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EMD Analysis of Annual Rainfall in Chennai

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***Abstract*: This paper presents an in-depth Empirical Mode Decomposition (EMD) analysis of the annual rainfall in Chennai, India, covering the period from 1901 to 2021. EMD is employed to decompose the complex and non-linear rainfall time series into intrinsic mode functions (IMFs) and a residual trend component, thereby revealing underlying patterns and periodicities in the data. Six IMFs and one residue were extracted, each representing different frequency components and long-term trends. The results highlight significant oscillatory modes linked to various climatic phenomena, such as the El Niño-Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD), which impact Chennai's rainfall. Furthermore, the long-term residue indicates notable trends that have implications for understanding climate change effects in the region. The insights derived from this EMD analysis can inform water resource management, agricultural planning, and urban development strategies in Chennai, providing a foundation for improving resilience to climatic variability and extreme weather events. The study also underscores the potential of integrating EMD with advanced machine learning techniques to enhance rainfall prediction accuracy, paving the way for more effective climate adaptation measures.**

I. Introduction

Understanding the variability and trends in annual rainfall is crucial for water resource management, agricultural planning, and disaster preparedness, especially in the context of increasing climate variability. Climate change has been associated with shifts in monsoon patterns, more frequent extreme weather events, and overall changes in precipitation intensity and distribution. Chennai, located on the south-eastern coast of India, is particularly vulnerable to these variations due to its reliance on monsoon seasons. Changes in global climate systems, such as rising temperatures, melting polar ice, and the increasing frequency of El Niño events, could profoundly affect Chennai's rainfall patterns, exacerbating the region's susceptibility to droughts and floods.

II. Materials and Methods

Brief Review of Existing Methodologies for Annual Rainfall Data

Several methodologies have been applied to analyse annual rainfall data, including statistical analysis, Fourier Transform, Wavelet Transform, and machine learning techniques.

Statistical Methods

Traditional statistical methods, such as moving averages, regression analysis, and trend analysis, provide basic insights into the mean and variability of rainfall over time. These methods can identify long-term trends and seasonal patterns but often fail to capture non-linear and non-stationary characteristics inherent in rainfall data (Box, 2015). Autoregressive Integrated Moving Average (ARIMA) models and other time series forecasting methods have also been used to predict future rainfall based on historical data (Chatfield, 2003). However, these methods may not fully account for the complex interactions between various climatic factors.

Fourier and Wavelet Transforms

Fourier Transform and Wavelet Transform offer frequency domain analysis, allowing for the identification of periodic components in the data. Fourier Transform decomposes a time series into a sum of sinusoidal functions, each characterized by a specific frequency and amplitude (Compo, 1998). While powerful, Fourier analysis assumes that the underlying processes are linear and stationary, which may not be the case for rainfall data (Addison, 2017). Wavelet Transform, on the other hand, provides a time-frequency representation, making it suitable for analysing non-stationary time series (R. Gencay, 2001). However, both Fourier and Wavelet Transforms require predefined basis functions, which may not be optimal for all data types (Huang, 1998).

Machine Learning Approaches

Machine learning approaches, including neural networks, support vector machines, and ensemble methods, have gained popularity for rainfall prediction and analysis (Huang N E, 2009). These techniques can capture complex, non-linear relationships in the data and make accurate predictions. However, they often require large datasets for training and significant computational resources (Jones, 1985). Moreover, the black-box nature of many machine learning models can make it difficult to interpret the underlying patterns and trends in the data (Rummel, 1996).

Empirical Mode Decomposition (EMD)

EMD, introduced by Huang et al. (1998), offers a robust alternative by decomposing data into IMFs without the need for predetermined basis functions (Gamage, 2011). EMD is particularly suitable for analysing non-linear and non-stationary time series like rainfall data. It adaptively decomposes the data into a finite number of IMFs, each representing different frequency components of the original time series (Mandic, 2012). This makes EMD a powerful tool for identifying intrinsic oscillatory modes and long-term trends in rainfall data (Ahmad, 2013).

Methodology in EMD

Empirical Mode Decomposition (EMD) is a data-driven adaptive method designed to decompose non-linear and non-stationary time series into a finite set of Intrinsic Mode Functions (IMFs) and a residual. The following steps outline the EMD methodology, accompanied by relevant equations.

Step 1: Identify Local Extrema

Identify all local maxima and minima in the time series x(t). This involves scanning the data to find points where the direction of the trend changes. (A. Nunes, 2010).

