LCA report
Cisco public

ISO-Aligned Life Cycle Assessment Report

C9300-48P

Version 1
Date: February 2024
Catalyst 9300 48-port PoE+ Switch

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Abbreviations

ADP	abiotic depletion potential
BOM	bill of materials
BPA	bisphenol A
BWC	blue water consumption
Cisco	Cisco Systems, Inc.
CO_2	carbon dioxide
CO_2e	carbon dioxide equivalent
CTUe	Comparative Toxic Units equivalent (ecotoxicity)
CTUh	Comparative Toxic Units equivalent (human toxicity)
EOL	end-of-life
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
LAN	local area network
LCA	life cycle assessment
LCI	life cycle inventory
LCIA	life cycle impact assessment
MJ	megajoule
MWh	megawatt hour
PCB	printed circuit board
PED	primary energy demand
PoE	power over ethernet
Sb	antimony
tkm	ton-kilometer
W	watt
WLAN	wireless local area network
WSP	WSP USA Inc.

Version History

Version & Date	Developed by	Changes Made	Version of Cisco Scalable LCA Model used
V 1.0 2024-02-05	WSP Team	Initial version created	Version 1

Disclaimer on comparability and model updates

As the 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.

The following LCI databases were used in Version 1.0 of the Scalable Model.

- LCA For Experts service pack 2023001000
  - "Professional 2023" database
  - "XI: electronics 2023" extension database
  - ecoinvent version 3.9.1

Data and other information 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, modelling, 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 Environmental, Social, and Governance (ESG) 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 informs the model’s parameters.

Cisco commissioned WSP to develop a LCA using the Scalable 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 C9300-48P switch. GWP is also referred to as greenhouse gas (GHG) emissions and the GWP results (excluding biogenic carbon) of the product life cycle are as 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 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 evaluate the potential for resource scarcity. Ecotoxicity assesses the potential toxicity of emissions to ecosystems and aquatic life and evaluate 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 C9300-48P from cradle-to-grave. The C9300-48P is a versatile switch with modular uplink options and can be stacked when extending the network. Therefore, the goal of this study was to determine the GHG emissions, PED, BWC, ADP, ecotoxicity, and human toxicity (cancer and non-cancer) impacts of Cisco’s C9300-48P switch 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 C9300-48P. This switch is well-suited for diverse applications, including powering devices such as WLAN deployments and security cameras. It ensures fast, secure, and reliable network operations, and it offers the added benefit of stackability for network extension and seamless communication for efficient data transfer among connected devices. In alignment with Cisco's commitment to environmental responsibility, an assessment of the environmental impacts of the C9300-48P switch has been undertaken, aiming to provide valuable insights for internal communication and further development considerations. 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 Cisco’s C9300-48P 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

[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/).

availability, requests from stakeholders, and commonly included metrics for electronic products. While the results of the model are in alignment with ISO Standards 14040 and 14044 for LCA, there currently is no ISO standard that applies to LCA models; therefore, the model itself cannot be considered "ISO-conformant" and the model's results can only be considered ISO-conformant if documented in an ISO-conformant LCA report that undergoes critical review.

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 C9300-48P switch.

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 Catalyst C9300-48P is a versatile, Power-over-Ethernet (PoE) enabled switch with modular uplink options (Figure 1). It is ideal for mid-sized businesses that want to power a broad range of devices like wireless local-area network (WLAN) deployments and security cameras. The C9300-48P is a fast, secure, and reliable switch that can be stacked for network expansion. A brief overview of the technical specifications of the product is provided in Table 1.

Table 1: Technical Specifications of the Products

Technical Data	C9300-48P
Product weight	7.11 kilograms
Typical power consumption	112 Watts
Dimensions	1.73 x 17.5 x 17.5 Inches
Product Configuration	**Quantity**
C9300-48P-E	1
C9300-NM-8X	1
PWR-C1-715WAC-P	2
CAB-TA-EU=	2
SSD-240G	1
FAN-T2	3

Figure 1: Image of the product – C9300-48P switch

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.

2.3 System Boundary

The 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 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.

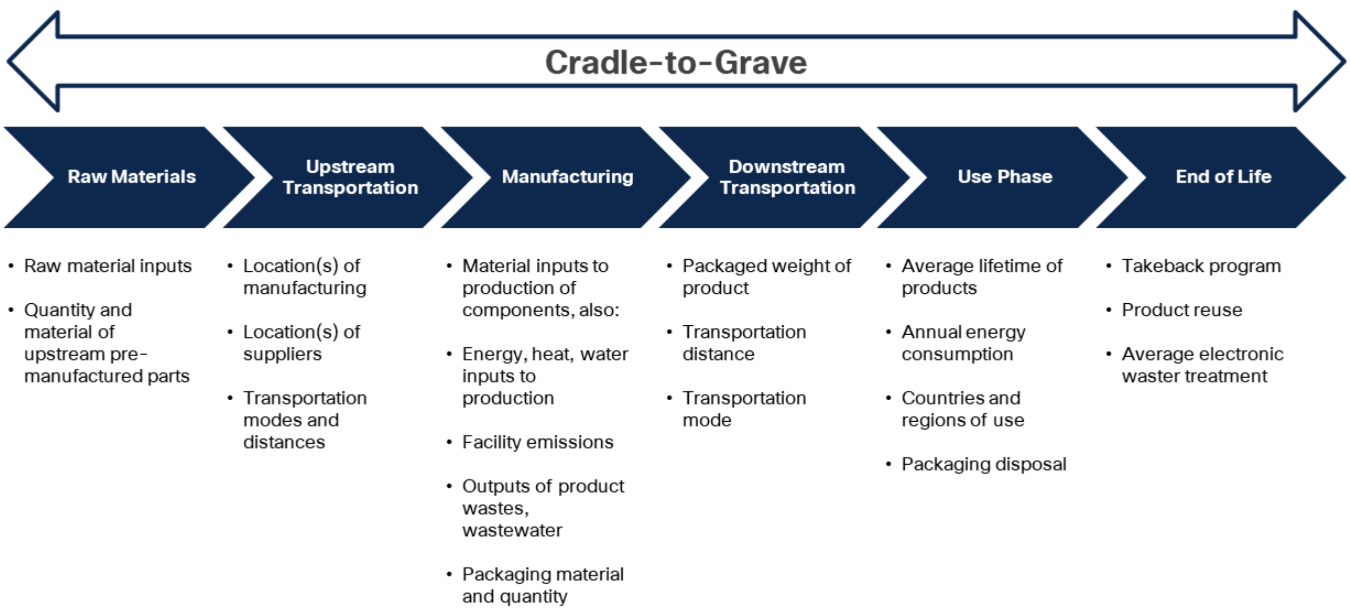

Figure 2: The system boundaries of the Scalable LCA model

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 2022 and 2023. The data that are matched to the material inputs are valid for 2023, 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 modelled 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 v3.9.1 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 was 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 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 key electrical components 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 represents different levels of complexity in the assembly and testing processes. This is a significant limitation that should be addressed in future iterations of the 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 C9300-48P Life Cycle Inventory

This section outlines the inventory compiled to assess the life cycle impacts of the C9300-48P switch. A network switch is typically composed of electronic components such as integrated circuits, connectors, and ports housed within a durable metal or plastic chassis, designed to facilitate the efficient routing of data within a computer network. 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 provides efficient data traffic management within a local area network (LAN). Finally, the products reach EOL and are recycled, landfilled, or returned to Cisco for testing and reuse.

