1 TimeSformer and CNN models convergence curves

As we can see on the plots selected number of epochs for each model training is enough achieve convergence. At the same time, for SwinLSTM and CNN, slight overfitting is observed.

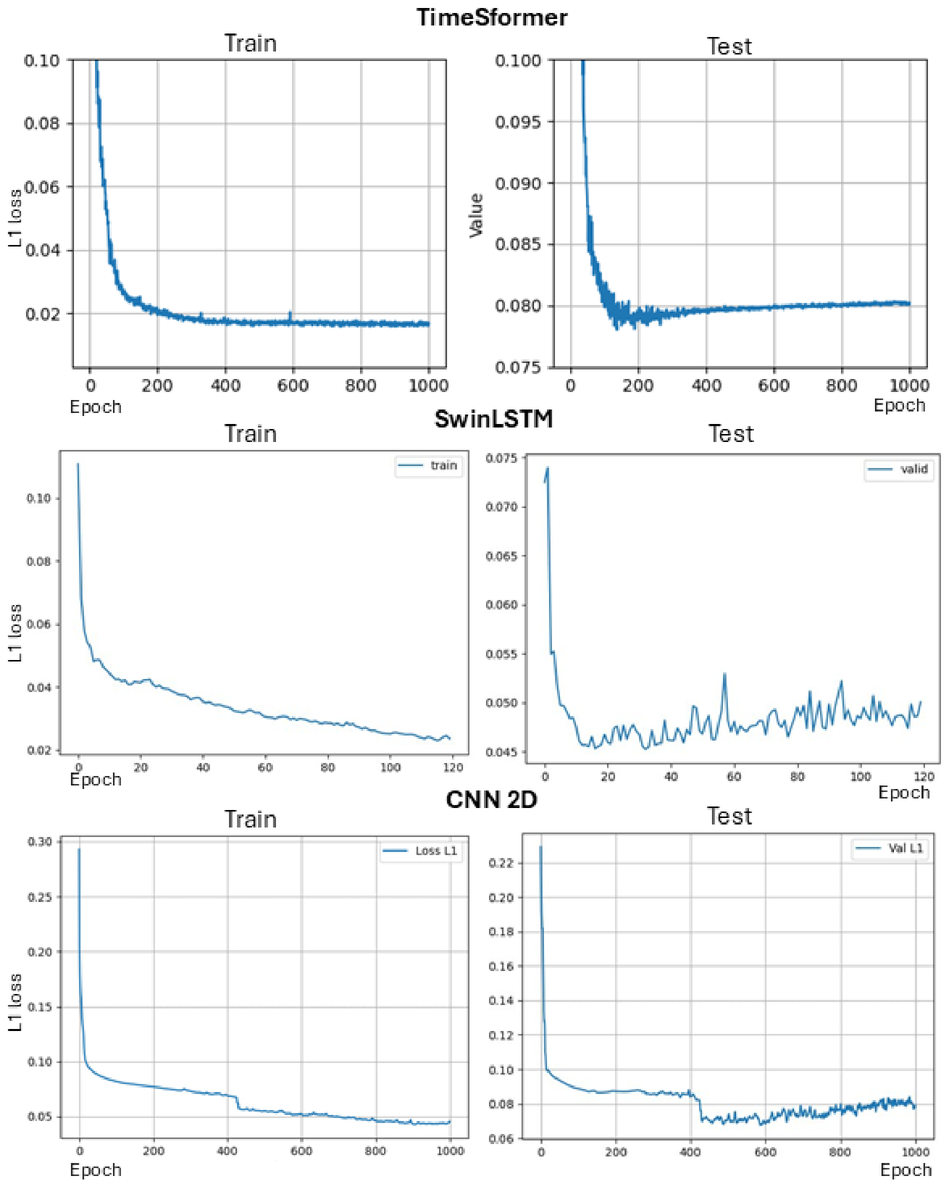

Figure 1: Comparison of convergence curves values on train and test samples

2 The spatial position of test water areas - Arctic seas

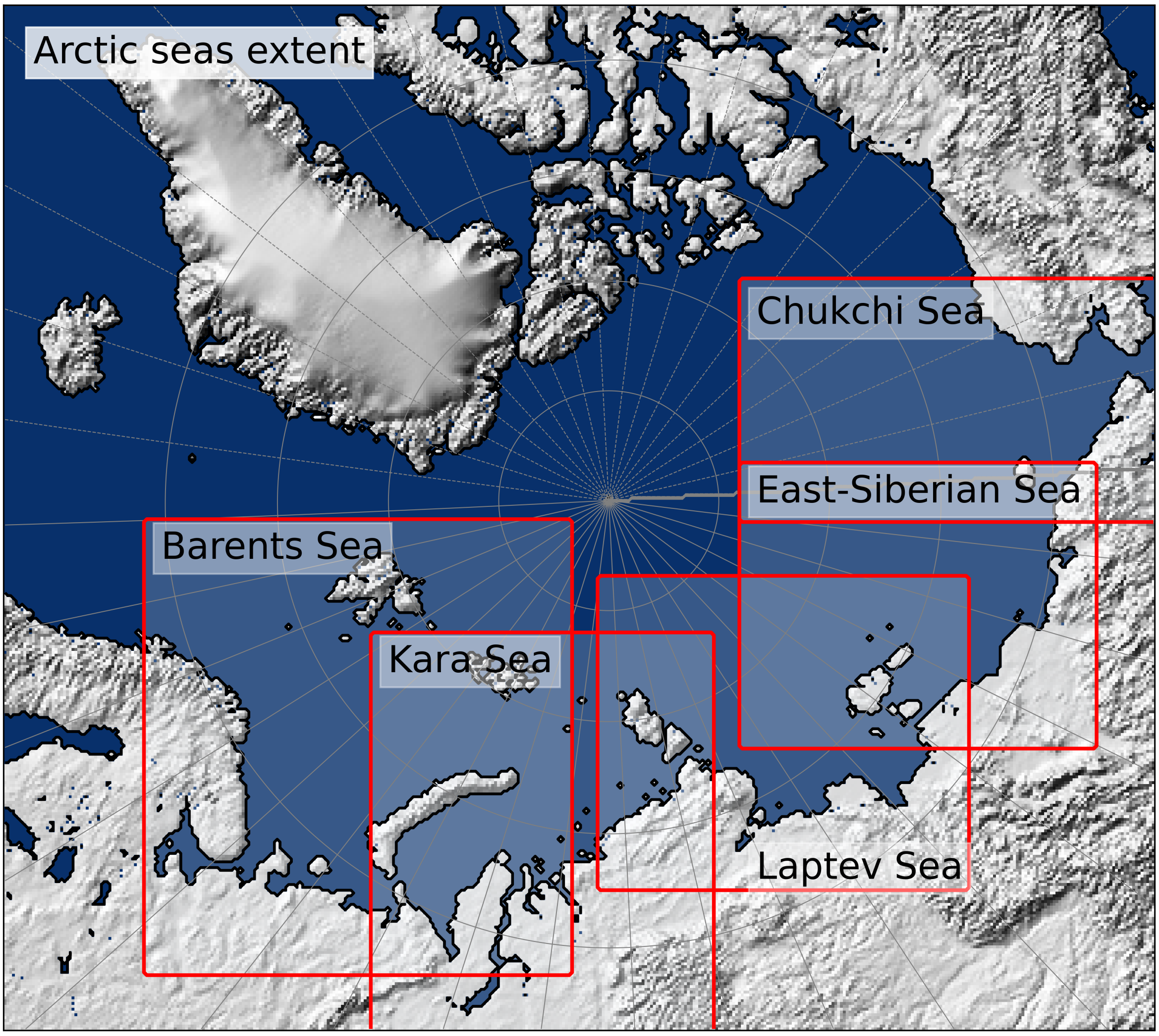

Figure 2: Extent of test water areas for local models

3 Detailed table with quality metrics for models comparison

Metric	Mean Absolute Error (MAE)			Structural Similarity Index (SSIM)			Accuracy (0.2 threshold)		
Year and quarter	2D Conv-based	3D Conv-based	TimeSformer	2D Conv-based	3D Conv-based	TimeSformer	2D Conv-based	3D Conv-based	TimeSformer
Kara Sea									
2020Q1	0,0619	0,0645	0,0775	0,7564	0,7524	0,7167	0,9682	0,9659	0,9576
2020Q2	0,0910	0,0891	0,1074	0,6753	0,6757	0,6617	0,9268	0,9235	0,9059
2020Q3	0,0552	0,0518	0,1866	0,6677	0,6216	0,2843	0,9222	0,9217	0,7341
2020Q4	0,0979	0,1233	0,1179	0,6168	0,5753	0,3380	0,8755	0,8390	0,8612
2021Q1	0,0809	0,0837	0,0706	0,7052	0,7059	0,7311	0,9554	0,9538	0,9588
2021Q2	0,1240	0,1119	0,0909	0,6102	0,6192	0,6768	0,8944	0,9087	0,9392