Step 2: Envelope Construction

Construct upper and lower envelopes by interpolating between the local maxima and minima using cubic splines. The envelopes provide a smooth representation of the oscillatory modes in the data (S. K. Dash, 2005). Let $e_{max}(t)$ be the upper envelope and $e_{min}(t)$ be the lower envelope.

Step 3: Mean Envelope Calculation

Compute the mean of the upper and lower envelopes:

$$\frac{m(t) = e_{max}(t) + e_{min}(t)}{2}$$

...............Eq.(1)

The mean envelope captures the overall trend around which the data oscillates (D. V. N. B. Prasad, 2013).

Step 4: Extraction of IMF

Subtract the mean envelope $m(t)$ from the original time series $x(t)$ to obtain a component $h(t)$

$$h(t) = x(t) - m(t)$$

......................Eq.(2)

This component $h(t)$ is considered an IMF if it satisfies the following conditions:

1. The number of zero crossings and the number of extrema must either be equal or differ at most by one.
2. The mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero at any point (Kleemann, 2018).

If $h(t)$ is not an IMF, treat $h(t)$ as the original data and repeat steps 1 to 4 until an IMF is obtained.

Step 5: Iteration

Repeat the above steps on the residual $r(t)$ the original time series minus the extracted IMF to obtain subsequent IMFs. The process continues until the residue is a monotonic function or contains only a single extremum (Shi, 2011).

Mathematically, if $x(t)$ is decomposed into n IMFs, the original data can be expressed as:

$$x(t) = \sum_{i=1}^{n} IMF_i(t) + r_n(t)$$

...................Eq.(3)

Where:

- $IMF_i(t)$ is the $i\ th$ IMF.
- $r_n(t)$ is the final residual after extracting all n IMFs.

The process is repeated until the entire time series is decomposed into a set of IMFs and a residual component. For this study, six IMFs and one residue were extracted from the annual rainfall data for Chennai. The IMFs represent different oscillatory modes, while the residue represents the long-term trend in the data.

III. Results and Discussion

The results of the EMD analysis suggest that the oscillatory modes captured by the intrinsic mode functions (IMFs) are increasingly influenced by global climatic shifts linked to climate change. For instance, IMF 2 and IMF 3, which show periodicities potentially related to inter-annual and decadal climatic phenomena, might be increasingly driven by anthropogenic climate changes. Recent research suggests that changes in the frequency and intensity of phenomena like the El Niño-Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD), which are linked to global warming, could be contributing to altered rainfall patterns in Chennai.

IMF 4 and IMF 5, representing longer-term oscillations, may reflect a more sustained impact of climate change. These modes capture multi-decadal variability, which could be affected by long-term trends such as increased greenhouse gas concentrations, shifts in oceanic currents, and changing atmospheric circulation patterns. Such environmental changes are not only altering the timing and intensity of rainfall but also increasing the unpredictability of monsoonal rains. This is consistent with global observations of more erratic weather patterns due to climate change, which can contribute to both extreme rainfall and prolonged dry spells. The calculated IMFs and residues are given in Table 2.

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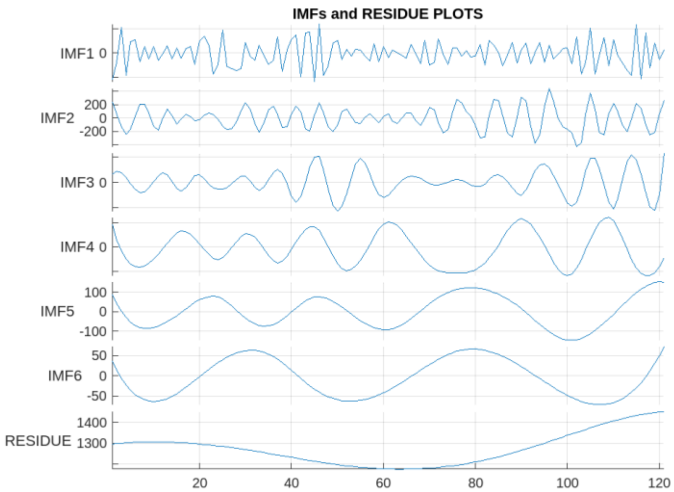