3.1.1 Component Manufacturing

The components utilized in manufacturing Cisco products fall into four main categories: key electrical, electrical, electro-mechanical, and mechanical components. The key electricals category is defined as printed circuit boards (PCBs) and ICs. 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 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 Electrical Components

The list of electrical components includes ICs, PCBs, capacitors, resistors, transistors, and inductors. Furthermore, ICs and PCBs are considered key electrical components. 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 was identified as a key driver of environmental impacts from PCBs, and as such, the most commonly used parts expressed as number of layers was 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 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" 2023, as well as all other databases, can be found here.

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 Cisco 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 assigned to
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
PCBs	16 layers
Diodes	Diode power DO214/219 (93mg) 4.3×3.6×2.3

Modeling of Electro-mechanical Components

The electro-mechanical component 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 1,000 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 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, 1,000 miles is approximately equivalent to transportation between in-land locations in China.

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	5.96 tkm	ecoinvent 3.9.1	2023	Rest of the World
transport, freight, sea, container ship	9.18 tkm	ecoinvent 3.9.1	2023	Global
transport, freight, aircraft, dedicated freight, long haul	0.15 tkm	ecoinvent 3.9.1	2023	Global

3.1.3 Assembly

For assembly, manufacturing burdens were proxied using secondary datasets from ecoinvent. As the product under study was a switch, it was deemed that the smartphone dataset from ecoinvent was deemed a suitable proxy for assembly burdens (details in Table 4). Both smartphones and network 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 network 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 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 was modelled 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)	19.78	Sphera	Electricity grid mix	China
Water use (liter)	3649.43	Sphera	Tap water from ground water	China
Wastewater output (cubic meter)	3414.67	ecoinvent	Market for waste water, unpolluted	Rest of World

3.1.4 Testing

For testing, manufacturing burdens were proxied using secondary datasets from ecoinvent. 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	Dataset	Data Source	Geographical Coverage
Electricity (kWh)	35.57	Electricity grid mix	Sphera	China
Heat (kWh)	14.23	Market for heat, district or industrial, other than natural gas	ecoinvent 3.9.1	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, sea freight, and air freight (Table 7). Distances were assumed based on international distribution with an average transportation distance of 7,000 miles, distributed as 30 percent truck transport, 65 percent sea freight, and 5 percent air freight. Exact distances between manufacturing facility and consumer were not calculated for the reasons provided in Section 0 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	31.48 tkm	ecoinvent 3.9.1	2023	Rest of the world
transport, freight, sea, container ship	68.21 tkm	ecoinvent 3.9.1	2023	Global
transport, freight, aircraft, dedicated freight, long haul	5.25 tkm	ecoinvent 3.9.1	2023	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 forwarding of data packets within a local area network, facilitating the seamless communication and data transfer between connected 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
- Typical annual energy consumption: 981.12 kWh
- Lifespan of product: 5 years

The typical energy consumption and lifespan of the product was provided by Cisco. The annual energy consumption was 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	4905.6	Sphera	2023	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 U.S. national average treatment of electronic products and the Cisco takeback program. The U.S. 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 model.

Electronics that are sent to landfilling or recycling 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 landfill, Cisco also has a takeback program. The specifics of how this influences the EOL flows is detailed in the confidential appendix, along with a table summary of all EOL flows. Of the takeback flow, one share of the products is assumed to go to recycling and one share is assumed to be refurbished.

As data on refurbishment are not readily available, the takeback program was proxied as reuse. The reuse was modeled as an extension of the lifespan of the product. It was assumed that the product to be reused is transported back (assuming same distance as product distribution) for testing, which is proxied through the testing in the manufacturing stage, followed by further use for 2 years. To accommodate for this further use, the burdens from transportation to customers and energy consumption during the use phase were proportionally added. 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 for reuse (including the additional electricity consumption from the reuse). 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. In addition, for power supplies, a generic dataset for computer power supplies was used and scaled by wattage. While technologically similar, it is a different product than that of switch power supplies and may lead to an overestimation of impacts due to its larger size compared to a switch power supply.

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 to 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 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)
  - Assess the depletion of non-living resources, such as metals and minerals, and evaluate 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
  - Assess the emission of GHGs into the atmosphere and evaluate the contribution to GWP over a 100-year period and exclude 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
  - Assess 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
  - Assess the potential toxicity of emissions to ecosystems and aquatic life and evaluate 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
  - Assess 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
    - Assess 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.[2] 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.

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

4.2.1 Global Warming Potential

The GHG emissions (excluding biogenic carbon) per C9300-48P switch were 2,720 kg CO_2e. As shown in Figure 3, the GHG emissions were categorized into different life cycle stages covering manufacturing, transport, use phase, disposal, and reuse. The use phase significantly influences the overall impact, contributing 85 percent of the total for the C9300-48P switch. As stated above, the product was modeled as being used in the United States. The U.S. 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 like coal and natural gas are known to be large contributors to GHG emissions from the U.S. grid electricity.

