Business Analytics Toolkit Portfolio Ch 01–02

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Course: BUSI 6532 - Business Analytics & Data Visualization

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Dalhousie University • 2026

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Chapter 1 Microsoft Excel Pivot Tables

1.1 Introduction of Microsoft Excel Pivot Tables

Microsoft Excel Pivot Tables are a useful starting tool for making sense of large datasets without needing advanced technical skills. They allow users to quickly summarize and reorganize raw data by simply dragging and dropping fields, making it easy to view information from different perspectives, such as sales by region or by time period. Since Excel is commonly used in most business environments, pivot tables are an accessible and familiar way to generate basic business insights and is still effective for turning large amounts of data into clear summaries and simple visuals that support decision-making.

1.2 Dataset and Research Questions

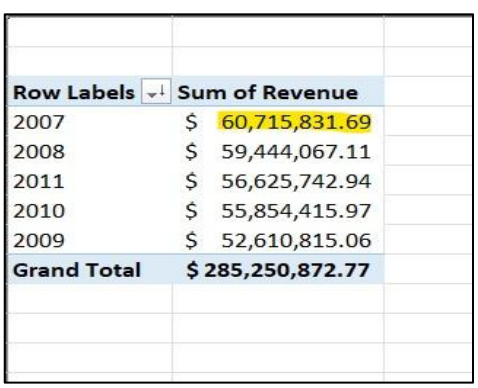
This section presents the analysis conducted using Microsoft Excel Pivot Tables based on the Global Bike Inc. wholesale dataset. The dataset consists of approximately 29,000 transactional records, covering multiple years of wholesale sales activity from 2007 to 2011. Key data fields used in the analysis include Calendar Year and Month, Customer Description, Country, Region, Sales Quantity, Revenue, Net Sales, Cost of Goods, and Discount. Each research question is addressed using a dedicated pivot table and supported by a corresponding visualization, allowing patterns and comparisons to be identified clearly below:

- How did Global Bike Inc.'s sales change from year to year, and which year had the strongest overall performance?
- Which product category has the highest total cost of goods sold (COGS)?
- How does the regional net sales per unit sold in a country look like?
- Which are the top 5 profitable products (as per the Gross Margin)?
- What is the monthly sales revenue trend, yearly? Which months show spike and which shows dip?
- How is the total discount distributed across different products?

1.3 Deriving Business Insights and Findings

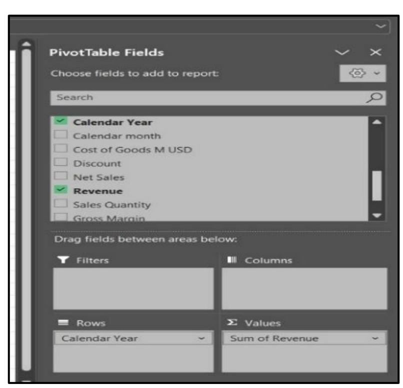
1.3.1. How did Global Bike Inc.'s sales change from year to year, and which year had the strongest overall performance?

To analyze changes in sales performance over time, a pivot table was created (Fig.1) using Calendar Year as the row variable and Revenue as the value field, summarized using the sum function (Fig.2). This compared total sales across different years and helped identify which year performed the strongest overall. In some cases, Sales Quantity was also included as an additional value field to provide further context (Fig.3). Including sales quantity makes it possible to determine whether changes in revenue were driven by higher sales volume or by other factors such as pricing or product mix.



Row Labels	Sum of Revenue
2007	$ 60,715,831.69
2008	$ 59,444,067.11
2011	$ 56,625,742.94
2010	$ 55,854,415.97
2009	$ 52,610,815.06
Grand Total	**$ 285,250,872.77**

(Figure – 1)

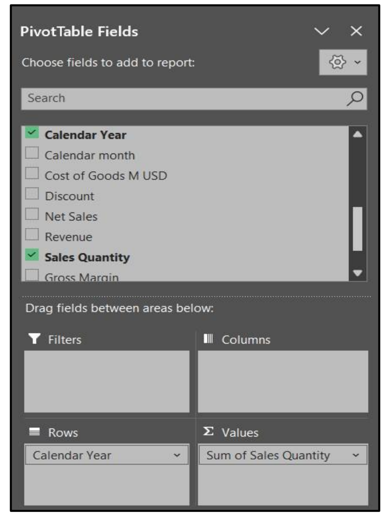


(Figure – 2)

The analysis shows that 2007 was the strongest overall year for Global Bike Inc.'s wholesale business. During this year, the company recorded the highest total revenue, reaching $60,715,831.69, which was higher than any other year in the dataset. In addition to revenue, 2007 also had the highest sales volume, with 37,537 units sold.

Row Labels	Sum of Sales Quantity
2007	37,537
2008	36,088
2010	32,237
2011	31,880
2009	31,112
Grand Total	**168,854**

(Figure – 3)



(Figure – 4)

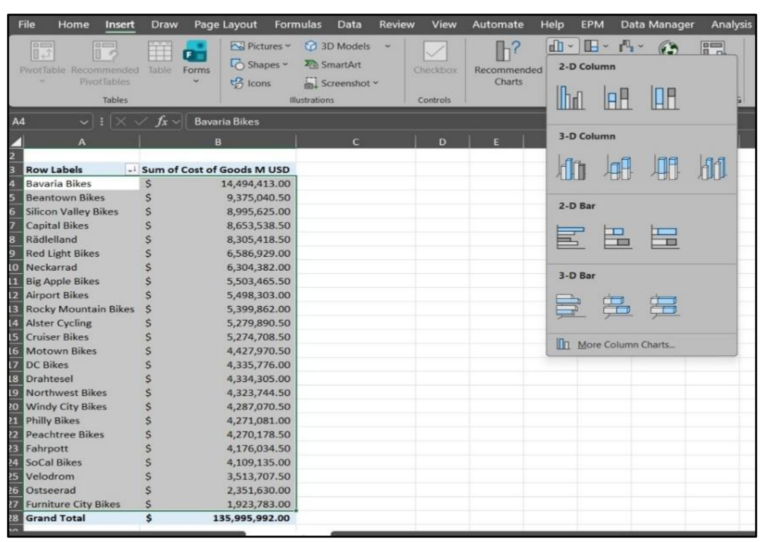
When revenue was compared with sales quantity, it suggested that Global Bike Inc. was able to maintain a higher average price per unit in 2007 compared to later years such as 2011. This indicates that strong performance in 2007 was driven not only by higher sales volume, but also by more efficient pricing.

1.3.2. Which product category has the highest total cost of goods sold (COGS)?

To analyze cost performance, a Pivot Table was built using Customer Desc for the rows and Sum of Cost of Goods M USD for the values. Sorting this data in descending order highlighted Bavaria Bikes as the top cost driver at $14,494,413.00 as shown in the (Fig.5). To make these figures easier to understand, a 2-D Column chart was created via the Insert tab (Fig.6). As shown in the PivotChart Fields pane, placing Customer Desc in the "Axis" area and the cost sum in "Values" generated a dynamic bar graph. (Fig.7)

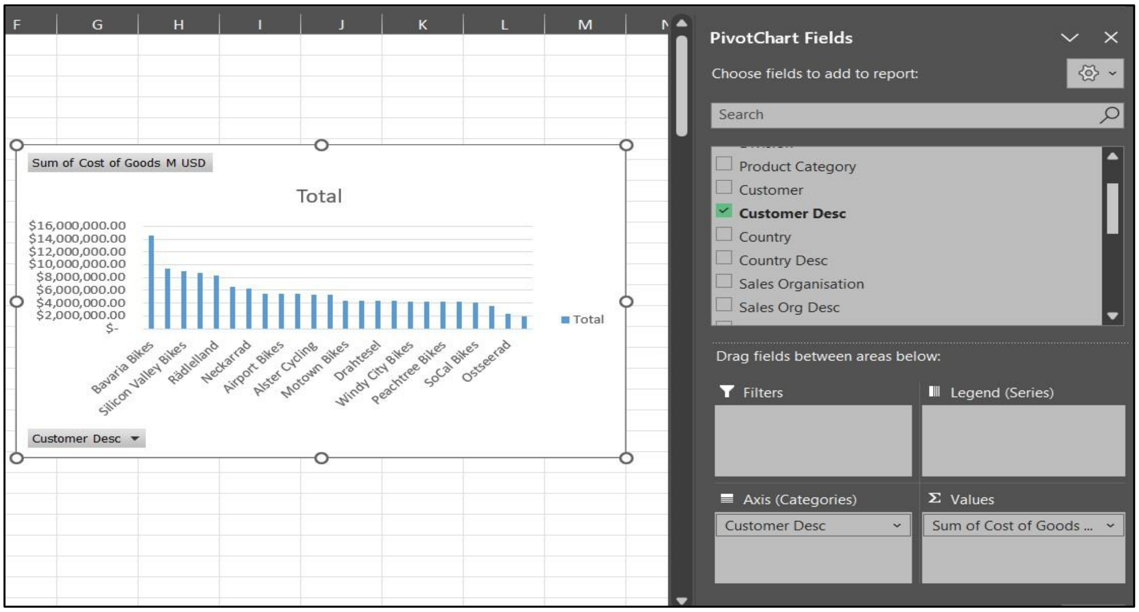
Row Labels	Sum of Cost of Goods M USD	
Bavaria Bikes	$	14,494,413.00
Beantown Bikes	$	9,375,040.50
Silicon Valley Bikes	$	8,995,625.00
Capital Bikes	$	8,653,538.50
Rädlelland	$	8,305,418.50
Red Light Bikes	$	6,586,929.00
Neckarrad	$	6,304,382.00
Big Apple Bikes	$	5,503,465.50
Airport Bikes	$	5,498,303.00
Rocky Mountain Bikes	$	5,399,862.00
Alster Cycling	$	5,279,890.50
Cruiser Bikes	$	5,274,708.50
Motown Bikes	$	4,427,970.50
DC Bikes	$	4,335,776.00
Drahtesel	$	4,334,305.00
Northwest Bikes	$	4,323,744.50
Windy City Bikes	$	4,287,070.50
Philly Bikes	$	4,271,081.00
Peachtree Bikes	$	4,270,178.50
Fahrpott	$	4,176,034.50
SoCal Bikes	$	4,109,135.00
Velodrom	$	3,513,707.50
Ostseerad	$	2,351,630.00
Furniture City Bikes	$	1,923,783.00
Grand Total	**$**	**135,995,992.00**

(Figure – 5)



(Figure – 6)

To analyze costs, a Pivot Table and 2-D Column chart were used to identify key cost drivers. Bavaria Bikes emerged as the top customer contributor with a Cost of Goods Sold (COGS) of ($14,494,413.00), followed by Beantown Bikes ($9,375,040.50) and Silicon Valley Bikes ($8,995,625.00). These visuals highlight a concentrated market where a few top-tier partners drive the majority of wholesale volume.



