Cross-Border Environmental Collaboration for Climate Governance

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Abstract- This paper aims to conduct a network analysis to map the actors involved in climate action towards the achievement of the Paris Agreement. We are extracting data from the Global Climate Action portal (GCAP) where we will be analysing collaboration between individual countries on cooperative initiatives aimed towards mitigating climate change. Focusing on initiatives that took place from 2021-2022, this study reveals 14.764 connections between 193 countries. This analysis will shed light on how actors with common agendas interact and potentially influence policy directions and initiatives.
Keywords: climate change, cross-border collaboration, global network

I. INTRODUCTION

Climate change is a global challenge that requires coordinated efforts at both international and national levels. Thus, cross-border environmental collaboration is of paramount importance in addressing climate change. International climate agreements and national climate policies play a crucial role in addressing this critical issue as many countries are aiming to achieve them. Therefore, we will explore individual actors and their engagements in climate action using the progress-tracking framework of the Global Climate Action Portal (GCAP). On the portal, currently, 32,522 actors are engaging in climate action. We will be exploring the 196 countries collaborating on 149 International cooperative initiatives (ICIs). This data highlights cross-border collaboration amongst non-state and subnational actors including cities, regions, businesses, investors, and other organisations [1]. Our focus is limited to countries collaborating between 2021-2022 aiming to achieve the Paris Agreement in alignment with the UN Sustainable Development Goals (SDGs).

This paper aims to adopt a multi-sectoral approach to analyse cross-border environmental collaborations and discern which countries' approaches align with global climate objectives. The end goal is to create visualisations of the climate governance network to help stakeholders and policymakers better understand the complex web of actors and their interactions.

Furthermore, the paper aims to assess clusters of actors within the climate governance network and discern if actors within the same cluster tend to have more aligned climate goals.

II. LITERATURE REVIEW

As climate change is becoming a global issue, countries are aligning on a singular objective to achieve the Paris Agreement initiated by the United Nations Framework Convention on Climate Change (UNFCCC) to adapt to, and mitigate, the effects of climate degradation. This alignment between multiple stakeholders is a form of environmental governance (EG) [2]. The Agreement expects developed countries' parties to create economy-wide policies that address the increasing amount of greenhouse gas emissions. Moreover, it expects the developing countries' parties to implement mitigation efforts to limit these emissions [3]. Per the Agreement, countries are expected to create Nationally Determined Contributions (NDCs), which many have updated to achieve the 17 Sustainable Development Goals. This update has increased the activities aimed at reducing the effects of climate change as many countries are taking an active role in fulfilling Goal 13 of climate action [4].

Moreover, to expect collaborations on an international level, it is pertinent that we assess the collaborative efforts taking place on a national level. Many of these efforts can take the form of policy implementation frameworks, like the Irish Climate Action Plan's implementation network aimed toward fulfilling Ireland's *Climate Action Plan 2019* [5]. Such networks include state and non-state actors since their involvement enables a comprehensive approach [6]. This approach, when tested by a multi-level and cross-sectoral analysis, yielded that certain actors, like the Sustainable Energy Authority of Ireland and the Department of Communications, Climate Action and Environment play the role of bridging actors that facilitate resource circulation and knowledge transfer within the network [5]. Therefore, these actors within the network serve as intermediaries for information exchange across various sectors, as a way to bridge potential gaps between governmental bodies and other stakeholders.

Furthermore, collective action to enhance climate governance is also dependent on who the actors are and what their intentions entail to discern effective collaboration networks [7]. Various countries and regions within global climate governance may collaborate on similar goals, but the networks between such countries are sometimes fragmented [6]. This is why it is important to consider both social and ecological dimensions in collaborative environmental governance as explored through a network analysis of collaborative environmental action which entails how the structure of collaborative networks contributes to governance outcomes and how it interacts with agency and leadership [7]. It is pertinent to identify and address these structures to analyse the power dynamics present among actors working towards climate goals.

Similarly, these power dynamics can be seen in multi-level governance. A theoretical framework that looks at land use sectors of Indonesia and Brazil shows that collaboration and communication are hindered by power imbalances within different levels of governance [8]. These networks entail the importance of considering various factors that can affect the role a country plays toward global climate action because not all actions will be aimed toward tangible outcomes as some might be influenced by individual actors' interests [7]. Moreover, the establishment of collaborative networks is not a guarantee of effective environmental problem-solving which is why it is important to assess the contribution of specific network structures to governance outcomes [7]. Therefore, analysing network structures helps in highlighting various actors with diverging interests and assessing their roles comprehensively.