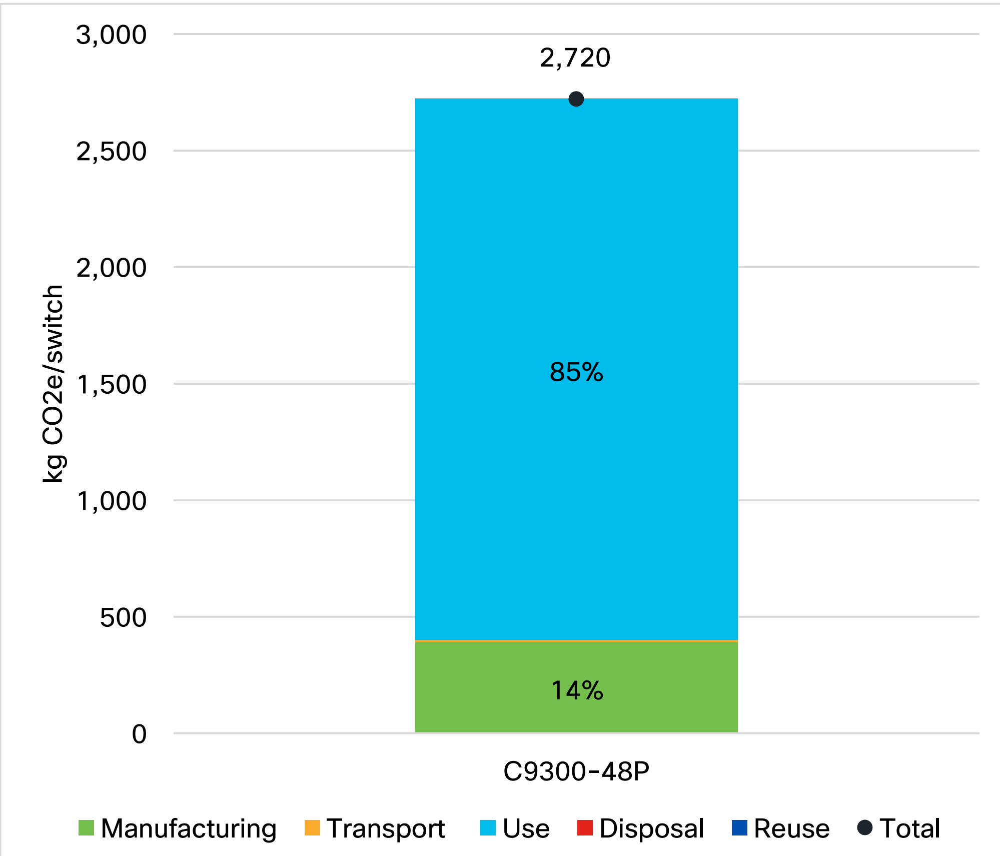

Figure 3: Global Warming Potential Per C9300-48P by Life Cycle Stage

The manufacturing phase was the second-largest contributor to GHG emissions, accounting for 14 percent of total GHG emissions per C9300-48P (Figure 4). Within the upstream supply chain, which includes packaging materials, electrical components, and other components such as cables, battery, fans, and some other minor contributors, electrical components are one of the significant impact drivers, contributing 36 percent of GHG emissions in the manufacturing stage. Another significant contributor is the power supply unit, accounting for 56 percent of the total impact within the manufacturing phase. This is mainly driven by the PCBs that the power supply consists of.

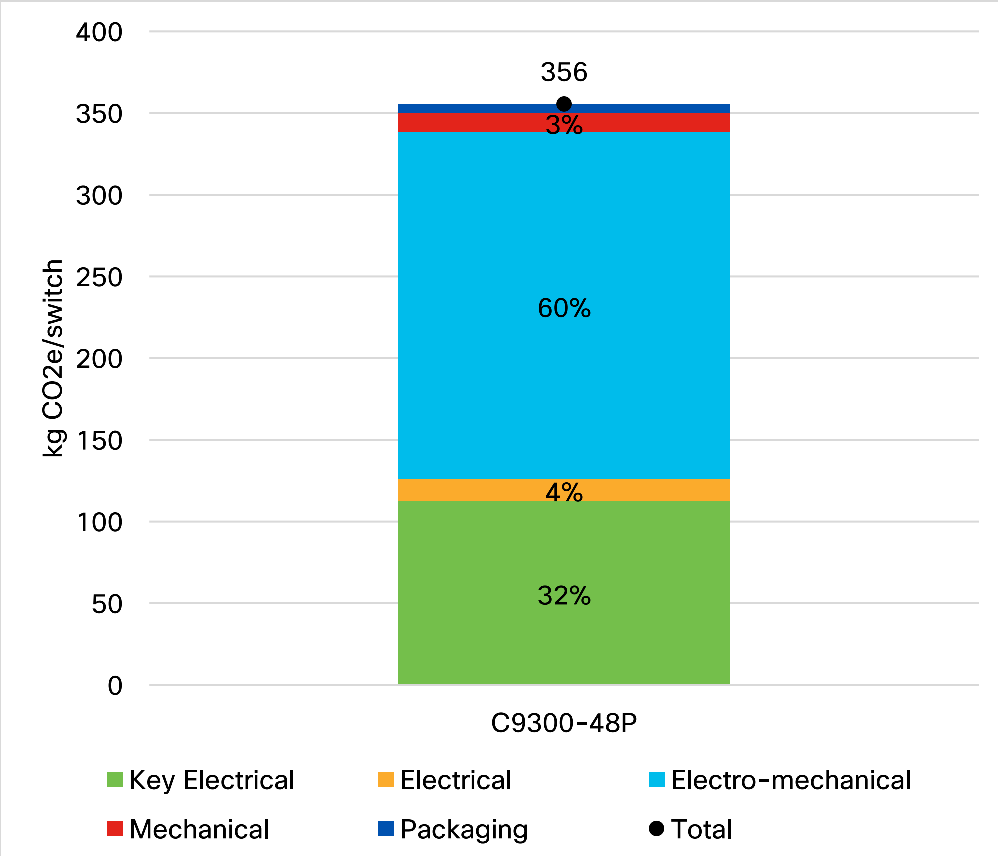

Figure 4: Global Warming Potential per C9300-48P in the Manufacturing Stage

Examining the contribution from electrical components, PCBs are the primary source of GHG emissions, followed by ICs (Figure 5). The manufacturing processes for PCBs and ICs (61 and 28 percent of GHG emissions from electrical components, respectively) involve energy-intensive production steps and complex fabrication processes, contributing significantly to the overall impact of electronics. While PED and BWC are important impact categories, the contribution breakdown of the supply chain and material components within the GHG emission category was found to be representative for these two impact categories as well, i.e., the contributors to supply chain GHG emissions were similar for PED and BWC. The supply chain breakdown is therefore only presented for GHG emissions. Other electrical components such as capacitors, resistors, and transistors have a relatively minor impact, constituting less than 11 percent of the combined electrical components impacts. This is mainly attributed to the smaller amount of material used in their simpler production processes, leading to lower GHG emissions, which is in line with the findings of other electronics product LCAs.