2021Q3	0,0790	0,0706	0,1704	0,6461	0,5915	0,3043	0,8896	0,9051	0,7921
2021Q4	0,1114	0,1068	0,1332	0,6318	0,6239	0,3656	0,9157	0,9272	0,9119
2022Q1	0,0727	0,0715	0,0740	0,7368	0,7386	0,7377	0,9575	0,9561	0,9583
2022Q2	0,0728	0,0791	0,0898	0,6874	0,6647	0,7042	0,9525	0,9403	0,9354
2022Q3	0,0580	0,0773	0,1517	0,6645	0,5910	0,3385	0,9321	0,9135	0,7910
2022Q4	0,0853	0,0985	0,0972	0,6406	0,6293	0,3980	0,8963	0,8986	0,9139
2023Q1	0,0710	0,0657	0,0701	0,7255	0,7321	0,7364	0,9568	0,9629	0,9464
2023Q2	0,0799	0,0850	0,0881	0,6984	0,6812	0,7198	0,9485	0,9466	0,9252
2023Q3	0,0673	0,0653	0,1362	0,6298	0,5895	0,3688	0,9333	0,9372	0,8278
2023Q4	0,0787	0,0654	0,1140	0,6700	0,6836	0,3952	0,9387	0,9519	0,9092
Barents Sea									
2020Q1	0,0691	0,0585	0,0988	0,6596	0,6875	0,5886	0,9472	0,9570	0,9274
2020Q2	0,0941	0,0685	0,1131	0,6098	0,6636	0,5278	0,9018	0,9328	0,9067
2020Q3	0,0492	0,0499	0,1849	0,6607	0,6257	0,3845	0,9289	0,9287	0,7247
2020Q4	0,0748	0,0798	0,1832	0,5958	0,5881	0,4154	0,9055	0,8812	0,7457
2021Q1	0,0889	0,0970	0,1299	0,6581	0,6333	0,5377	0,9310	0,9186	0,8965
2021Q2	0,0876	0,0816	0,1082	0,6241	0,6237	0,5114	0,9026	0,9139	0,9055
2021Q3	0,0363	0,0347	0,1596	0,7210	0,6671	0,3905	0,9511	0,9558	0,7496
2021Q4	0,0742	0,0644	0,1333	0,6701	0,6810	0,4919	0,9339	0,9472	0,8271