(Figure – 7)

1.3.3. How does the regional net sales per unit sold in a country look like?

To create the visual analysis for regional net sales per unit, a combination of Excel Pivot Tables and manual formula calculations was utilized across figures 8 and 9. First, the raw data was organized into a Pivot Table using the columns Country Desc and Sales Desc (such as Germany North and US West) as the row labels, with Sum of Net Sales and Sum of Sales Quantity assigned as the value fields. To calculate the net sales per unit sold of each region, a manual formula was applied outside the Pivot Table as demonstrated in the (Fig. 8) where total Net Sales was divided by Sales Quantity (e.g., =B13/C13) to derive the specific value for each unit sold. These results were then consolidated into a clean, formatted table to compare the four main regions, revealing that Germany South achieved the highest net sales per unit at $1,750.46, while the US West had the lowest at $1,527.01.

Row Labels	Sum of Net Sales	Sum of Sales Quantity	
Germany	**$ 158,897,607.43**	**91,939**	
Germany North	$ 85,978,819.57	50,282	
Germany South	$ 72,918,787.86	41,657	
United States	**$ 117,483,539.23**	**76,915**	
US East	$ 65,585,038.22	42,928	
US West	$ 51,898,501.01	33,987	
Grand Total	**$ 276,381,146.66**	**168,854**	
	Net Sales	Sales Quantity	Net Sales per Unit Sold
Germany	**$ 158,897,607.43**	**91,939**	=B13/C13
Germany North	$ 85,978,819.57	50,282	
Germany South	$ 72,918,787.86	41,657	
United States	**$ 117,483,539.23**	**76,915**	
US East	$ 65,585,038.22	42,928	
US West	$ 51,898,501.01	33,987	

(Figure – 8)

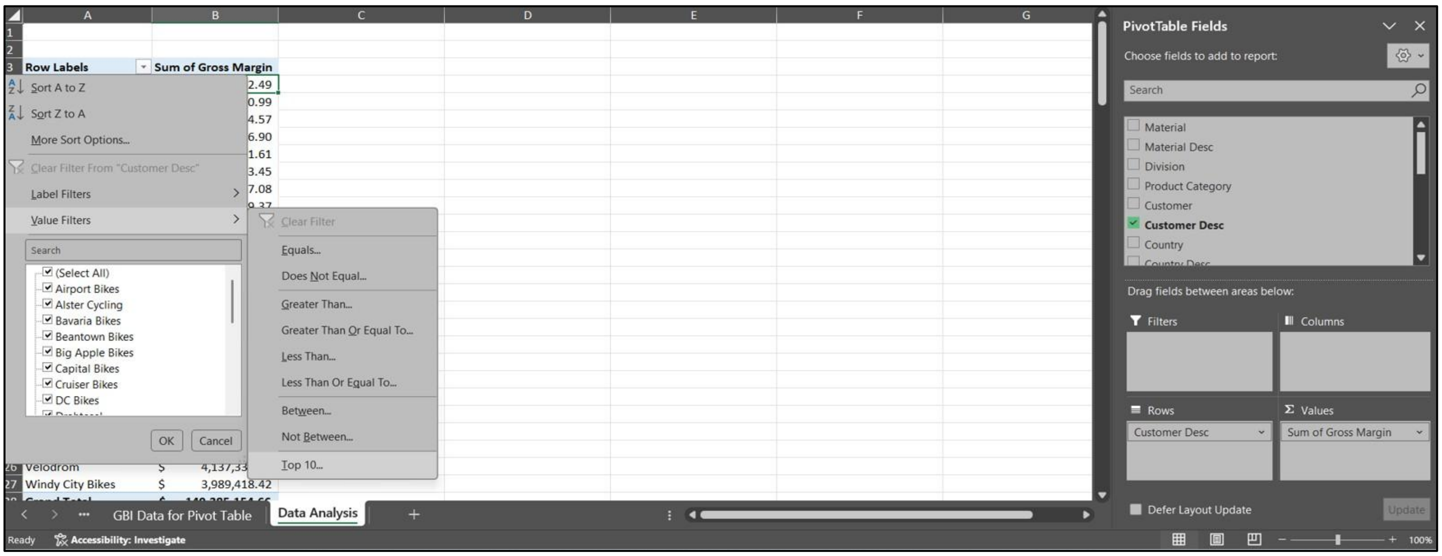
	Net Sales	Sales Quantity	Net Sales per Unit Sold
Germany South	$ 72,918,787.86	41,657	$ 1,750.46
Germany North	$ 85,978,819.57	50,282	$ 1,709.93
US East	$ 65,585,038.22	42,928	$ 1,527.79
US West	$ 51,898,501.01	33,987	$ 1,527.01

(Figure – 9)

Looking at the data in the above figures, the biggest takeaway is that not all sales volumes are created equal across regions. While the total revenue numbers might look impressive, the Net Sales per Unit reveals a significant gap in the average revenue earned per unit between the German and US markets. Germany South is the clear leader, pulling in $1,750.46 per unit, whereas the US West lags behind at just $1,527.01 per unit.

1.3.4. Which are the top 5 profitable products (as per the Gross Margin)?

To get the top 5 performing customers, Excel's Value Filters were utilized. After building a Pivot Table with Customer Desc in the Rows and Sum of Gross Margin in the Values area, filter dropdown on the Row Labels was accessed. From there, Top 10... option (Fig.10) was selected and then modified to specifically show only the Top 5 items based on the Sum of Gross Margin.



(Figure – 10)

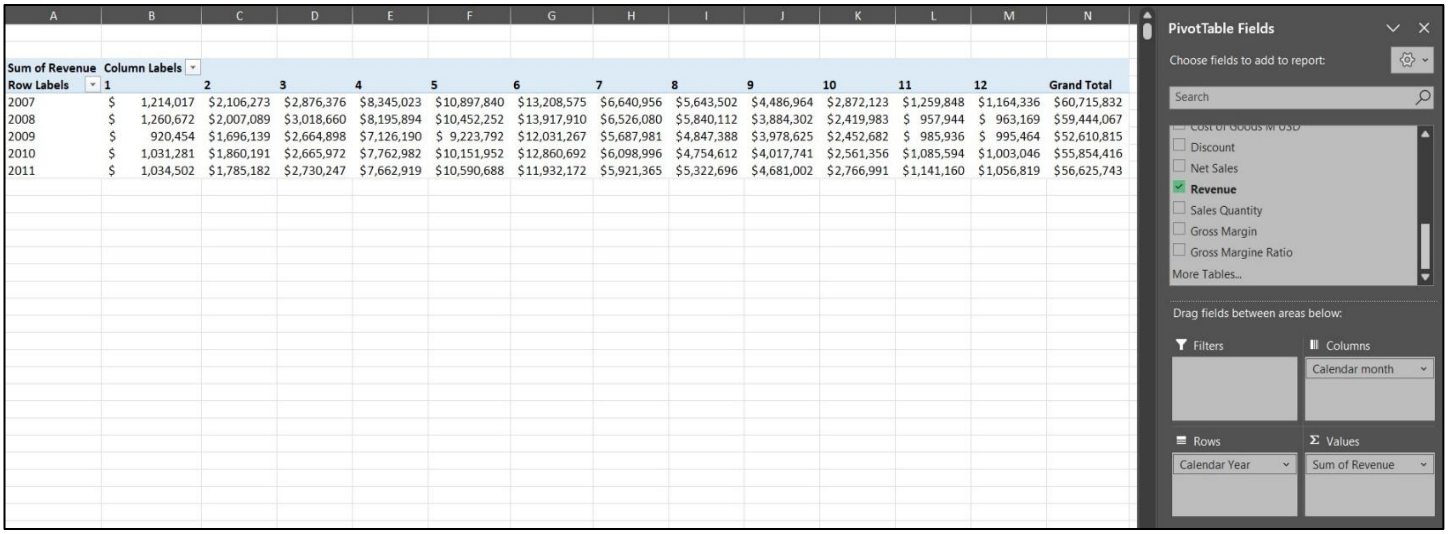
By applying the Top 5 filter to the Sum of Gross Margin, Bavaria Bikes clearly stands out as our most profitable product, contributing a massive $15,787,424.57. The rest including Capital Bikes, Rädlelland, Beantown Bikes, and Silicon Valley Bikes; all perform strongly in the $7.8M to $9.7M range as can be seen in (Fig.11).