Moreover, many countries are facing adverse effects on their natural resources due to the effects of climate change. This becomes an issue as many people's livelihoods depend on these resources. The Guinea Current Large Marine Ecosystem (GCLME) is an area where coastal states like Benin, Nigeria, and Cameroon exist [9]. dependence on oceanic resources is hindered by the lack of institutional frameworks aimed towards cross-border ocean governance [9]. These areas are dependent on collaboration and communication which is required to address the issues collectively. Therefore, to support such needs, transboundary networks have emerged as a way to create an opportunity for multi-stakeholder collaboration [2]. Due to the lack of a consistent framework to understand and assess transmitted effects, it acts as a systematic approach that draws from research on transboundary risks and cross-border spillovers [10].

Similarly, the transboundary network of "MAP Initiative" in the tri-national frontier consists of Madre de Dios (Peru), Acre (Brazil), and Pando (Bolivia) of the southwestern Amazon, where diverse stakeholders exist with different interests, facilitated collaboration by providing spaces for cross-border dialogues and offering opportunities for innovative capacity building [2]. Therefore, transboundary networks enhance collaborative efforts on an international level and help progress steps taken towards climate change mitigation.

The concept of cross-border governance, therefore, provides us with a framework aimed toward achieving a policy or a goal such as one about climate change [11]. And, a strong policy convergence across borders has the potential to enhance environmental mechanisms aimed toward global climate action [9]. Moreover, the formation of transboundary networks has the potential to focus on the network's structural and strategic dynamics to enhance its contributions towards environmental governance [2]. Therefore, using the transboundary approach, our paper will not only assess and map the cross-border environmental collaboration for climate governance but also analyse the countries' mechanisms and frameworks established for cross-border governance, and their effectiveness in achieving climate-related policies and goals.

III. METHODOLOGY

We gathered our data set from the Global Climate Action Portal (GCAP) made by the United Nations Framework Convention on Climate Change (UNFCCC). This process involved data extraction, cleaning, and the derivation of network values to analyse the structure of the graph and its properties. The aforementioned structures and properties aided us in identifying their real-world implications, from which we assessed the strengths and weaknesses.

The data website had robust security measures in place to prevent bot traffic and conventional scraping techniques using BeautifulSoup and Selenium and had rate limits enforced per IP. They enacted these restrictions by having a simple "request challenge" that browsers could solve and hence legitimate traffic was able to browse the site without issues. To make this efficient, the site would set a "Cookie" that would indicate a "trusted session" aka a user that the site previously verified as "good traffic". We picked up the Cookie by inspecting the request data in the network tab of the browser and made simple HTTP requests by using the requests package in Python. We also extracted all the data in 2 API calls to get around the rate-limiting and then cleaned the data.

Furthermore, for this study, we employed a tri-brid data cleaning method that incorporated manual cleaning, the programming language R, and the JSON package in the libraries of Python and R. This methodology provided a robust and systemic approach to ensuring the highest possible level of data quality and accuracy.

Below, we break down the tri-brid method and explain each:

1. Manual: The first stage of our data cleaning process involved a manual inspection of the data. We were able to identify any mistakes, discrepancies, or missing data during this stage that needed to be addressed. Through manual cleaning, we were able to use our critical thinking abilities to guarantee the dependability and correctness of the data.
2. R: Moving on, we utilised this programming language to automate the cleaning process. R offers a wide range of tools and functions for data manipulation, transformation, and analysis. For eg. we used R to visualise the mass amounts of data that were extracted. From there onwards, we converted this data to make it JSON compatible, which would then facilitate its integration into other data processing and analysis pipelines.
3. JSON Package in the Python Library: The third and final stage in the process of cleaning involved the usage of JSON package to clean and finalise the data. Here, the cleaning involved the handling of missing values. The code provided loads data from 'data3.txt' into a JSON object and writes the relevant 'country' information into a CSV file named 'output.csv'. It associates each initiative with its respective country, or an empty string if no country is found. The script then confirms completion by printing a message stating the successful transfer of data written into 'output.csv'.