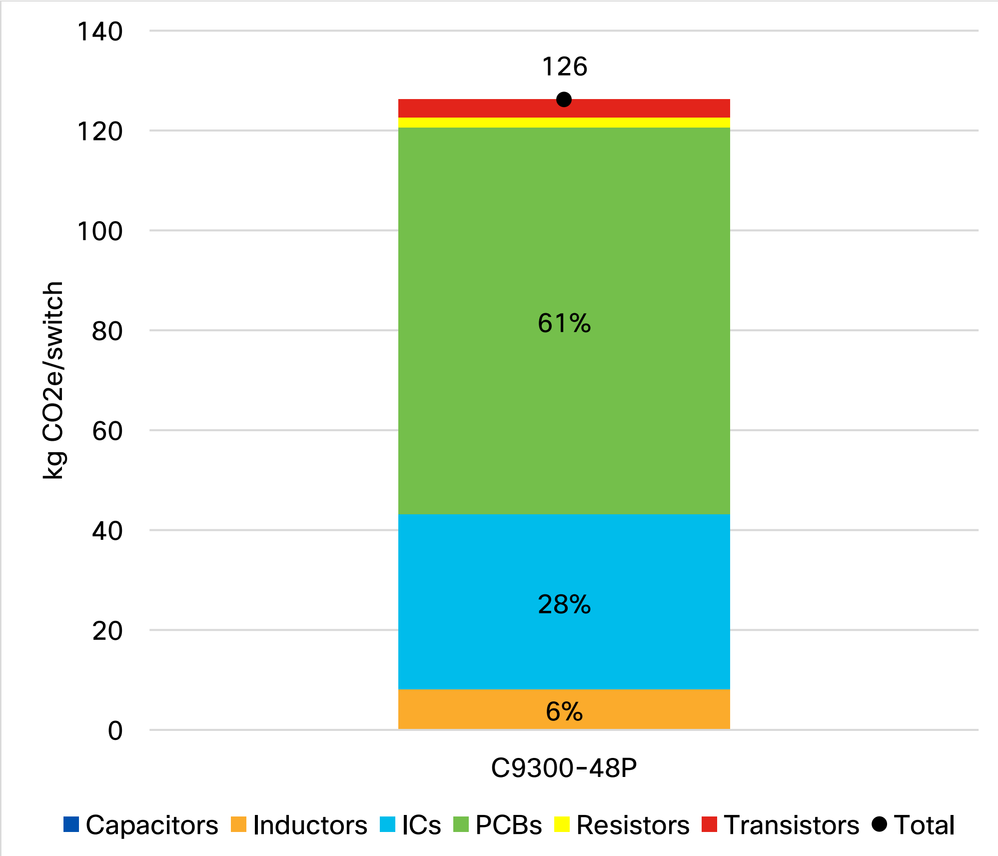

Figure 5: Global Warming Potential per C9300-48P by Electronic Component

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 6, the total PED, characterized by fossil-based energy demand, was 45,470 megajoules (MJ) per C9300-48P switch. The use phase dominates the overall impact, contributing 87 percent to the total non-renewable energy consumption, due to the annual energy consumption of 981 kWh over a 5-year lifetime. The primary contributors within the manufacturing stage are electro-mechanical components and mechanical parts, accounting for 67 percent of the total energy consumption. The power supply unit is the most significant contributor among these material components, responsible for an 86 percent impact share. Power supplies often contain complex electronic circuits, specialized components, and precise manufacturing requirements, leading to higher energy consumption.

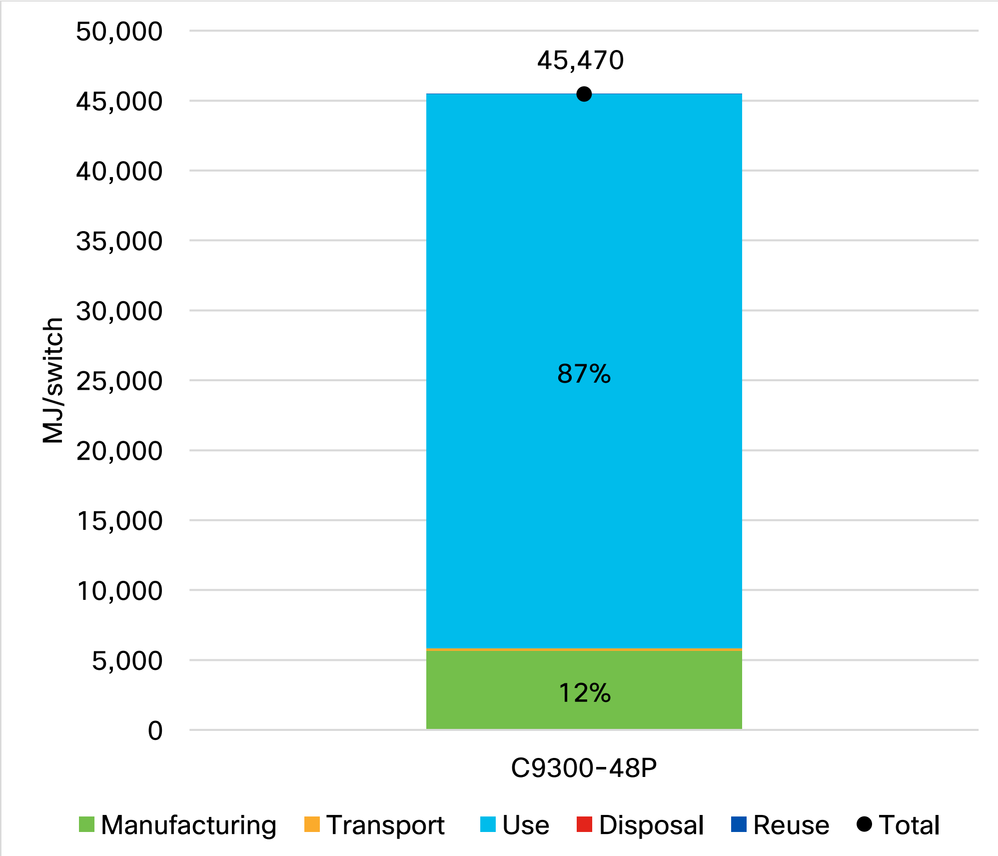

Figure 6: Primary Energy Demand per C9300-48P by Life Cycle Stage

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 7, the BWC results are 21,002 liters (L) per C9300-48P switch. Approximately 76 percent of this is consumption occurs in the use phase. As previously mentioned, the U.S. electric grid mix is primarily dependent on fossil fuels such as coal and natural gas. Both these sources need water for their extraction and electricity generation, where water is converted to steam post resource combustion (Union of Concerned Scientists, 2010; WRI, 2020).

The water consumption during the manufacturing phase is the second-largest contributor to BWC, accounting for 24 percent of the total consumption for the C9300-48P switch. The electro-mechanical components and mechanical materials including the manufacturing of aluminum, steel, and power supply unit are the main contributors to the BWC in the manufacturing phase, constituting over 60 percent of the total consumption per C9300-48P switch. Manufacturing of these components requires water for cooling, cleaning, and various steps in the manufacturing. The electrical components within the switch are another significant driver to the BWC during the manufacturing stage, primarily attributed to their demand for ultra-clean water in the production process. For example, the production of semiconductor devices like ICs involves water-intensive fabrication processes. Electricity usage is the main factor influencing BWC during the assembly stage, as the energy sources used to generate electricity, such as natural gas and coal, require significant amounts of water for cooling and processing. This reliance on water-intensive energy sources for electricity generation contributes notably to the blue water consumption.