Row Labels	Sum of Gross Margin
Bavaria Bikes	$ 15,787,424.57
Capital Bikes	$ 9,715,803.45
Rädlelland	$ 9,266,373.78
Beantown Bikes	$ 8,361,276.90
Silicon Valley Bikes	$ 7,888,045.74

(Figure – 11)

1.3.5. What is the monthly sales revenue trend, yearly? Which months show spike and which shows dip?

To build this visual, the data was organized into a matrix-style Pivot Table to get a clear view of sales cycles. Calendar Year was placed in the Rows and Calendar month in the Columns, creating a grid that makes it easy to compare years and spot seasonal trends. By putting Revenue in the Values area, sales were totaled for every single month. The final result is a table where each row shows a year from 2007 to 2011 and each column shows a month, ending with a Grand Total for each year as shown in (Fig.12)



Sum of Revenue	Column Labels												
Row Labels	1	2	3	4	5	6	7	8	9	10	11	12	Grand Total
2007	$ 1,214,017	$2,106,273	$2,876,376	$8,345,023	$10,897,840	$13,208,575	$6,640,956	$5,643,502	$4,486,964	$2,872,123	$1,259,848	$1,164,336	$60,715,832
2008	$ 1,260,672	$2,007,089	$3,018,660	$8,195,894	$10,452,252	$13,917,910	$6,526,080	$5,840,112	$3,884,302	$2,419,983	$ 957,944	$ 963,169	$59,444,067
2009	$ 920,454	$1,696,139	$2,664,898	$7,126,190	$ 9,223,792	$12,031,267	$5,687,981	$4,847,388	$3,978,625	$2,452,682	$ 985,936	$ 995,464	$52,610,815
2010	$ 1,031,281	$1,860,191	$2,665,972	$7,762,982	$10,151,952	$12,860,692	$6,098,996	$4,754,612	$4,017,741	$2,561,356	$1,085,594	$1,003,046	$55,854,416
2011	$ 1,034,502	$1,785,182	$2,730,247	$7,662,919	$10,590,688	$11,932,172	$5,921,365	$5,322,696	$4,681,002	$2,766,991	$1,141,160	$1,056,819	$56,625,743

(Figure – 12)

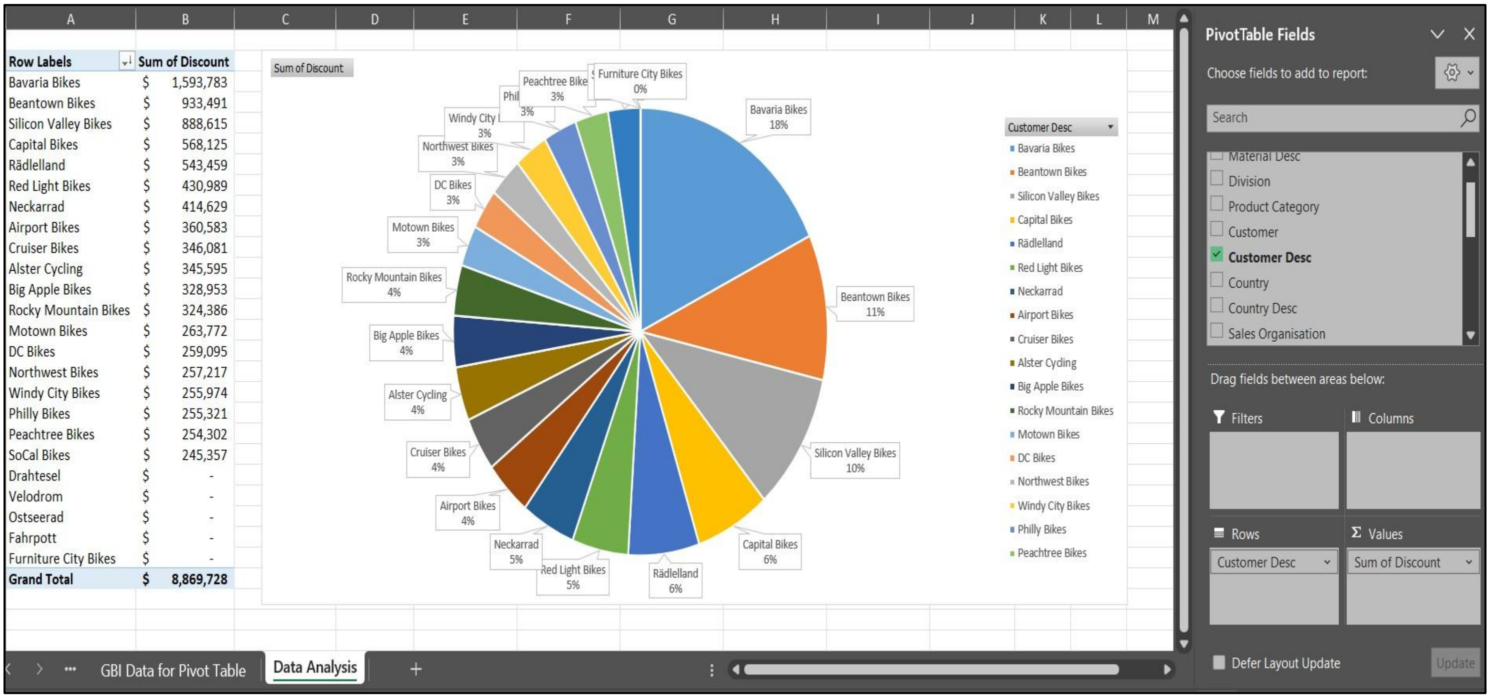
The line chart shows a very consistent seasonal pattern where revenue climbs sharply from March and peaks every June. During this surge, sales hit between $11.9 million and $13.9 million. After the summer high, business declines, bottoming out in December and January as shown in (Fig.13). This "revenue mountain" shape stayed the same even during the 2009 dip, proving the business is tied heavily to the cycling season.

	January	February	March	April	May	June	July	August	September	October	November	December
2007	1,214,017	2,106,273	2,876,376	8,345,023	10,897,840	13,208,575	6,640,956	5,643,502	4,486,964	2,872,123	1,259,848	1,164,336
2008	1,260,672	2,007,089	3,018,660	8,195,894	10,452,252	13,917,910	6,526,080	5,840,112	3,884,302	2,419,983	957,944	963,169
2009	920,454	1,696,139	2,664,898	7,126,190	9,223,792	12,031,267	5,687,981	4,847,388	3,978,625	2,452,682	985,936	995,464
2010	1,031,281	1,860,191	2,665,972	7,762,982	10,151,952	12,860,692	6,098,996	4,754,612	4,017,741	2,561,356	1,085,594	1,003,046
2011	1,034,502	1,785,182	2,730,247	7,662,919	10,590,688	11,932,172	5,921,365	5,322,696	4,681,002	2,766,991	1,141,160	1,056,819

(Figure – 13)

1.3.6. How is the total discount distributed across different products?

To build the discount visual, the data was organized into a Pivot Table by dragging Customer Desc into the Rows area and Sum of Discount into the Values area. A Pie Chart was inserted to visualize how the total discount pool is distributed among various wholesalers. To make the chart more readable, data labels were added to show the percentage each customer receives, and a legend was included to help distinguish the different accounts at a glance.



(Figure – 14)

The pie chart above shows that nearly half of all discounts go to just a few big customers. Bavaria Bikes gets the biggest slice at 18%, followed by Beantown Bikes at 11% and Silicon Valley Bikes at 10%.

1.4 Critical Analysis of Using Excel Pivot Tables

From my experience working with this dataset, Microsoft Excel pivot tables are very effective for quickly exploring large amounts of transactional data. Since most business users are already familiar with Excel, it feels very accessible and easy to start working with. The drag-and-drop functionality of pivot tables made it simple to reorganize rows, columns, and values, allowing me to analyze revenue, sales quantity, discounts, and costs without needing to write complex formulas.

However, I also noticed some limitations while working with pivot tables and visualizations. As the analysis became more detailed, it was easy to lose track of applied filters, which could lead to confusion or incorrect interpretation if not checked carefully. In addition, while Excel provides many charting options, turning pivot tables into clean and professional-looking visuals often requires a lot of manual effort.

Overall, Excel pivot tables are extremely useful for initial basic exploration and everyday data analysis, especially for small to medium-sized datasets. They provide quick insights and flexibility with minimal setup. However, for more advanced analysis, more specialized analytical or visualization tools may be better suited.

1.5 Conclusion

Overall, Excel proved to be a practical and accessible tool for initial business data analysis. While it has some limitations when it comes to automation and advanced visual designing, pivot tables are highly effective for quickly summarizing data and supporting basic decision-making. This exercise demonstrated how even simple analytical techniques can generate meaningful insights when applied thoughtfully.

Chapter 2 Data Challenge with 'Sustainability' Data using Microsoft Excel for Cleansing and SAC for Visualization

2.1 Microsoft Excel vs SAP Analytics Cloud

i. The Power of Cleansing: Excel – Cleaning data in Excel is a deeply meaningful part of the data analysis process because it transforms a cluttered mess into a reliable dataset by allowing for a hands-on approach to cleaning out the junk, manually removing thousands of irrelevant rows and highlighting inconsistencies that would otherwise ruin the final analysis.

ii. Storytelling via SAP Analytics Cloud – If Excel is the engine room, SAP Analytics Cloud (SAC) is the stage where the data finally tells its story. Instead of getting lost in endless rows of numbers, SAC uses visual cues to make the most important trends jump off the screen immediately.