As a result, the tri-brid data cleaning approach we used was able to effectively handle the difficulties and complexity associated with cleaning actual data. In a thorough and organised approach to data cleaning, this technique illustrated the value of human cleaning combined with automated tools and transformation. The effectiveness of the data-cleaning procedure was further improved by the integration of the R programming language and JSON package.

The output.csv file needed to be visualised as the following stage in our process. The script was written in R, and the output was a bipartite graph. We listed all of the files in the current directory and showed the result as we needed a unipartite graph. Each row in the "output.csv" file corresponds to one edge in a graph that can be found in the edge list of the graph. Since the first result we had was a bipartite, we used the edge list to generate an undirected graph. This allowed us to filter the graph data to only include the vertices that had a non-empty "Country" attribute within. By calculating the bipartite mapping for the filtered graph, the mapping then assigns values to Project 1 and Project 2. The next step was to save the resulting bipartite projections as two separate unipartite graphs in the GraphML format. This was a crucial step for visualisation, as the previous graph resulted in bipartite projects which denoted a relation between projects and countries. Although it was what we required, to visualise data properly and in accordance, we divided them into two separate projects aka Project 1 representing the Initiatives, and Project 2 representing the Countries. These would then allow us to properly analyse the relationships between the initiatives and countries.

After obtaining the final files titled "unipartite_countries.graphml" and "unipartite_projects.graphml", we used the igraph library function in RStudio to gain the statistical values and we directly imported them to Gephi as "updated_unipartite_countries.graphml" to generate the final graphs that would aid in visual analysis.

IV. RESULTS

For the results, we used the unipartite graph for countries to create visualisations. The cross-border environmental collaboration unipartite network that we created between 193 countries revealed 14,764 connections amongst each other on international cooperative initiatives (ICIs).

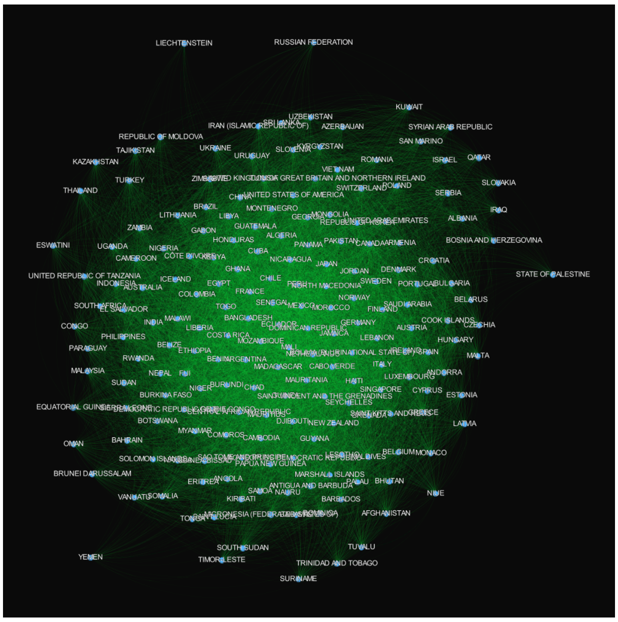

Fig. 1 Cross-border environmental collaboration network where nodes are countries and edges are collaborations between them on ICIs.

As shown in Fig 1, the network is very dense with highly inter-connected nodes. Based on the R values, this intricate network topology reveals a high graph density of 0.7968, showing a robust structure. The compact diameter of 2, combined with an Average Path Length (APL) of 1.20315, hints at a network that is characterised by efficiency in communication and small-world properties within the network.

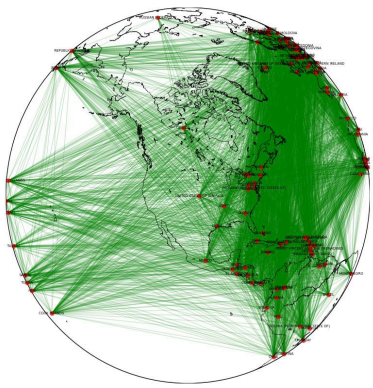

Fig 2. A GeoMap of all the countries showing Small-world properties.