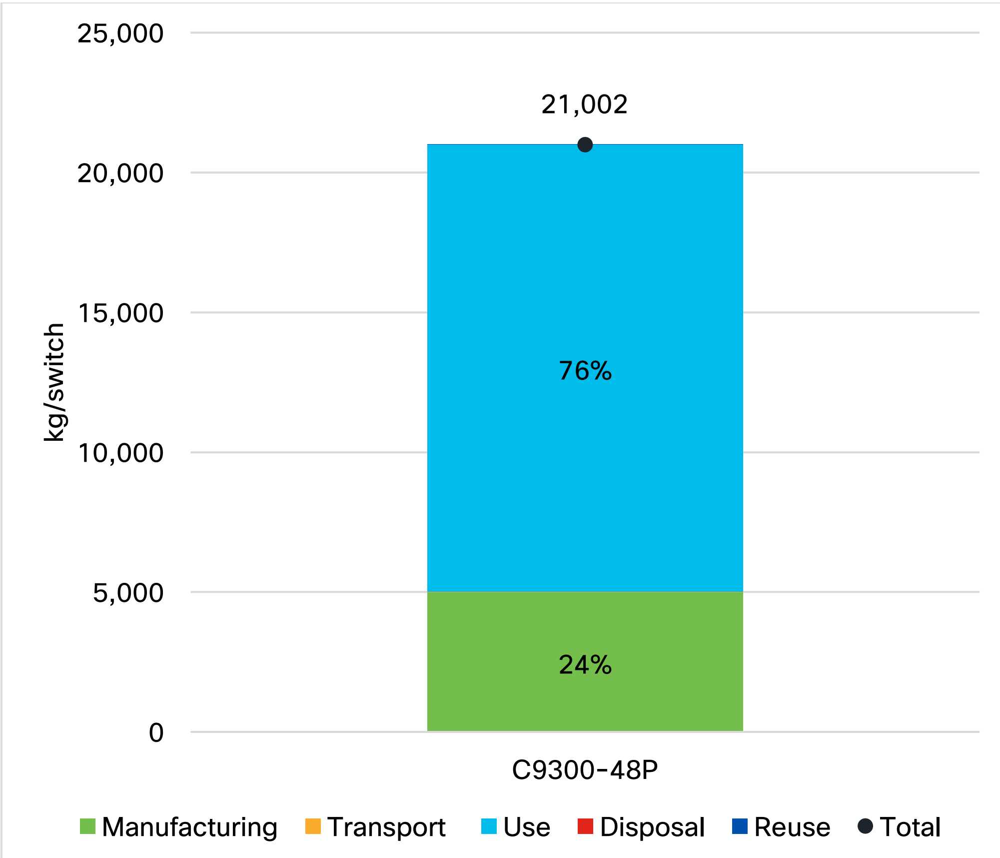

Figure 7: Blue Water Consumption per C9300-48P by Life Cycle Stage

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 8, the ADP result is characterized as 0.05 kg Sb-equivalent per C9300-48P switch.

The manufacturing phase is the largest driver of ADP, contributing to over 99 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. Electrical components and mechanical components or materials contribute to approximately 38 percent and 62 percent of the impact within the manufacturing phase, respectively. The power supply unit manufacturing, coupled with the resource-intensive materials involved, results in a dominant contribution to abiotic depletion within the overall production of electro-mechanical components, accounting for almost 97 percent.

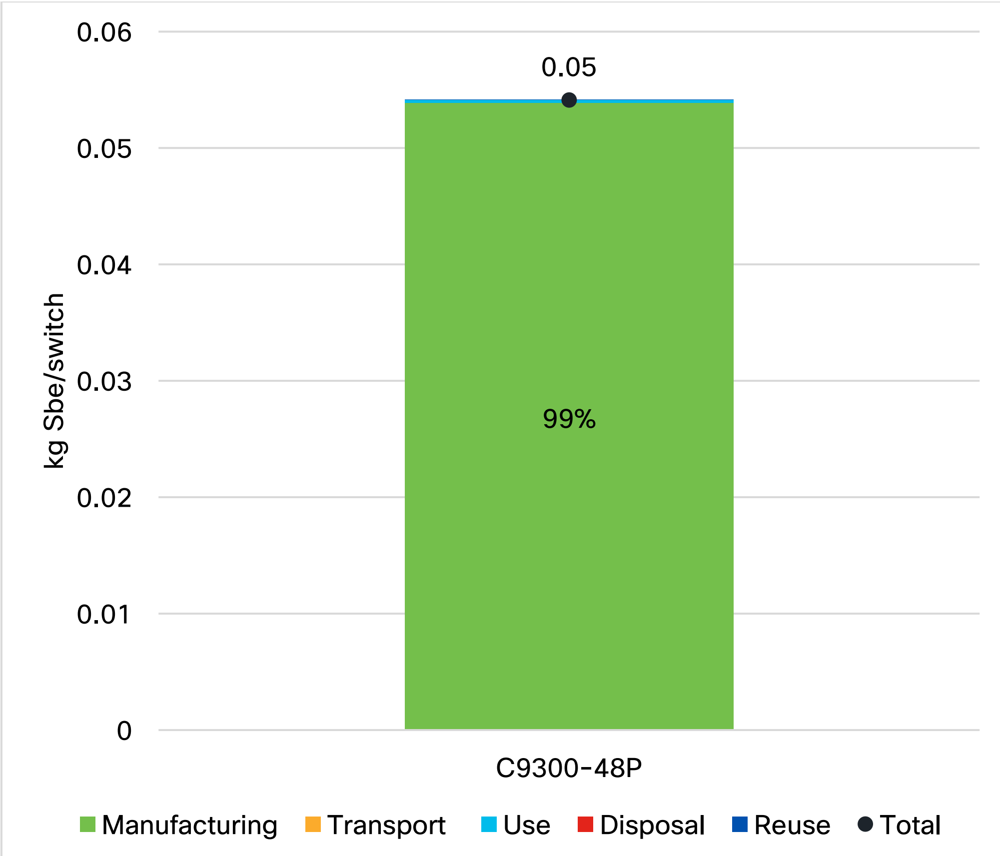

Figure 8: Abiotic Depletion Potential per C9300-48P by Life Cycle Stage

4.2.5 Ecotoxicity

Ecotoxicity measures 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 9, the ecotoxicity result is quantified as 34.6 CTUe per C9300-48P switch. Within the network switch, ecotoxicity impact is driven by manufacturing, accounting for 96 percent of the total impacts. Within manufacturing, mechanical components and materials yield the highest impact, constituting around 93 percent. This high percentage is attributed to the complex composition of a network switch, which includes a variety of metals, plastics, and other materials requiring resource-intensive production processes. Metals such as copper and aluminum, essential for circuitry and connectivity, are extracted and processed through mining and smelting operations that often release toxic substances into the environment. Similarly, the production of plastics for the switch casing and insulation involves chemicals like bisphenol A (BPA) and phthalates, which can leach into ecosystems.

