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LAMPIRAN

Lampiran 1. Data Penelitian

No.	Waktu	Bujur (x)	Lintang (y)	Magnitudo
1	2021-01-01 00:22:54	117.80922	-8.21	3.48
2	2021-01-01 00:33:29	118.48936	-9.01	4.27
3	2021-01-01 00:33:29	118.48936	-9.01	4.28
4	2021-01-01 02:33:53	120.53139	-1.85	3.97
5	2021-01-01 02:33:53	120.53139	-1.85	3.92
6	2021-01-01 03:19:52	114.0378	-6.04	5.58
7	2021-01-01 03:21:15	120.74245	-9.9	3.05
8	2021-01-01 03:25:07	120.6063	-9.72	2.49
9	2021-01-01 03:27:03	96.51611	4.32	2.75
10	2021-01-01 03:31:03	101.02269	-5.39	4.83
11	2021-01-01 03:44:06	131.80984	-3.1	3.59
12	2021-01-01 04:05:15	124.45344	-0.22	4.68
13	2021-01-01 05:03:10	119.05688	-9.14	3.29
14	2021-01-01 05:51:06	119.83083	-9.69	2.87
15	2021-01-01 05:52:29	130.52267	-2.76	3.27
16	2021-01-01 08:44:49	120.66437	-9.78	2.99
17	2021-01-01 08:55:55	111.07145	-4.31	5.32
18	2021-01-01 08:57:43	119.03639	-8.9	2.77
19	2021-01-01 11:13:23	128.66589	-7.58	4.21
20	2021-01-01 11:32:18	127.28616	2.25	3.77
21	2021-01-01 20:35:22	119.44214	-9.25	2.55
22	2021-01-01 23:24:25	126.61842	0.3	3.06
23	2021-01-02 00:02:02	126.11481	-4.48	4.32
24	2021-01-02 00:02:02	126.11481	-4.48	4.11
25	2021-01-02 00:23:07	128.26082	1.9	2.84
26	2021-01-02 00:23:34	103.51709	-6.02	3
27	2021-01-02 00:24:09	116.23518	-8.45	1.97
28	2021-01-02 00:32:14	128.29002	-3.53	2.25
29	2021-01-02 01:07:12	114.85698	-8.39	2.32
30	2021-01-02 03:43:06	121.75929	-0.35	3.15
31	2021-01-02 04:24:54	134.25865	-2.21	3.53
32.	2021-01-02 05:18:58	121.92201	0.53	3.96
33	2021-01-02 06:33:23	138.31104	-4.31	4.78
34	2021-01-02 07:48:28	139.19608	-3.16	3.46
35	2021-01-02 08:03:52	125.16638	-7.18	4.07
⋮	⋮	⋮	⋮	⋮
39.324	2024-12-31 23:58:59	97.31882	1,66	2.95