As shown in Fig 2, the countries are strongly collaborating amongst each other, thereby, allowing a streamlined flow of information, and higher collaborative efforts amongst countries on climate initiatives. Moreover, we obtained a global clustering coefficient of 0.8674, which revealed a high propensity for collaborating countries to merge into cohesive clusters, therefore fostering localised collaborative ventures. Furthermore, to find groups of countries with strong internal connections, we utilised a community algorithm of modularity optimisation to find substructures that exhibit high internal connectivity and lower connectivity with the rest of the network.

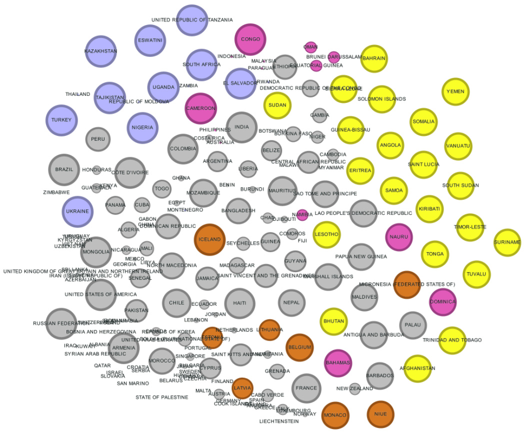

Fig 3 . Modularity optimization at a 0.7 resolution and with no edge weights to find communities within the network.

As shown in Fig 3, there are two distinct broad communities visualised to show a division where countries within each community participate in similar types of collaborative activities. Countries within each community likely share common goals and agendas regarding climate change.

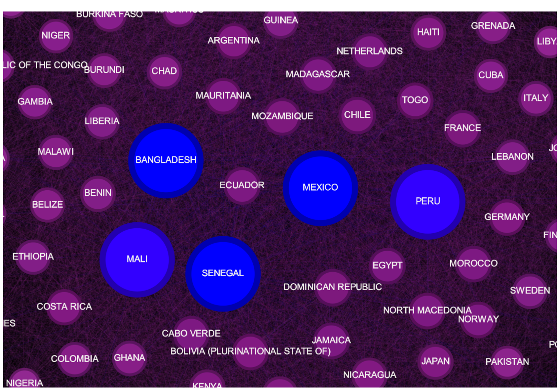

Fig 4. Nodes with the highest degree of centrality are coloured blue.

Moreover, we also identified central actors in the network. As shown in Fig 4, the network displayed many nodes as hubs with five specific nodes having the highest degree of 190, namely, Bangladesh, Mexico, Senegal, Peru and Mali. In relation to minimal degree centrality, “Liechtenstein” has its centrality at 19, which places it at the outskirts of the network, making it an outlier.

Further metrics used to analyse the network were Closeness Centrality, Betweenness Centrality, and Eigenvector. The contrast in Closeness Centrality is shown by “Bangladesh” as it has a higher closeness centrality, of 0.005155, thereby a shorter APL. “Liechtenstein”, on the other hand, has the shortest closeness centrality of 0.00273, thereby making it have the longest APL to other nodes. These values are important because they show that Bangladesh enjoys the position of strategic collaboration. Due to being resilient in the network, it becomes a point of efficient flow of information and allows Bangladesh to act as an intermediary for other countries.

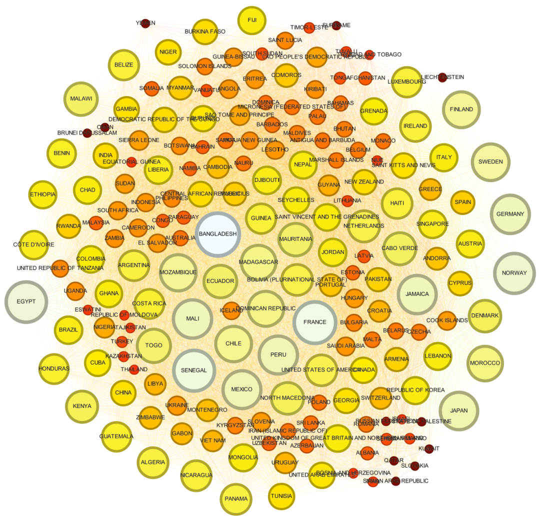

Fig 5. Betweenness centrality: the higher the centrality, the lighter and bigger the node is.