2.2 Datasets and Suggested Questions

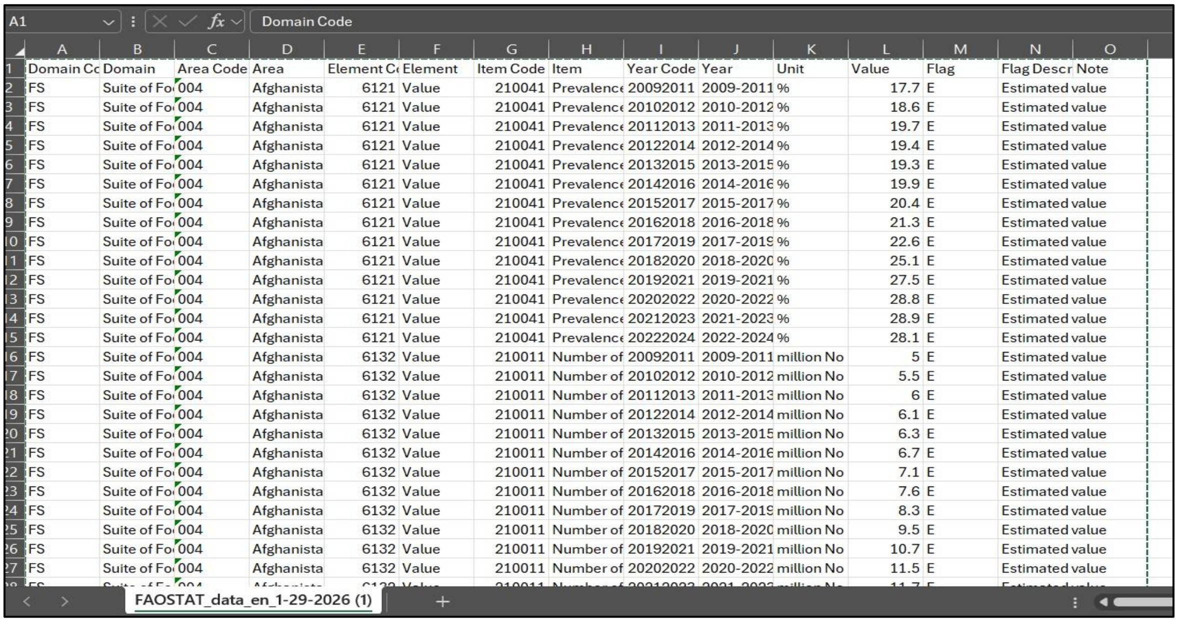
The analysis uses the FAOSTAT – Suite of Food Security Indicators dataset. Initially, the dataset included 27 indicators spanning 15 years. Data cleansing was carried out using Microsoft Excel to address missing values and inconsistencies. Following this process, 9 indicators with 7 years of reliable data were retained for analysis. On the other hand, The FAOSTAT – Emissions from Pre- and Post-Agricultural Production dataset was used to develop visualizations related to greenhouse gas emissions on SAP Analytics Cloud. The dataset contained the following variables: Area, Latitude, Longitude, Year, Emissions (CH_4), Emissions (CO_2), and Emissions (N_2O). The data cleansing process for this dataset followed the same structured methodology applied to the Food Security Indicators dataset. This included ensuring year-wise consistency, removing irrelevant or incomplete records, identifying and handling missing values, and retaining only those variables with sufficient data coverage for accurate analysis. Below are the questions on which the cleansing was done and visualization were crafted:

- How were irrelevant and unwanted columns identified and removed to align the dataset with the analytical objectives?
- How were three-year average columns restructured into a consistent annual format, and how was the RIGHT() function in Microsoft Excel used?
- How were missing and blank data points identified maintain analytical accuracy and comparability across countries and years?
- How was the final dataset further cleaned and validated to ensure it was fully analysis-ready?
- How does the contribution of (CH_4) emissions compare to CO_2 and N_2O emissions across countries?
- What is the emissions trend, and which specific pollutant shows the most significant steady increase over the ten-year period?
- For CO_2 emissions from 2014 to 2023, which countries demonstrate the highest contribution to global emissions?
- What is the emissions trend for N_2O emissions by area post-covid?

2.3 Application of Data Cleansing Techniques and Visualization Tool

2.3.1. How were irrelevant and unwanted columns identified and removed to align the dataset with the analytical objectives?

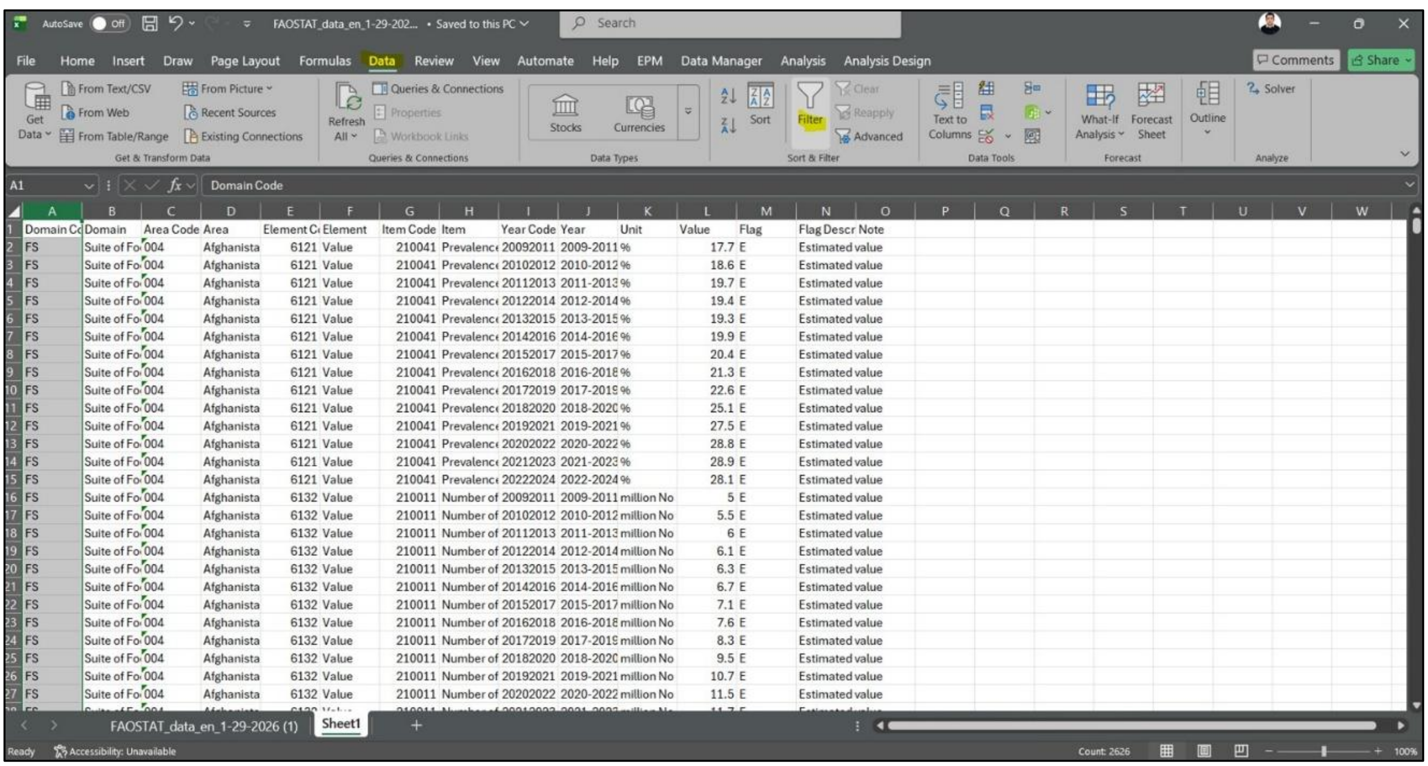
To get the FAOSTAT data ready for work, the first step was selecting the entire dataset to make sure not a single row, or entry was left behind (Fig.15).



Domain Cc	Domain	Area Code	Area	Element Cc	Element	Item Code	Item	Year Code	Year	Unit	Value	Flag	Flag Descr	Note
FS	Suite of Fo	004	Afghanista	6121	Value	210041	Prevalence	20092011	2009-2011	%	17.7	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6121	Value	210041	Prevalence	20102012	2010-2012	%	18.6	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6121	Value	210041	Prevalence	20112013	2011-2013	%	19.7	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6121	Value	210041	Prevalence	20122014	2012-2014	%	19.4	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6121	Value	210041	Prevalence	20132015	2013-2015	%	19.3	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6121	Value	210041	Prevalence	20142016	2014-2016	%	19.9	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6121	Value	210041	Prevalence	20152017	2015-2017	%	20.4	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6121	Value	210041	Prevalence	20162018	2016-2018	%	21.3	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6121	Value	210041	Prevalence	20172019	2017-2019	%	22.6	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6121	Value	210041	Prevalence	20182020	2018-2020	%	25.1	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6121	Value	210041	Prevalence	20192021	2019-2021	%	27.5	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6121	Value	210041	Prevalence	20202022	2020-2022	%	28.8	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6121	Value	210041	Prevalence	20212023	2021-2023	%	28.9	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6121	Value	210041	Prevalence	20222024	2022-2024	%	28.1	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6132	Value	210011	Number of	20092011	2009-2011	million No	5	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6132	Value	210011	Number of	20102012	2010-2012	million No	5.5	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6132	Value	210011	Number of	20112013	2011-2013	million No	6	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6132	Value	210011	Number of	20122014	2012-2014	million No	6.1	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6132	Value	210011	Number of	20132015	2013-2015	million No	6.3	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6132	Value	210011	Number of	20142016	2014-2016	million No	6.7	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6132	Value	210011	Number of	20152017	2015-2017	million No	7.1	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6132	Value	210011	Number of	20162018	2016-2018	million No	7.6	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6132	Value	210011	Number of	20172019	2017-2019	million No	8.3	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6132	Value	210011	Number of	20182020	2018-2020	million No	9.5	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6132	Value	210011	Number of	20192021	2019-2021	million No	10.7	E	Estimated value	
FS	Suite of Fo	004	Afghanista	6132	Value	210011	Number of	20202022	2020-2022	million No	11.5	E	Estimated value	