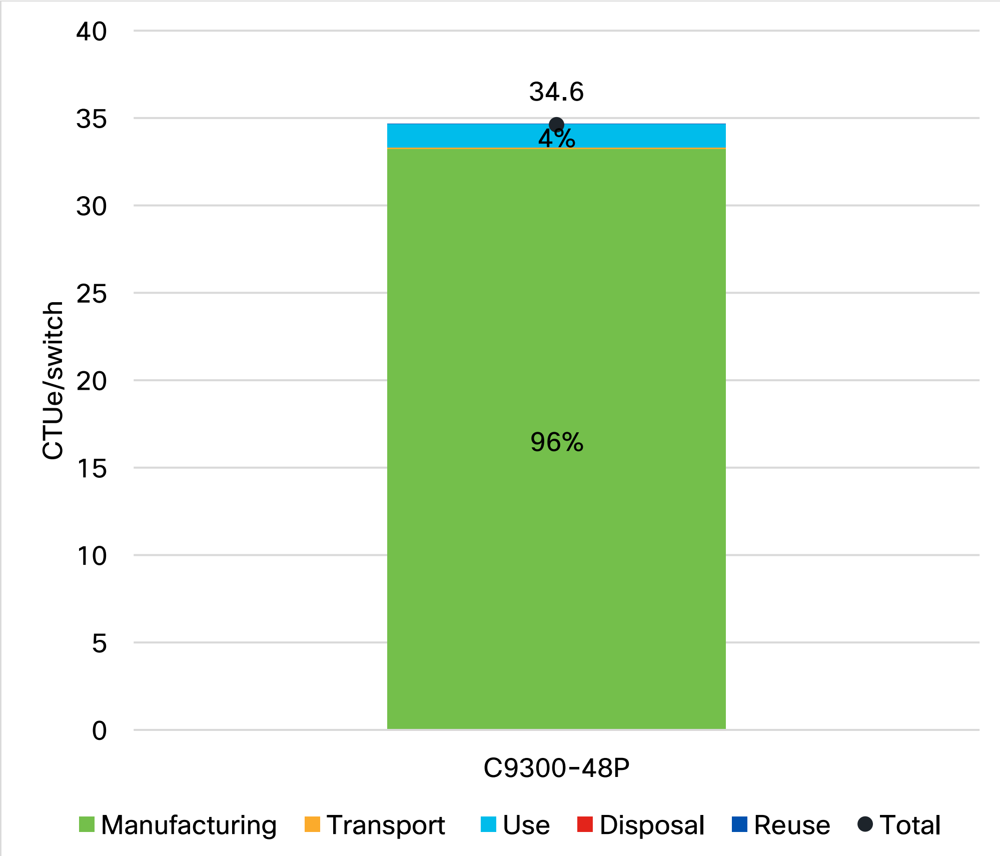

Figure 9: Ecotoxicity per C9300-48P by Life Cycle Stage

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 human. As shown in Figure 10, human toxicity (cancer) result is characterized as 2.78E-07 CTUh per C9300-48P switch. The main driver of human toxicity (cancer) impact is related to the electricity generated and consumed during the use phase. The generation of electricity often involves the combustion of fossil fuels or other processes that can release pollutants and toxins into the environment. These pollutants can contribute to human toxicity and increase the risk of cancer when they are released into the air or water.

Within manufacturing, mechanical components and materials have the highest impacts. This is due to several factors, such as the production processes associated with these materials often involving the use of toxic substances and chemicals, posing potential risks of human toxicity, including the risk of cancer. The extraction, refining, and processing of metals like steel and aluminum also contribute to pollution and toxicity.

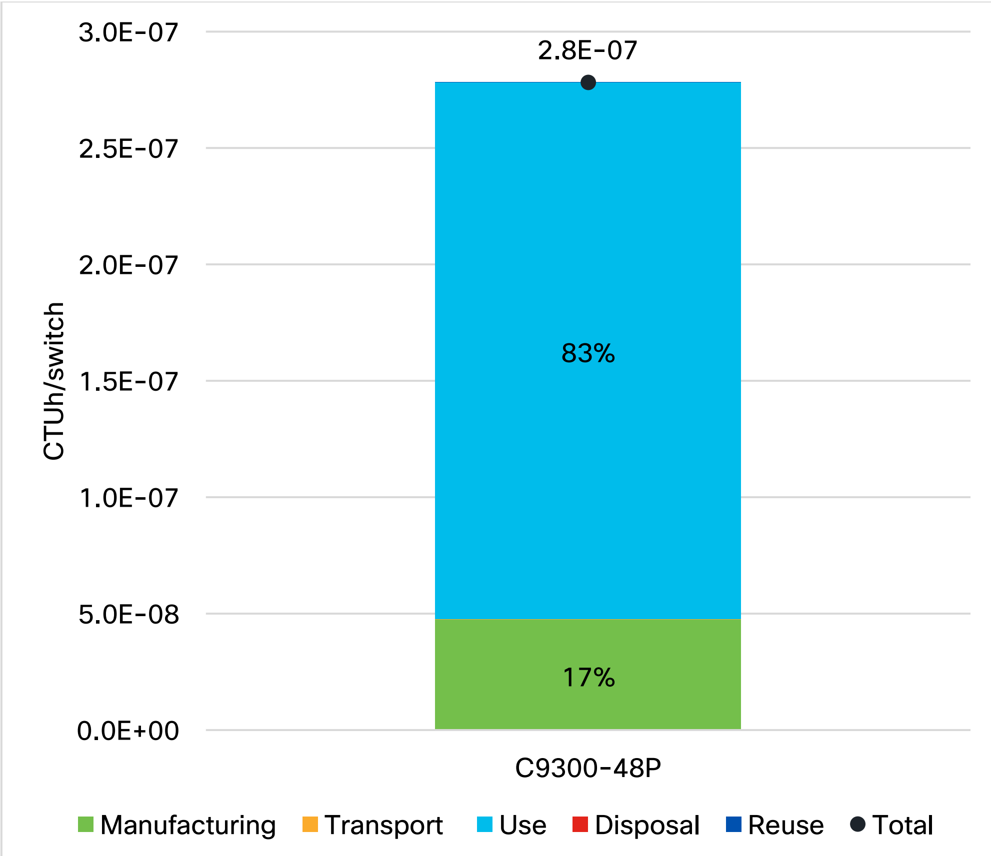

Figure 10: Human Toxicity (Cancer) per C9300-48P by Life Cycle Stage

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 11, human toxicity (non-cancer result) is quantified as 2.0E-08 CTUh per C9300-48P switch. The largest contributor to human toxicity (non-cancer) is the manufacturing phase, accounting for 77 percent of the total impacts for the switch. As described in the previous section, materials extraction and refinement can contribute to the emissions of toxic substances to air, water, and soil.

In general, the second significant contributor is the use phase, constituting approximately 14 percent of the total impacts for a switch. This is mainly attributed to electricity consumption during the use phase. As noted, a considerable portion of the electricity in the United States is generated from coal and natural gas in power plants, leading to emissions of pollutants and chemicals during fuel combustion for energy production. These emissions contribute to the potential harm to human health measured by this impact category metric.

It is noteworthy that the transportation stage is also a substantial driver of the human toxicity (non-cancer) results, accounting for around 9 percent of the total impact. The transportation of goods within a globalized supply chain often involves long-distance shipping and air freight. These transportation activities, especially those involving fossil fuel-powered vehicles, release pollutants into the air. Combustion of fuels like gasoline and diesel generates emissions containing harmful substances such as particulate matter, nitrogen oxides, and volatile organic compounds. Exposure to these pollutants during transportation can contribute to non-cancerous adverse health impacts.