Figure 1 Plots of IMFs 1 to 6 and Residue

- IMF 1 captures the highest frequency variations in the rainfall data. These short-term fluctuations are likely due to annual variability in monsoon patterns and local weather events.
- IMF 2 represents intermediate frequency components, capturing inter-annual variability in rainfall. This IMF may be influenced by phenomena such as the El Niño-Southern Oscillation (ENSO) and other regional climatic patterns.
- IMF 3 shows lower frequency oscillations, potentially corresponding to decadal variations in rainfall. These oscillations may be linked to larger climatic cycles, such as the Indian Ocean Dipole (IOD) and other long-term atmospheric processes.
- IMF 4 represents even lower frequency components, capturing multi-decadal variability in the rainfall data. This IMF may reflect changes in long-term climatic conditions and global warming effects.
- IMF 5 shows very low frequency oscillations, possibly indicating long-term shifts in rainfall patterns over several decades. These shifts could be influenced by persistent changes in oceanic and atmospheric circulation patterns.
- IMF 6 captures the lowest frequency oscillations, representing the most extended periods of variability in the data. This IMF may correspond to century-scale climatic trends and long-term environmental changes.
- The residue shows the overall trend in the rainfall data after removing all oscillatory components. This trend indicates a general pattern of increasing or decreasing rainfall over the studied period, providing insights into long-term changes in the climate of Chennai.

The multi-decadal oscillations (IMF 5 and IMF 6) and the residue component demonstrate an emerging trend of changing rainfall patterns, which may be linked to the broader environmental impacts of climate change. The long-term shift in Chennai's rainfall is consistent with global patterns of altered precipitation due to rising global temperatures and shifting oceanic currents. These shifts pose significant challenges for Chennai’s water security and agricultural resilience, with potential knock-on effects for urban planning and infrastructure.

IMF 5 and IMF 6 indicate a pattern of more frequent extreme weather events, as predicted by climate change models. For example, the increase in frequency of extreme rainfall events, interspersed with periods of drought, reflects the global trend of intensified hydrological cycles driven by increased atmospheric moisture from global warming. These insights underline the necessity of factoring in climate change when planning for future water resource management and disaster mitigation strategies.

Short-term Fluctuations (IMF 1 and IMF 2)

IMF 1 and IMF 2 capture the short-term fluctuations due to annual and inter-annual variability in monsoon patterns. These components reflect the immediate response of rainfall to local weather conditions and short-term climatic phenomena such as ENSO. Understanding these short-term variations is crucial for accurate weather forecasting and effective water resource management (Kothari, 2011).

Decadal Variations (IMF 3 and IMF 4)

IMF 3 and IMF 4 represent decadal variations in rainfall, potentially influenced by larger climatic cycles such as the IOD and other long-term atmospheric processes. These IMFs highlight the importance of considering decadal climatic patterns in long-term planning and policy-making. For instance, the identification of dry and wet decades can inform agricultural strategies and infrastructure development (Kodali, 2013).

Multi-decadal Oscillations (IMF 5 and IMF 6)

IMF 5 and IMF 6 capture multi-decadal oscillations, indicating long-term shifts in rainfall patterns over several decades. These components are essential for understanding the impact of global climate change on regional rainfall. The study of these IMFs can provide insights into the potential future trends in rainfall and help in developing adaptation strategies for climate change (M. K. Dash, 2015).

Long-term Trend (Residue)

The residue shows the overall trend in the rainfall data after removing all oscillatory components. This trend provides a comprehensive view of the long-term changes in rainfall over the studied period. The analysis of the residue is crucial for identifying persistent trends and developing long-term strategies for water resource management and urban planning in Chennai (H. L. Zhang, 2016).

The EMD analysis highlights the complexity of rainfall dynamics in Chennai, revealing significant periodicities and long-term trends that are not immediately apparent from the raw data. The identification of these intrinsic modes and trends can inform various aspects of water management, agricultural planning, and disaster preparedness in the region. (Santos, 2018)

IV. Conclusion

This study highlights the growing influence of climate change on regional rainfall patterns, underscoring the importance of understanding the different oscillatory modes in the context of global climate shifts. The long-term trend uncovered by the EMD analysis suggests that Chennai may experience increasing variability in its rainfall, with more frequent extremes. These findings align with climate change projections, which predict greater rainfall variability due to the enhanced hydrological cycle. The integration of EMD with climate models could provide more precise rainfall forecasts, aiding in the development of more resilient strategies for water management, urban planning, and agricultural adaptation to climate change.