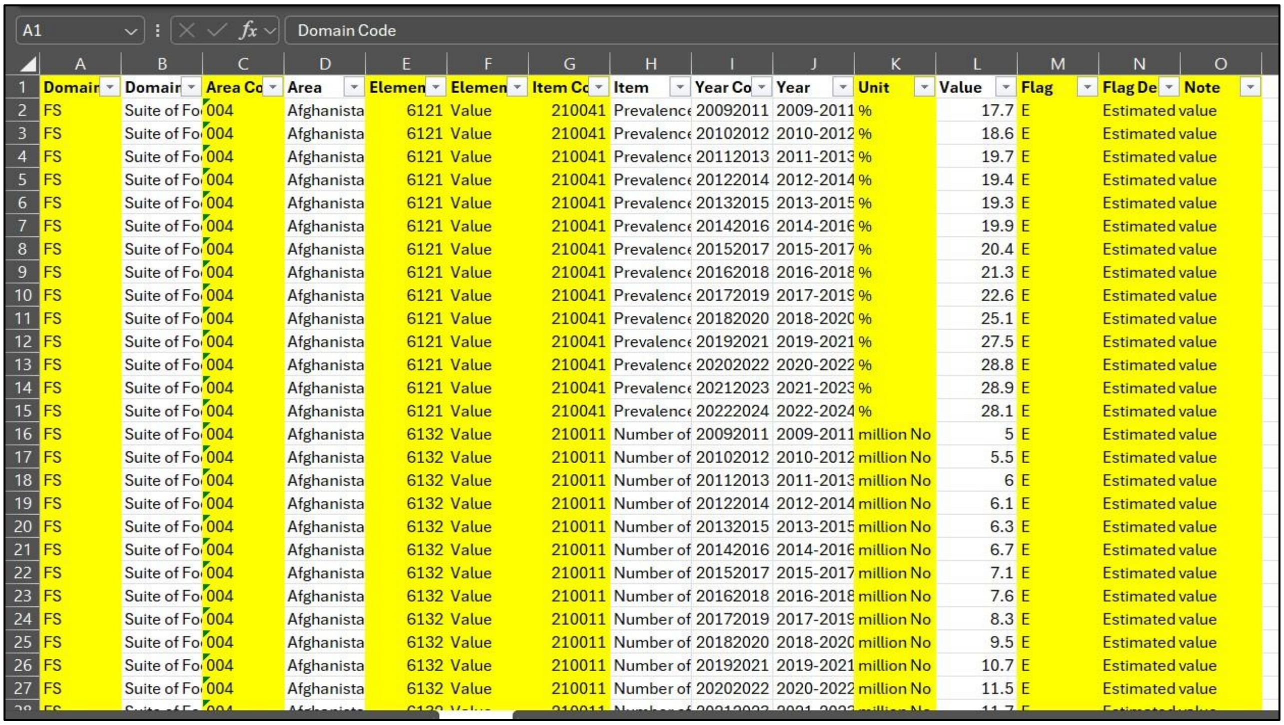
(Figure – 15)

Once everything was highlighted, the Filter tool was clicked for the header row, which allows quickly sorting through thousands of lines by country, year, or item type as shown in the (Fig.16).



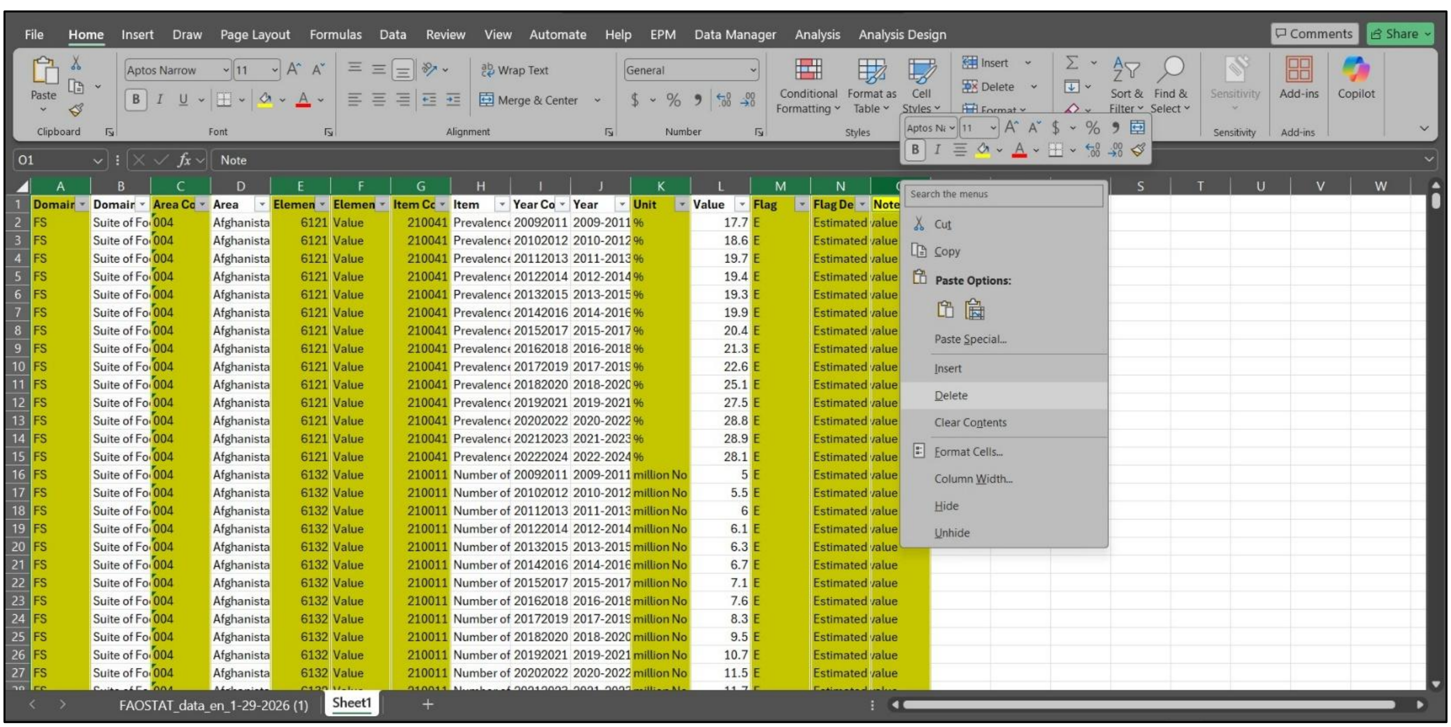
(Figure – 16)

With the filters in place, the next task was to figure out what was worth keeping. There were several columns — like domain, area code, elements, and flags etc. that didn't add any real value to the analysis, so they were highlighted in bright yellow in the picture below.



(Figure – 17)

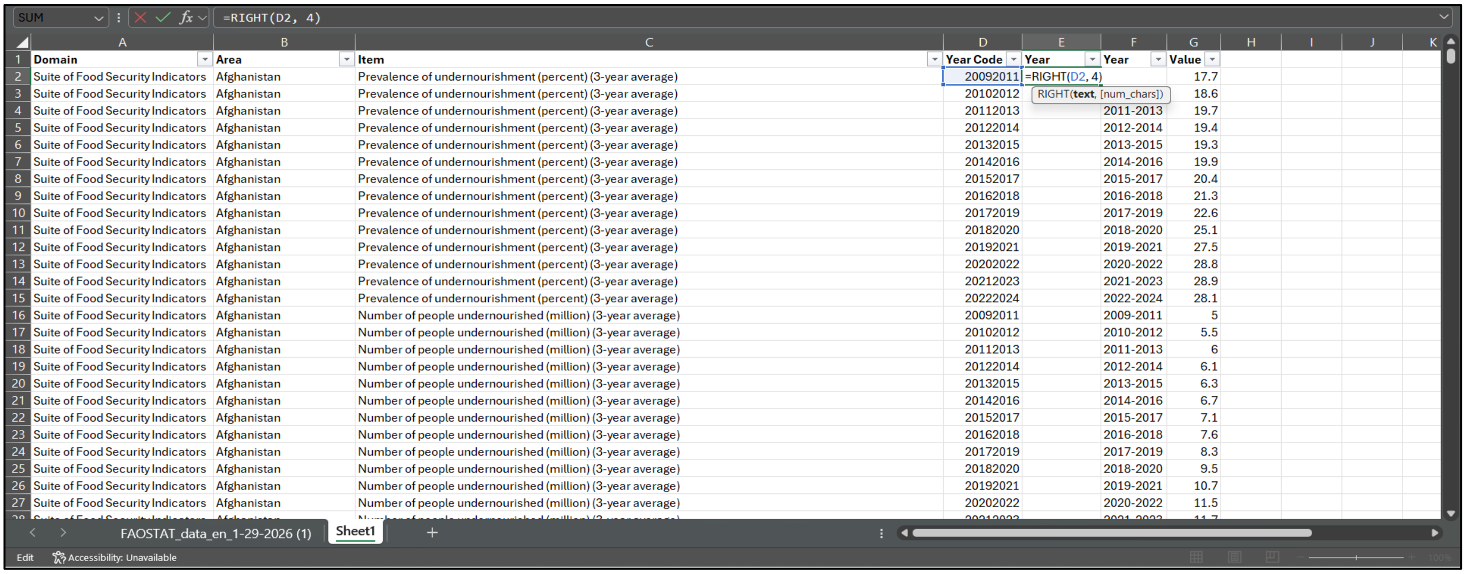
After selecting the entire dataset and applying filters to manage the information, the highlighted columns in yellow were deleted to leave behind a clean and focused spreadsheet as shown in (Fig.18)



(Figure – 18)

2.3.2. How were three-year average columns restructured into a consistent annual format, and how was the RIGHT() function in Microsoft Excel used?