Moreover, in terms of betweenness centrality, as shown in Fig 5, we found “Bangladesh” as the highest betweenness centrality at a normalised value of 0.00283. This value alludes to Bangladesh facilitating connections across the regions, which would otherwise not be connected to each other perhaps due to differing goals and international relations. Lastly, our findings resulted in revealing “Mali” as the node with the Highest Eigenvector Centrality at 1. Therefore, it shows Mali’s importance within the network due to being connected to more influential neighbours. It allows Mali to itself become influential through its well-connected neighbours.

V. DISCUSSION

The environmental collaboration network demonstrates salient features which are indicative of a Barabâsi-Albert network, characterised by a noticeable power-law degree distribution.

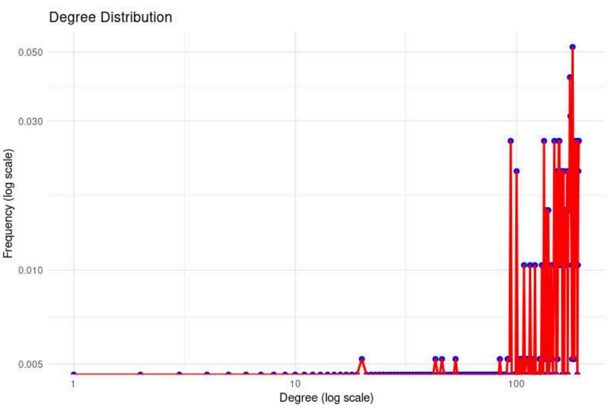

Fig 6. Degree Distribution

The observed degree distribution in Fig 6 conforms to a power-law function:

$$P(k) \sim k^{(-\gamma)}$$

Here, the parameter falls within the empirically observed range of 2-3. This advanced structural property indicates a network of heterogeneity. Whilst some countries actively collaborate with numerous others, the majority chooses a more restricted number of connections. This pattern of distribution contributes to the overall resilience of the network because it allows for a diverse range of collaborations; widespread to focused partnerships among the influential hubs.

Our collaborative network's expansion dynamics strongly support the Preferential Attachment principle, which is a fundamental concept of Barabási-Albert networks. In line with preferential attachment, in which newly connected nodes have a tendency to form high-degree connections with already-existing nodes, our collaborative environment shows that countries that are heavily involved in international environmental initiatives tend to draw in more connections over the course of time. The aforementioned occurrence leads to the formation of significant hubs that can potentially increase climate action towards the achievement of the Paris Agreement.

In addition, the network exhibits Small-World property, which is defined by the short average path lengths among the participating countries. Even with the 193 countries involved, the average number of steps needed to connect two countries is still low. This quality facilitates effective communication and a streamlined flow of information, both of which are essential to the success of international cross-border cooperation.

Moreover, some interesting things we noted were that despite having different agendas and complicated international relations, many countries still align and work collaboratively when it comes to global climate objectives. Globally, Russian-Ukraine relationships are unfriendly. In the network, Russia has the second lowest degree centrality of 42. However, despite these circumstances, one of Russia’s neighboring nodes is Ukraine. It shows that there is some level of interaction or cooperation between these two countries.

Moreover, the presence of densely linked hubs and central actors plays a crucial role in the dissemination of information. In this network, Bangladesh enjoys the central position of a hub and the highest betweenness. This result was the most unexpected for us as the expectation was that highly developed countries would be more proactive with climate action. However, it should be noted that Bangladesh is vulnerable to the extreme effects of climate change and it is great to see that Bangladesh is actively trying to participate in international cooperative initiatives to reduce carbon footprint. The high betweenness shows give it a strategic position that can allow more developed countries to reach less developed countries through Bangladesh.

Moreover, policymakers, environmental groups, and stakeholders can benefit from the critical insights provided by the environmental cooperation network's observed features. Firstly, the significance of focused cooperation is highlighted by the knowledge of the power-law degree distribution and the existence of significant hubs. Policymakers can engage these countries strategically in order to promote larger collaboration. This is something that policymakers may use to improve the efficacy of global climate initiatives. Given the network's susceptibility to intentional attacks, governments and organizations are urged to strengthen their partnerships with these countries and implement preventative measures around prominent hubs.