Future Directions

Future research can extend this analysis to explore the impact of specific climatic phenomena on each IMF and to apply EMD to other regions for comparative studies. Additionally, integrating EMD with other analytical methods and machine learning techniques can enhance the understanding of rainfall dynamics and improve the accuracy of rainfall predictions. For instance, EMD can be used to pre-process rainfall data before feeding it into AI models, such as neural networks and support vector machines, to improve prediction accuracy. The decomposition of rainfall data into IMFs can help in isolating noise and focusing on the significant components that drive rainfall variability. This approach can lead to the development of more robust and interpretable AI models for rainfall prediction, ultimately contributing to better water resource management and disaster preparedness.

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ANNEXURES

TABLE 1
Chennai Annual Rainfall (in mm) for the years 1901 to 2021
(https://data.opencity.in/dataset/chennai-rainfall-data)

Year	*Annual Rainfall*	*Year*	*Annual Rainfall*	*Year*	*Annual Rainfall*
1901	1352.83	1941	1685.34	1981	1077.43
1902	1375.31	1942	837.886	1982	714.714
1903	1741.14	1943	1665.79	1983	1612.73
1904	480.036	1944	1775.67	1984	1842.39
1905	1115.79	1945	1065.88	1985	1716.5
1906	1273.77	1946	2407.15	1986	1257.08
1907	954.575	1947	1035.61	1987	1228.65
1908	1264.47	1948	771.205	1988	1405.15
1909	934.899	1949	944.34	1989	1260.02
1910	1082.16	1950	973.886	1990	1808.34
1911	827.528	1951	742.958	1991	1896.51
1912	1201.1	1952	1067.77	1992	1107.4
1913	1571.04	1953	929.029	1993	1095.12
1914	1205.33	1954	1087.37	1994	1391.83
1915	1325.48	1955	1148.13	1995	1337.78
1916	1191.48	1956	1108.09	1996	1842.79
1917	1504.44	1957	1043.91	1997	1244.47
1918	1576.04	1958	1309.96	1998	928.304
1919	1186.37	1959	849.484	1999	782.179
1920	1662.73	1960	1269.95	2000	691.034
1921	1762.52	1961	1125.39	2001	290.617
1922	1545.52	1962	1216.23	2002	713.508
1923	886.155	1963	1157.79	2003	204.016
1924	985.238	1964	1193.95	2004	1101.48
1925	1596.57	1965	1214.35	2005	2338.34
1926	833.678	1966	1472.21	2006	1230.16
1927	860.475	1967	1146.24	2007	1282.79
1928	991.145	1968	819.582	2008	1538.83
1929	1244.05	1969	1381.29	2009	1188.33
1930	1897.2	1970	997.333	2010	1820.11
1931	1459.86	1971	1005.66	2011	1432.33
1932	1072.14	1972	1299.96	2012	1171.05
1933	1169.57	1973	847.394	2013	1015.08
1934	1057.35	1974	716.84	2014	1097.7
1935	1068.43	1975	1363.01	2015	2311.1
1936	1212.36	1976	1556.87	2016	991.032
1937	1578.54	1977	1346.55	2017	1571.59
1938	662.643	1978	1314.1	2018	607.03
1939	1080.47	1979	1130.33	2019	1183.24
1940	1440.61	1980	1008.16	2020	1310.85
				2021	2157.37