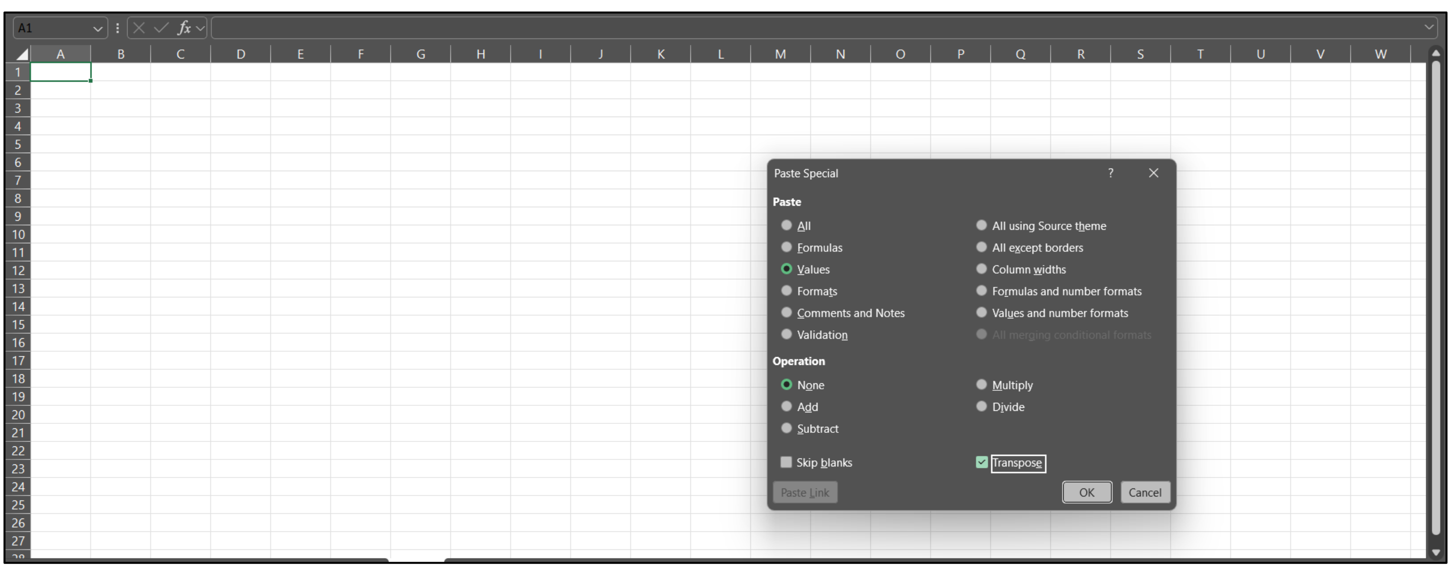
To extract year values, a new column named Year (Column E) was inserted next to Column D to extract absolute year values to ensure consistency. Within this column, the formula = RIGHT(D2, 4) was applied to extract the final four digits from the "Year Code". As shown in the visual (Fig. 19), this function converted range formats like "20092011" into a singular "2011" entry.



(Figure – 19)

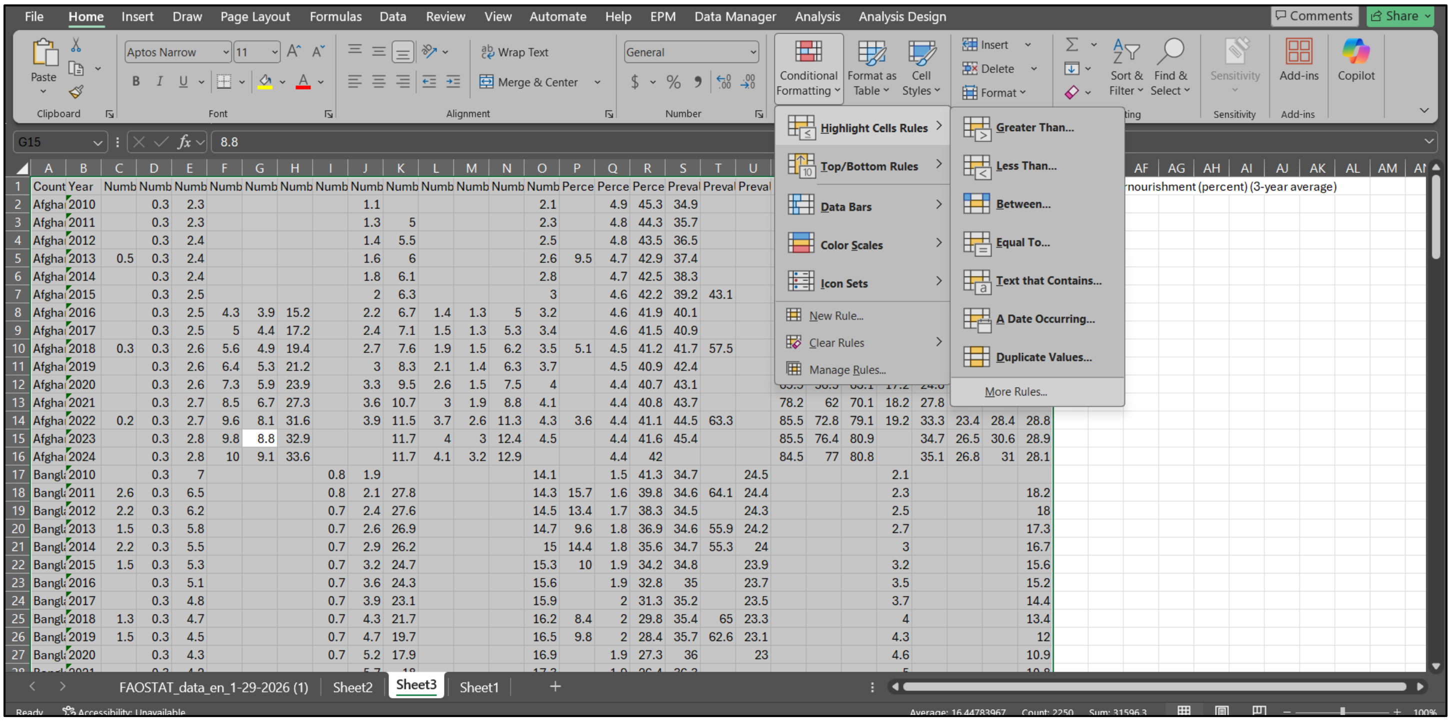
2.3.3. How were missing and blank data points identified maintain analytical accuracy and comparability across countries and years?

After ensuring consistency across all selected columns, a new worksheet was created. The cleaned data was copied and pasted as values using the TRANSPOSE function to restructure the dataset and align columns and years in a consistent, analysis-ready format, as shown in Figure 20.

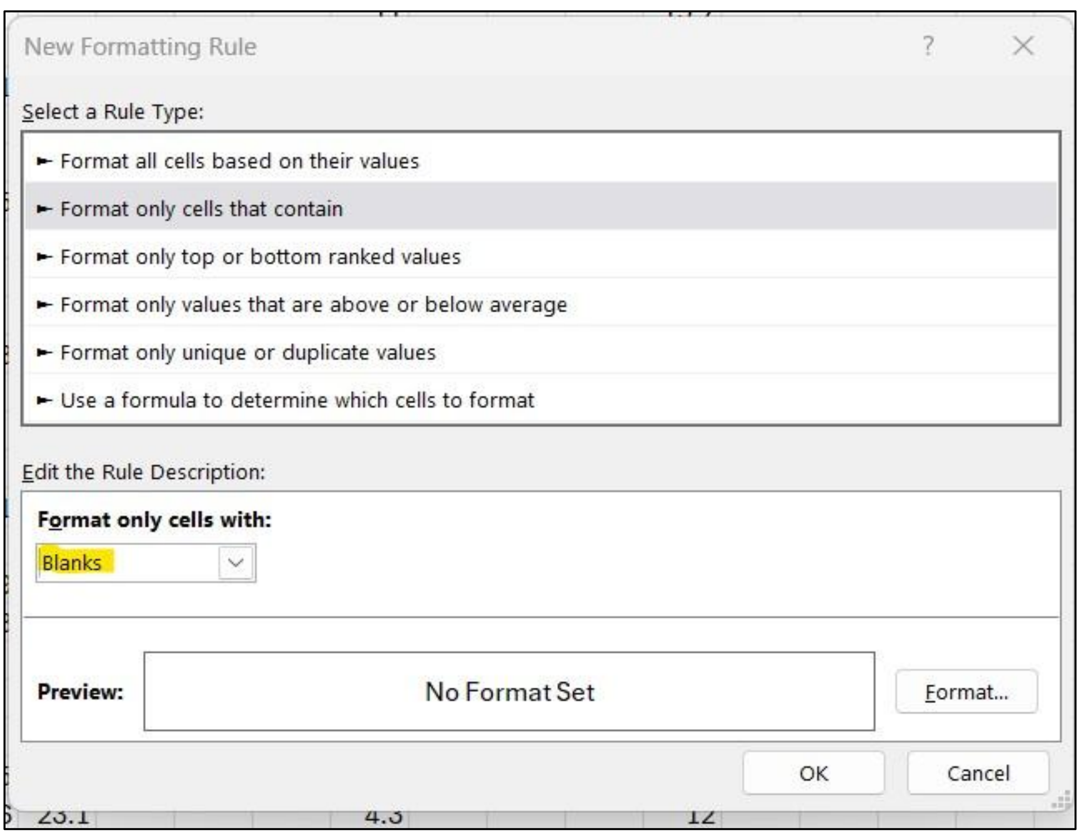


(Figure – 20)

Once the data was consolidated, a substantial number of null and blank values were observed across multiple columns. To identify these gaps, the dataset was copied and the Conditional Formatting feature was applied to highlight missing values. Blank cells were visually flagged in yellow, enabling clear identification and assessment of data completeness, as illustrated in Figures 21 and 22.



