data and the dataset chosen for the model. The quality of materials used in the production process are high for Cisco and in the datasets used, but the material types used are not equivalent between the Cisco products and the products used as proxy. The technological correlation of the data is low with equivalence in only one category. Therefore, the score is 4. Transport: The transportation datasets used assume standard fuel efficiencies for these modes. The scale at which parts and products are moved are relatively consistent with some variation in packaging ratio and storage capacities, but overall, the technological correlation of transport is good and is scored at 2. Use: The products under consideration from Cisco consume electricity. The process flow, operation conditions, and scale of electricity production technology (for coal, natural gas, solar, wind, hydroelectric, etc.) are largely consistent across the world and are accurately captured in the datasets used for different regions. The quality of material used to generate electricity can change between regions. But all efficiencies, source distribution, and losses are captured accurately by energy datasets that are used. Therefore, the technological correlation of the use phase is high and is scored at 1. End-of-Life: The product is typically disposed of by either landfilling or recycling. The datasets used accurately represent the process of disposal, incorporating the efficiencies and recovery associated with the corresponding disposal technology. Disposal operations and scale of these operations vary significantly across the world, which are not represented well by a global average dataset. Therefore, the technological correlation of end-of-life is scored at 3.	

5.4 Conclusions and Recommendations

The findings of this report demonstrate that one N9324C-SE1U switch creates 16,638 kg CO_2e of GHG emissions, demands 294,439 MJ of fossil fuel based primary energy, and consumes 120,426 liters of blue water. According to the EPA GHG equivalence calculator, driving 2.6 miles in a passenger vehicle emits 1 kg CO_2e (US EPA, 2019). The GHG emissions created by one N9324C-SE1U switch are equivalent to driving 43,258 miles in an average United States passenger vehicle over the product's lifetime of average use.

When evaluating the influence of shifting use phase energy mix, the overall environmental results had a significant change. This indicates that user location and the associated grid mix and behavior play an important role in the results. Therefore, Cisco could consider developing customer education programs to promote renewable energy adoption, influencing users to minimize environmental impacts when using the product. However, when shifting the scaling metric from weight to watts, the overall environmental results did not change significantly. This indicates that the change in the measurement base does not have a large impact on the product's lifecycle impacts in the broader context.

Based on this study, it is recommended that Cisco consider the following actions to reduce GHG emissions, PED, and BWC. First, continue to focus on energy efficiency during the use phase of N9324C-SE1U switch products to reduce impacts. This could include implementing features like Energy Efficient Ethernet (EEE), which allows devices to enter low-power idle states during periods of low data activity, thus reducing energy consumption and environmental impacts. In addition, Cisco could empower customers to adopt energy conservation practices. This could involve providing guidance or system recommendations that encourage the use of low-power idle states during low data activity, helping build customer awareness and engagement in energy-efficient practices, and offering energy optimization assessments. Second, Cisco could empower customers to transition to renewable energy sources, such as facilitating the integration of renewable energy into network operations, thus increasing more renewable energy during the use of the smart switch. Third, Cisco could focus on partnerships with manufacturers to increase the use of renewable energy in production to further reduce the environmental impact of this product.

5.5 Limitations and Assumptions

The Scalable LCA Model has some limitations and assumptions that affect its precision. The main limitations are related to the assumptions made for the electrical components and the manufacturing processes. The model focuses on the most impactful electrical components, such as ICs and PCBs, but it does use scaling factors and proxies when direct matches are not available in the relevant LCI databases. This means that there is uncertainty in the comparison of component related impacts between the products. As an uncertainty range has not been quantitatively assessed due to a lack of quantitative data for uncertainty analysis, comparing the component impacts between the products should be done with the understanding that the underlying model lacks the precision for comparison for small differences (less than a 20% difference should be considered essentially on par) in results.

The model also uses secondary data from ecoinvent to estimate the manufacturing burdens for assembly. This is a significant gap that should be filled with primary data in the future. In addition, the model uses average data for the EOL disposal and manufacturing waste, which could be improved with more specific data. As a result, it does limit the results' utility in identifying areas of improvement and tracking changes over time for these operations.

An important consideration regarding the scope of the assessment is the functional unit. This assessment presents results per a declared unit of one device across its life cycle, including the use phase, compared to a functional unit which would relate the burdens of the products to its function. Without a functional unit, it is not possible to analyze its environmental performance in relation to its technical performance.

Another limitation of the model is the data quality, which varies across the life cycle stages and has some instances of low representativeness as noted in the data quality assessment. The data quality assessment shows that the data have an average score of 2 to 3, As such, while the assessment encompasses all the relevant mass and energy flows of the systems under study, it assesses Cisco-specific products and their components using generic electronics processes and data. This limitation should be addressed by collecting more primary data and updating the secondary data sources in the future iterations of the model.

No co-products during manufacturing were identified. Therefore, this study did not perform allocation. Allocation of environmental burdens to material and energy co-products throughout the upstream supply chain is embedded in the LCI data used in this study and described in the documentation of these datasets. In addition, no mass was excluded within non-electricals, plastic, or product packaging. One exclusion was made in packaging materials for raw materials and semi-finished components. In terms of energy, one exclusion was made in the case of warehouse storage burdens. No other primary data or mass and energy flows were knowingly excluded.

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