TABLE 2
Decomposed IMFs 1 to 6 and Residue

IMF1	*IMF2*	*IMF3*	*IMF4*	*IMF5*	*IMF6*	*Residue*
-553.53	244.339	63.5531	177.752	88.2229	36.1493	1296.3
-190.01	66.7817	87.9937	57.8992	40.9572	13.288	1298.4
537.732	-133.7	74.7166	-33.74	2.123	-6.1779	1300.2
-464.66	-243.44	37.4724	-99.763	-28.869	-22.439	1301.7
228.028	-174.21	-9.9887	-142.77	-52.606	-35.686	1303
282.086	22.6754	-53.916	-165.35	-69.678	-46.109	1304.1
-175.46	210.411	-80.56	-170.11	-80.673	-53.899	1304.9
128.422	212.169	-76.489	-159.65	-86.18	-59.246	1305.4
-119.73	75.8969	-41.374	-136.55	-86.787	-62.341	1305.8
135.895	-117.28	7.5199	-103.43	-83.083	-63.374	1305.9
-150.29	-178.51	51.587	-62.876	-75.657	-62.537	1305.8
-24.116	-11.567	73.8883	-17.485	-65.097	-60.019	1305.5
148.702	134.49	60.834	30.0378	-51.992	-56.011	1305
-127.95	33.1926	8.1422	75.3272	-36.93	-50.703	1304.3
111.907	-86.801	-49.214	111.049	-20.5	-44.287	1303.3
-113.12	-17.831	-68.311	128.777	-3.2911	-36.952	1302.2
86.4013	50.4938	-43.691	125.113	14.1087	-28.889	1300.9
129.947	24.3862	8.054	103.447	31.0749	-20.29	1299.4
-229.86	-40.857	55.6905	68.1825	46.8069	-11.343	1297.8
248.24	-24.528	60.7098	24.2483	60.3891	-2.2403	1295.9
345.535	41.3068	25.9802	-21.935	70.8997	6.828	1293.9
159.129	79.2426	-14.296	-63.375	77.4168	15.6714	1291.7
-431.52	58.3148	-40.108	-93.052	79.0183	24.0994	1289.4
-230.93	-21.163	-52.338	-103.95	74.7746	31.9292	1286.9
469.374	-115.86	-54.38	-89.992	64.0996	39.0352	1284.3
-272.75	-172.02	-42.189	-54.422	48.1932	45.3396	1281.5
-315.89	-162.76	-11.936	-7.1002	28.7872	50.768	1278.6
-357.19	-55.995	24.0083	41.8944	7.6135	55.2456	1275.6
-324.65	119.489	49.2366	82.4841	-13.596	58.6978	1272.4
222.834	225.416	47.2122	104.699	-33.111	61.0475	1269.1
-64.386	133.576	9.1191	103.01	-49.375	62.2128	1265.7
-151.78	-79.466	-39.174	79.9803	-61.74	62.1114	1262.2
157.787	-213.64	-63.387	39.4479	-69.933	60.6608	1258.6
-46.415	-83.302	-37.973	-14.049	-73.685	57.7789	1255
-234.74	121.986	19.4502	-70.222	-72.729	53.3869	1251.3
-153.43	175.918	76.2515	-114.53	-66.903	47.5087	1247.5
329.792	53.2204	100.53	-132.9	-56.205	40.3289	1243.8
-379.89	-142.89	72.0926	-117.72	-41.001	32.0802	1240
58.0215	-128.01	-9.0839	-77.092	-22.573	23.0281	1236.2
276.051	50.6822	-107.97	-21.606	-2.3695	13.4402	1232.4
376.046	178.619	-158.02	38.3405	18.1632	3.5837	1228.6
-493.43	91.4365	-110.43	94.1261	37.5778	-6.2737	1224.9
423.097	-157.13	1.4556	138.62	54.4273	-15.865	1221.2
427.052	-194.66	118.556	164.829	67.2653	-24.922	1217.5
-597.85	43.3018	199.214	165.735	74.6896	-33.197	1214

IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	Residue
595.729	227.602	203.046	134.555	76.1843	-40.471	1210.5
-456.6	81.9706	101.621	75.7335	72.4166	-46.652	1207.1
-267.08	-128.03	-52.089	2.0841	64.2387	-51.767	1203.9
204.699	-200.83	-183.52	-73.369	52.5101	-55.851	1200.7
267.735	-104.36	-228.73	-137.6	38.0902	-58.935	1197.7
-140	96.2828	-190.17	-178.75	21.8384	-61.055	1194.8
83.5888	136.689	-93.021	-193.98	4.6142	-62.244	1192.1
-63.993	28.5743	36.1951	-186.07	-12.733	-62.534	1189.6
75.6241	-73.719	147.614	-157.94	-29.494	-61.961	1187.2
68.3098	-76.582	189.332	-112.29	-45.18	-60.56	1185.1
-69.737	11.3225	152.917	-51.878	-59.345	-58.368	1183.2
-160.58	65.9937	66.2344	17.7337	-71.545	-55.412	1181.5
197.201	7.4577	-28.968	87.3081	-81.336	-51.715	1180
-175.32	-67.348	-98.332	147.284	-88.271	-47.299	1178.8
133.335	24.8023	-120.44	188.593	-91.901	-42.194	1177.8
-94.788	69.875	-103.95	205.477	-91.733	-36.471	1177
69.7242	-46.194	-65.62	199.411	-87.305	-30.223	1176.4
7.1558	-75.957	-21.719	174.501	-78.787	-23.545	1176.1
-46.297	-1.8564	14.0457	135.325	-66.823	-16.53	1176.1
-103.41	78.351	37.9121	86.5793	-52.077	-9.2691	1176.3
173.28	77.6839	47.9254	33.693	-35.213	-1.8567	1176.7
-3.5346	-42.933	45.4789	-18.86	-16.897	5.6146	1177.4
-222.93	-114.51	31.9566	-68.499	2.2097	13.0518	1178.3
267.458	-5.0318	10.6568	-113.07	21.441	20.362	1179.5
-244.24	153.266	-9.765	-150.43	40.1333	27.4522	1180.9
-196.6	126.72	-20.368	-178.56	57.6228	34.2294	1182.6
289.012	-70.455	-19.918	-197.17	73.32	40.6007	1184.6
-27.004	-226.37	-11.485	-207.87	86.8629	46.4731	1186.8
-237.49	-173.83	1.7322	-212.67	98.0794	51.7536	1189.3
110.324	96.4464	14.6443	-213.73	106.948	56.3494	1192
101.134	279.081	21.1864	-213.3	113.561	60.1673	1195
-60.861	225.1	15.8247	-213.03	118.068	63.1146	1198.3
45.9635	90.9197	0.206	-210.61	120.624	65.0981	1201.9
-74.554	33.5259	-18.553	-203.24	121.368	66.042	1205.7
-59.096	-107.56	-32.799	-188.55	120.353	65.9553	1209.9
176.169	-296.38	-33.836	-165.27	117.59	64.8936	1214.3
-251.65	-282.32	-13.613	-132.64	113.088	62.9206	1218.9
263.273	28.8029	20.9604	-91.117	106.851	60.1026	1223.9

IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	Residue
164.577	283.34	51.772	-41.743	98.8841	56.5066	1229.1
9.0102	256.204	60.9793	14.4238	89.1932	52.1994	1234.5
-263.08	37.2563	42.533	75.1789	77.783	47.2477	1240.2
-34.511	-227.67	4.4813	133.888	64.6587	41.7184	1246.1
213.592	-285.4	-43.767	182.998	49.8253	35.6783	1252.2
-204.25	14.0803	-87.258	216.378	33.2879	29.1969	1258.6
65.6021	311.757	-99.845	228.262	15.0711	22.3531	1265.1
200.458	257.588	-60.426	216.318	-4.5284	15.2278	1271.9
-224.74	-129.46	15.8821	183.991	-24.937	7.902	1278.8
7.1075	-380.95	92.222	136.054	-45.559	0.4565	1285.8
216.527	-258.03	136.502	76.732	-65.798	-7.0277	1292.9
-197.98	182.08	143.56	9.4898	-85.06	-14.47	1300.2
163.782	440.62	116.069	-60.603	-102.75	-21.789	1307.5
-117.59	264.56	56.8408	-126.98	-118.27	-28.904	1314.8
-20.845	-2.8448	-20.434	-183.01	-131.02	-35.734	1322.2
90.4737	-134.92	-98.29	-222.05	-140.42	-42.198	1329.6
102.943	-158.07	-159.26	-237.46	-145.86	-48.216	1337
-220.06	-224.67	-185.81	-222.56	-146.87	-53.706	1344.3
329.111	-434.55	-155	-175.42	-143.62	-58.587	1351.6
-430.56	-372.43	-47.421	-105.05	-136.52	-62.779	1358.8
-199.37	58.9328	90.2514	-22.034	-125.98	-66.201	1365.9
524.442	370.085	189.08	63.0442	-112.41	-68.771	1372.9
-440.8	126.583	191.687	139.602	-96.218	-70.409	1379.7
-46.671	-215.96	109.652	198.228	-77.816	-71.034	1386.4
318.543	-255.36	-22.156	233.082	-57.611	-70.565	1392.9
-264.4	73.695	-154.69	239.467	-36.014	-68.921	1399.2
270.201	220.372	-208.98	212.715	-13.435	-66.021	1405.3
-50.439	99.4982	-127.17	151.481	9.6643	-61.784	1411.1
-210.13	-109.5	29.8475	67.5877	32.7475	-56.13	1416.6
-356.69	-198.77	166.08	-23.727	55.2716	-48.977	1421.9
-459.89	-17.037	218.634	-107.29	76.6938	-40.244	1426.8
589.571	214.909	180.761	-172.21	96.4713	-29.851	1431.5
-532.73	142.346	65.6089	-216.25	114.061	-17.717	1435.7
423.142	-98.723	-79.12	-238.47	128.921	-3.7607	1439.6
-301.59	-254.9	-194.26	-237.92	140.508	12.0989	1443.1
203.479	-210.34	-220.62	-213.67	148.279	29.9425	1446.2
-140.51	64.791	-99.009	-164.77	151.691	49.8512	1448.8
72.7711	272.015	229.771	-90.274	150.202	71.9057	1451