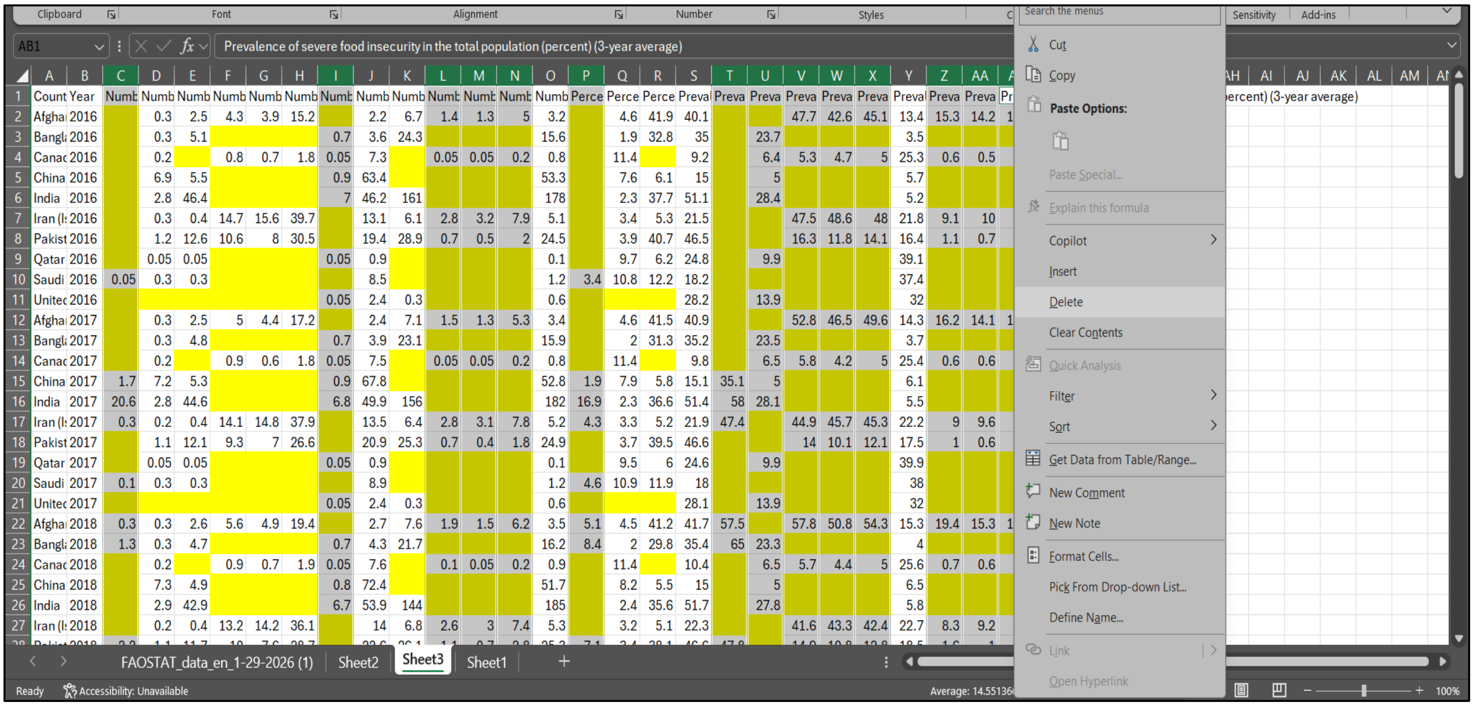
(Figure – 21)



(Figure – 22)

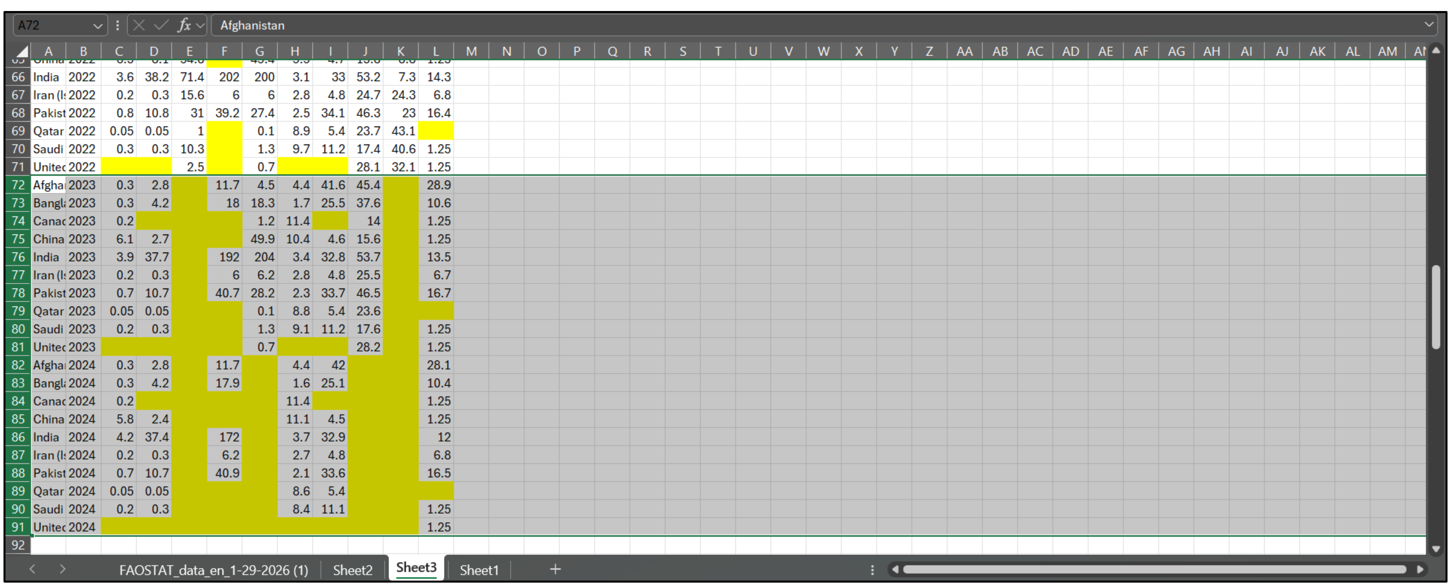
2.3.4. How was the final dataset further cleaned and validated to ensure it was fully analysis-ready?

To finalize the data cleaning process, the dataset was first sorted on a year basis to ensure proper temporal alignment across all columns. Following this, columns were reviewed to assess data completeness. Columns containing a high proportion of null or missing values were identified and selected for removal as shown in Figure 23.



(Figure – 23)

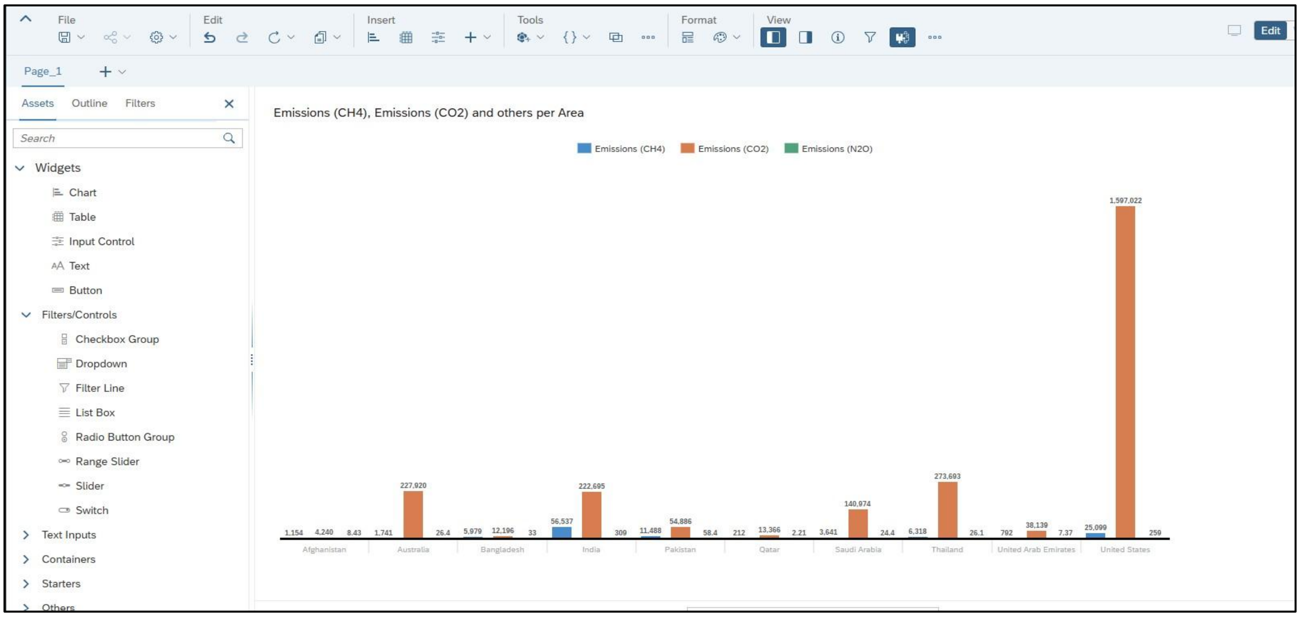
These columns were then deleted in a stepwise manner, retaining only those columns with sufficient and consistent data coverage across countries and years. This remaining iterative cleaning process is illustrated in Figure 24.