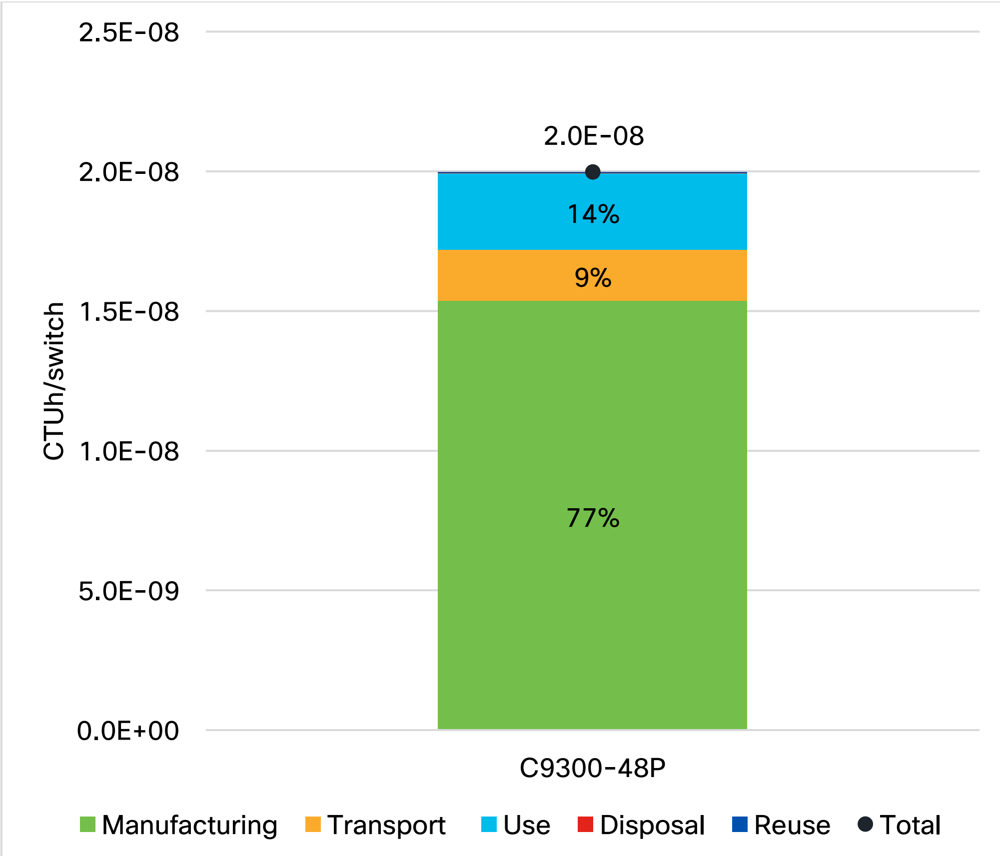

Figure 11: Human Toxicity (Non-cancer) per C9300-48P by Life Cycle Stage

4.3 Limitations

The primary limitations of the Scalable 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 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. 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 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. Furthermore, since primary data for the reuse of Cisco products was not available, the burdens of processing a used Cisco product for further use was proxied using the manufacturing testing burdens from the production life cycle phase. 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 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. In the current model iteration, the user cannot choose specifically between virgin and recycled material flows. Rather, the industry averages of recycled content are included as part of the datasets chosen. This somewhat limits the efficacy of the recycled content 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 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 be 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 driver of GHG emissions, PED, and BWC is the use phase, the generation and consumption of electricity during this phase significantly contribute to these impact categories, primarily because a substantial portion of electricity in the grid is derived from coal and natural gas sources. Manufacturing of materials is another significant contributor to most of the impact categories, mainly due to the use of materials and energy in raw material processing. Within the material components, the power supply unit plays a pivotal role in contributing to most impact categories, and PCBs and ICs are also critical contributors. The complexity and precision of these components demand sophisticated facilities and equipment for their manufacturing, which often involve energy-intensive processes. Other electronic components have lower material usage and contribute less to the environmental impacts.

5.2 Sensitivity Analysis

To evaluate how inputs to the modelling in this study influence results, two sensitivity analyses were conducted by changing input parameters and assumptions. This included assuming the application of renewable energy in assembly, testing, and use phase, as well as assuming the usage of precious metals in capacitors. The GHG emissions impact category was considered in the sensitivity analyses, as it was deemed sufficiently representative for most impact categories for the two cases.

The first sensitivity analysis focuses on the use of renewable electricity sourcing in assembly, testing and use. The electricity dataset (referred to as “green electricity” in LCA for Experts) comprises 55 percent wind power, 26 percent solar power, and 16 percent hydro power, with the remaining approximately 3 percent being a combination of bio sources and thermal. This dataset provides a globally representative overview of electricity production labelled as “green.” As shown in Figure 12, the total GHG emissions throughout the life cycle generate an 82 percent reduction in this scenario compared to the base case where the grid mix is assumed for manufacturing in China and the products use in the United States. The reduction in use phase is the most significant at 96 percent. Manufacturing impacts only decreased 4 percent, primarily because most of the impacts generated within the manufacturing stage are from components like power supplies, ICs and PCBs which are aggregated datasets whose energy grids cannot be adjusted.

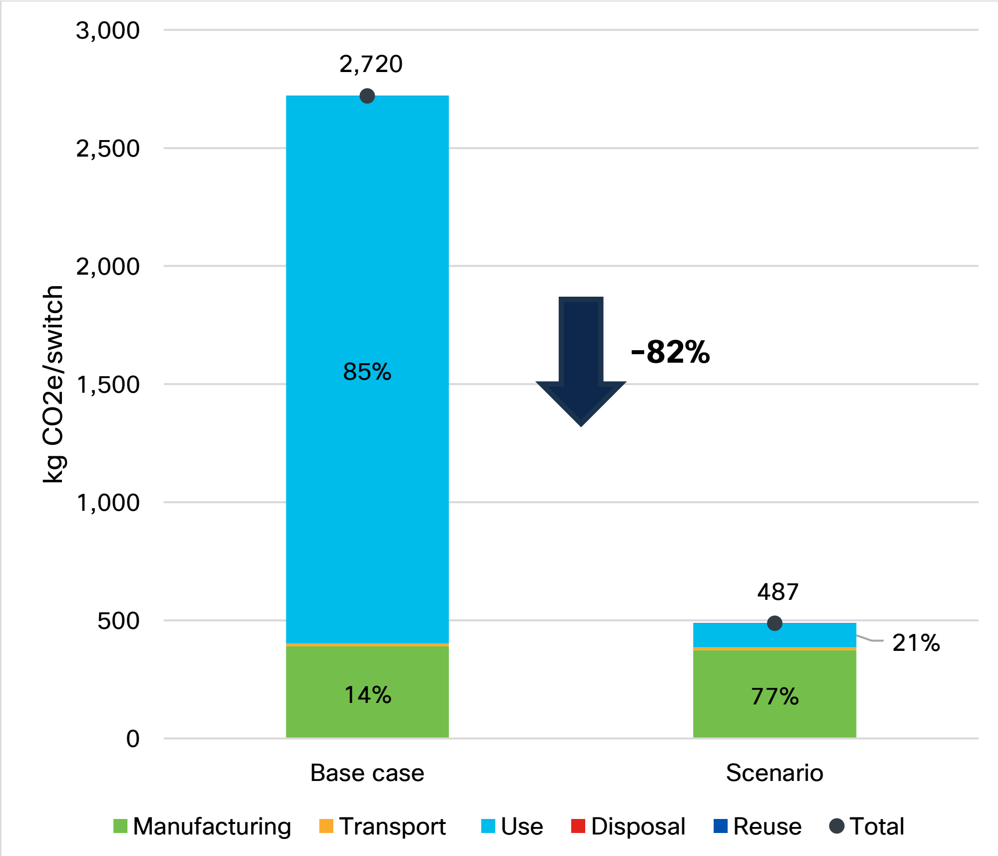

Figure 12: Sensitivity Analysis Results for GHG Emissions with Renewable Energy Sourcing

Another sensitivity analysis was conducted by considering the utilization of precious metals in capacitors. This analysis aimed to assess the influence of this factor, particularly given that there was limited information regarding the incorporation of precious metals in purchased capacitors and the base case assumes non-precious metals. GHG emissions and ADP were found to have the largest relative increases across all the impact categories when the capacitor datasets were switched to the equivalent with precious metals. The toxicity impact categories increased less than 1%, while the PED and BWC categories saw changes similar to that of GHG emissions. As shown Figure 13, including the usage of precious metal in capacitor manufacturing leads to a 1% increase in the total GHG emissions and a 5% increase in total ADP. The manufacturing stage specifically had 9% higher GHG emissions and 5% higher ADP with the inclusion of precious metals. As a reminder, the ADP impact category has inherent uncertainties that makes it unsuitable for comparisons. Consequently, the inclusion of precious metal in capacitors does not significantly impact the overall results