VI. IMPORTANCE OF UNIPARTITE

At the beginning of this paper, we mentioned the breakdown of "unipartite" and "bipartite". Our first observed bipartite environmental collaboration network is later transformed into unipartite graphs to improve the intricacy of our network research. Bipartite structures, which capture interactions between discrete groups of entities, are inherently complicated, therefore a closer examination of the underlying dynamics of each participating entity—countries and initiatives—was required.

We attempted to optimise the analytical process by dividing the collaborative landscape into two unipartite graphs: one for Initiatives and the other for Countries. By using network metrics designed for individual networks, this method enables a detailed analysis of the functions and importance of Initiatives and Countries in their own networks.

This split made it possible to look more deeply at crucial network metrics including eigenvector centrality, betweenness centrality, and degree centrality. Moreover, unipartite graphs are easier to understand and recognize. The creation of simple graphics that emphasize the linkages and organizational structures that set Initiatives apart from Countries is made possible by this distinction. Purposefully keeping things simple makes it easier for us to share our findings with a larger audience and to perform our analysis.

Additionally, unipartite graphs allowed further analysis, such as cluster identification and community exploration inside each set. Although difficult to implement directly on bipartite structures, these studies help to clarify the dynamics of collaboration between Initiatives and Countries.

VII. LIMITATIONS

While our study provides insights into the structural dynamics of the environmental collaboration network, there are some significant limitations to be mindful of that may limit the generalizability of our conclusions. The first factor affecting the quality and completeness of the data downloaded from the Global Climate Action Portal (GCAP) was the information accessibility of the platform. Due to heavy restrictions on access to data, streamlining the process of extraction can potentially become a hindrance for future analysis over time.

Moreover, due to the scope of the project, we omitted to look closely at the connections among non-state actors, subnational organisations, and other stakeholders, preferring to focus on the network of cooperation among countries. Given the critical role these organizations play in climate action, this narrow focus might impede a comprehensive understanding of the entire climate governance network. Although, there was a purpose behind this. If we had extended our dataset to include companies, NGOs, etc., we risked not completing this research on time. Thus, we sacrificed a larger dataset in order to complete what is, in our opinion, the first step towards a wider base for research.

Ultimately, maintaining the current relevance of our results is a problem given the changing nature of environmental policy and international relations. The features and structure of the network may change in ways that our static study was unable to predict when new initiatives and changes in the geopolitical scene take place. For a more comprehensive view of global environmental collaboration, additional research addressing these limits is encouraged.

Furthermore, we have discussed nodes that enjoy a central position in this paper, however, we did not look at notes with relatively less importance and low amounts of connections compared to other countries. This can potentially be an interesting place of research to assess why certain countries are more disconnected from the global climate network. Through the support of literature, we can identify reasons behind those countries' lack od participation in international cooperative initiatives.

Lastly, this study relied on datasets that focused on data from the years 2021-2022. Therefore, any new information from 2023 could not be input during the time of this research. And, any data prior to 2021 not being included, presents a limitation of restricted tracking and analysis.

VIII. CONCLUSION

Conclusively, this research gives an in-depth understanding of the structural dynamics of the environmental collaboration network, revealing characteristics suggestive of a Barabási-Albert network. The network is resilient in fostering worldwide collaboration on climate-related efforts due to its attributes such as preferential attachment, power-law degree distribution, heterogeneity, and small-world features. The hubs and clusters can potentially provide policymakers with important information, highlighting the importance of strategic engagement for larger-scale collaboration.

Transitioning from a bipartite to a unipartite network improves analytical clarity by enabling an in-depth investigation of particular entities, such as Countries and Initiatives. With the use of unipartite graphs, we can better comprehend connections, influence, and centrality.

Furthermore, these findings have the potential to strategically increase global collaboration among policymakers, environmental organisations, and stakeholders. Reiterating alliances and putting preventative measures in place around prominent hubs is crucial, as highlighted by the network's vulnerability to deliberate assaults.

However, it is essential to acknowledge the limits of the study. International relations and environmental policy may change over time, as evidenced by the analysis' static character and dependence on data from 2021–2022. Furthermore, the study's concentration on the international cooperation network leaves out a detailed analysis of the connections between non-state actors and subnational organisations, which calls for more research to provide a deeper understanding of global environmental collaboration. Notwithstanding these drawbacks, this project establishes the groundwork for further study and policy advancements in the field of cross-border environmental collaboration.

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