(Figure – 24)

2.3.5. How does the contribution of methane (CH_4) emissions compare to CO_2 and N_2O emissions across countries?

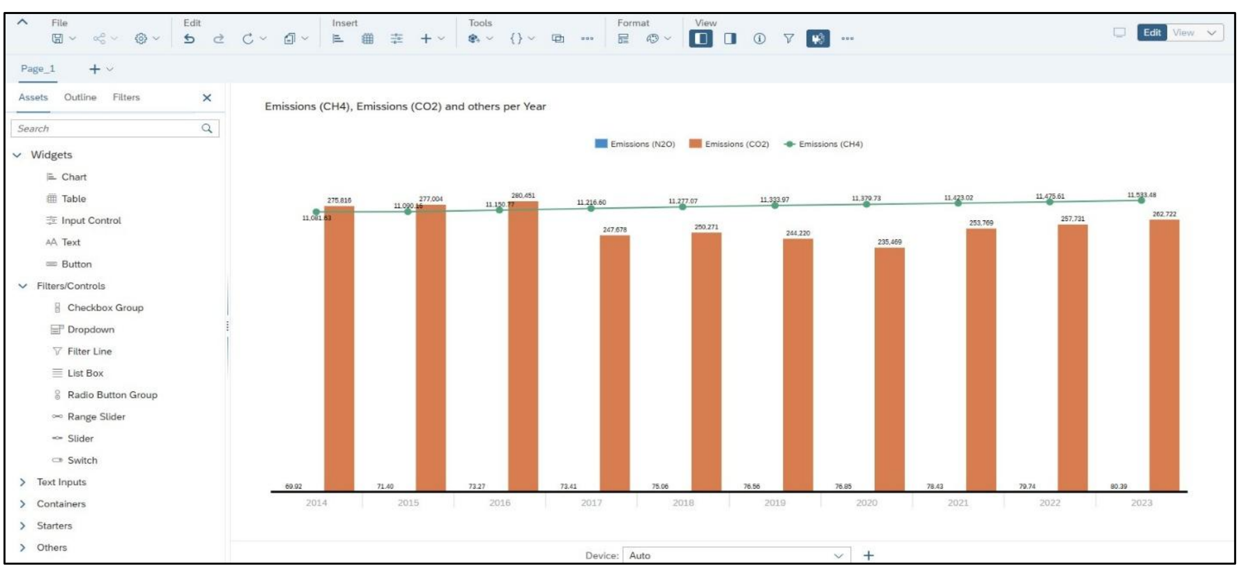
(CH4) emissions are significantly lower than CO2 emissions across all observed areas but remain noticeably higher than (N2O) emissions. Countries with large agricultural sectors such as India, Pakistan, and the United States show relatively higher CH4 emissions, suggesting the influence of livestock production and rice cultivation. However, CH4 does not exceed CO2 in any country, indicating that CO2 remains the primary emission source in (Fig. 25).



(Figure – 25)

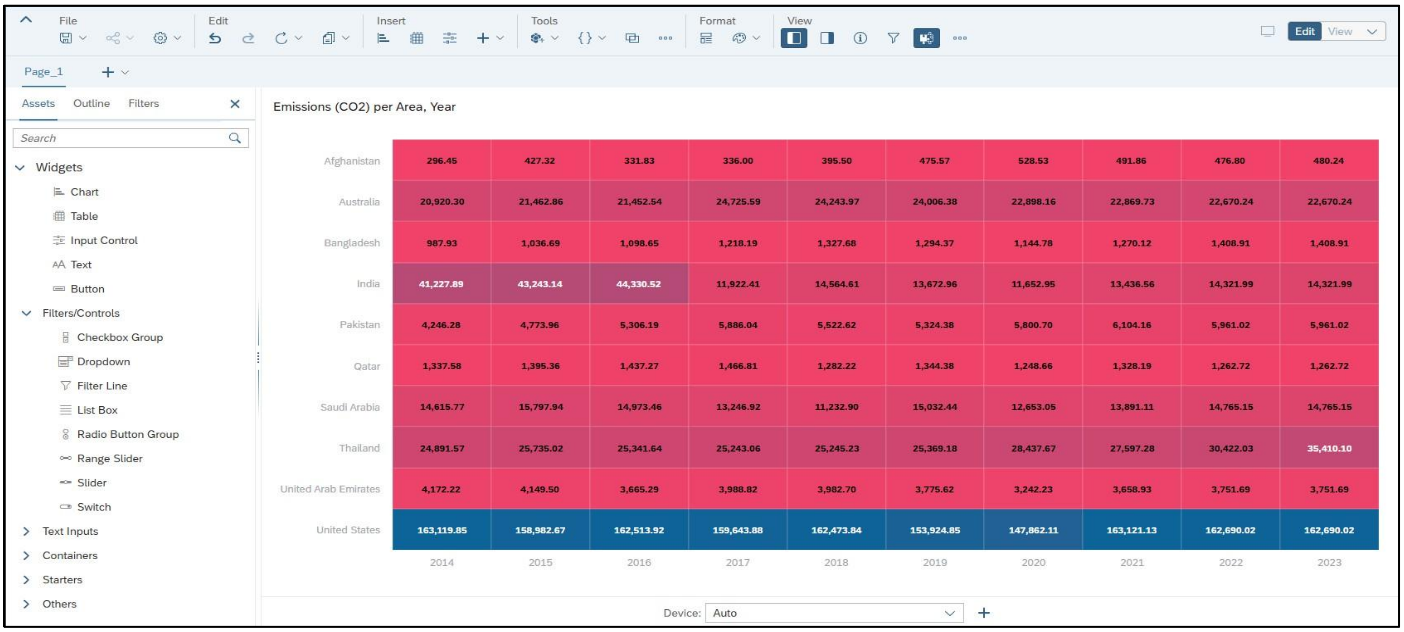
2.3.6. What is the emissions trend, and which specific pollutant shows the most significant steady increase over the ten-year period?

Figure 26 highlights a mix of steady growth and unexpected dips. CH4 is the most consistent; it has climbed every single year without fail, starting at 11,081.63 and hitting 11,533.48 by 2023. On the other hand, CO2 levels are much worse. While it hit a massive peak of 280,451 back in 2016, it actually saw a significant drop over the next few years, bottoming out around 2020 before starting to climb again recently. Finally, while N2O exists in much smaller volumes, it has quietly grown from 69.92 to over 80 in the same period, following the general global trend of rising emissions.



(Figure – 26)

2.3.7. For CO2 emissions from 2014 to 2023, which countries demonstrate the highest contribution to global emissions? The heatmap clearly in the figure 27 shows the US as the top emitter, with values consistently high between 162,000 and 163,000. India experienced a major change, dropping from over 40,000 to the 11,000 – 14,000 range after 2016, which drastically lightened its color on the map. Meanwhile, Thailand's emissions climbed from 24,891 to over 35,410, showing steady industrial growth.



(Figure – 27)

2.3.8. What is the emissions trend for N2O emissions by area post-covid?

Post-COVID, the waterfall chart describing N2O trends show a sharp divide between rising and falling emitters. India and the United States saw the biggest surges, reaching totals of 132 and 105, respectively, by 2023. Bangladesh also trended upward during this period. Conversely, Pakistan and Qatar managed to reduce their emissions, marked by consistent yearly declines. Australia and Thailand stayed almost entirely flat with minimal change to their footprints as shown in (Fig.28)

(Figure – 28)

2.4 Critical Analysis: Excel vs. SAP Analytics Cloud

Excel was highly effective for hands-on data cleaning tasks, enabling quick filtering of irrelevant rows and the use of conditional formatting to identify missing or blank values. Functions such as RIGHT() were critical for transforming inconsistent three-year average strings into clean, annual date values. However, Excel requires caution, as manual operations like deleting highlighted columns can introduce errors if not carefully managed. Once cleaned, the data was transferred to SAP Analytics Cloud (SAC), shifting the focus from preparation to analysis. While Excel supports detailed tabular work, SAC excels at pattern discovery. For instance, the Heat Map clearly exposed the emission gap between the United States and other countries, and the Waterfall Chart effectively highlighted country-level contributions to the Post-Covid N2O increase insights that are difficult to extract from spreadsheets alone.

2.5 Conclusion

To sum up, Excel is where the messy work happens, while SAP Analytics Cloud is where the results actually come to life. Excel is the perfect tool for getting hands-on with the data cleaning out the junk, highlighting what wasn't needed, and fixing broken dates so everything lined up correctly. It took a confusing pile of information and turned it into a solid, organized base. The real discoveries, though, happened in SAC. Instead of staring at endless rows of numbers, visuals like the Heat Map and Waterfall Chart made it obvious where the biggest problems were, like the sudden shifts in India’s data or the rising trends in the US. In short, I believe Excel makes the data clean, but SAC makes the data make sense.