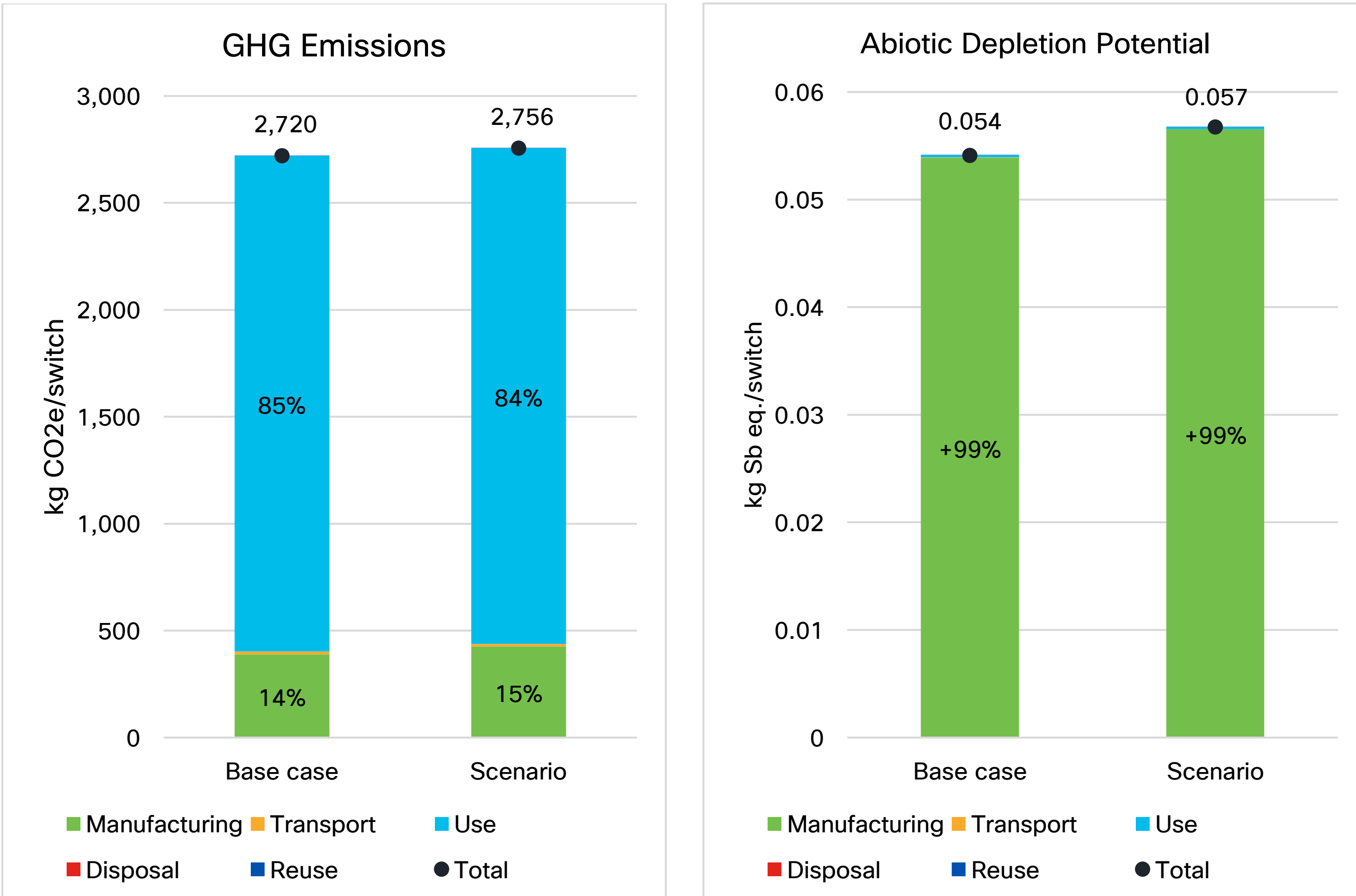

Figure 13: Sensitivity Analysis Results for GHG Emissions and ADP when Considering the Inclusion of Precious Metals in Capacitors

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 U.S. 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 60-79% 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 affect 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 U.S. 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 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 is 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**

Data Quality Indicator	Data quality description by phase	Average
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. 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 modelled using different location 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.	**3**
Temporal correlation	Materials: All material data inputs from the user and BOM are from 2022/2023. The data that are matched to the material inputs are valid for 2022, with some valid through 2025 and 2026. The input data used in the model have 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 2022, with some datasets having extended validity through 2025 and 2026. Manufacturing data for the model are highly representative and have a temporal correlation score of 1. Transport: Transport data for the product are provided as an input and are from 2022/2023. The transport datasets used in the model are all valid for the year 2022. Therefore, the transportation model has high temporal correlation with a score of 1 for both upstream and downstream transportation. Use: The product is used from 2022 and through end-of-life. The electricity dataset is valid for 2022, 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 produced in 2022/2023 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.	**2**

Data Quality Indicator	Data quality description by phase	Average
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 resolutions 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 in the tool. The dataset used is a global average for the truck, 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**

Data Quality Indicator	Data quality description by phase	Average
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 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. Product lifetime extension through reuse is also considered. 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.	**3**

5.4 Conclusions and Recommendations

The findings of this report demonstrate that one C9300-48P switch creates 2,720 kg CO_2e of GHG emissions, demands 45,470 MJ of fossil fuel based primary energy, and consumes 21,002 L 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 C9300-48P network switch are equivalent to driving 6,973 miles in an average US passenger vehicle over the product's lifetime of average use.

Besides the electricity consumption during the use phase, which is the leading contributor for most impact categories as is typical for electronics products, the manufacturing of materials also stands as a significant contributor to most impact categories, with a particular emphasis on the power supply. While electrical components contribute around 20-40% of the impacts for most categories, the electro-mechanical components and mechanical parts are larger contributors with between 40-99% of the impacts across all categories. As the power supply unit has been noted as a limitation due to being a generic dataset, a recommendation is to model Cisco specific power supplies as this generic dataset might overestimate the PCB inputs needed. Overall, transportation, assembly, testing and EOL have low contributions to environmental impacts, with the exception of BWC at the assembly stage.

Based on this study, it is recommended that Cisco consider the following actions to reduce GHG emissions, BWC, and PED. First, continue to focus on energy efficiency during the use phase of the C9300-48P switch to reduce impacts. This could include incentivizing sourcing more renewable energy during the use of the network switch. The sensitivity analysis conducted above shows that shifting electricity source to renewable energy in assembly, testing, and use phase is an effective way to reduce GHG emissions, resulting in an 82% emissions reduction. Second, since outside of the use phase and manufacturing of materials is the largest contributor to all of the impact categories, Cisco could focus on partnerships with manufacturers to increase the use of renewable energy in production and developing innovative ways to minimize the demand for ultra-clean water in these electrical component production processes.

5.5 Limitations and Assumptions

The Scalable 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 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. Additionally, the model uses the manufacturing testing burdens to proxy the processing of used Cisco products for reuse, but this may not be an accurate reflection of testing requirements. The model also uses average data for the EOL disposal and manufacturing waste, which could be improved with more specific data. Nevertheless, 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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