2022Q1	0,0684	0,0645	0,1092	0,7394	0,7372	0,5744	0,9534	0,9529	0,9232
2022Q2	0,0630	0,0610	0,1115	0,7010	0,6946	0,5299	0,9412	0,9468	0,9112
2022Q3	0,0363	0,0358	0,1539	0,7094	0,6839	0,3922	0,9526	0,9566	0,7423
2022Q4	0,0717	0,0608	0,1464	0,6671	0,6784	0,4469	0,9105	0,9204	0,7937
2023Q1	0,0652	0,0714	0,1286	0,7099	0,6866	0,5211	0,9432	0,9233	0,8731
2023Q2	0,0642	0,0645	0,1171	0,7038	0,7030	0,5180	0,9477	0,9519	0,8976
2023Q3	0,0349	0,0398	0,1374	0,7146	0,6622	0,4025	0,9584	0,9539	0,7770
2023Q4	0,0589	0,0519	0,1330	0,7131	0,7058	0,4850	0,9457	0,9464	0,8210
Laptev Sea									
2020Q1	0,0313	0,0456	0,0928	0,8622	0,8359	0,7068	0,9910	0,9889	0,9796
2020Q2	0,0594	0,0644	0,1097	0,7674	0,7472	0,6698	0,9755	0,9755	0,9543
2020Q3	0,0861	0,0924	0,2713	0,5669	0,5537	0,3840	0,8808	0,8609	0,6311
2020Q4	0,1463	0,1223	0,2281	0,6396	0,6253	0,5078	0,8304	0,8394	0,8026
2021Q1	0,0296	0,0409	0,1017	0,8647	0,8356	0,6846	0,9910	0,9892	0,9664
2021Q2	0,0618	0,0658	0,1145	0,7696	0,7561	0,6675	0,9682	0,9680	0,9440
2021Q3	0,0976	0,0925	0,2432	0,5790	0,5670	0,4101	0,8903	0,8858	0,7026
2021Q4	0,0654	0,0909	0,2148	0,7374	0,6946	0,5161	0,9395	0,9430	0,8677
2022Q1	0,0269	0,0368	0,0899	0,8709	0,8539	0,7150	0,9910	0,9891	0,9743
2022Q2	0,0614	0,0638	0,1127	0,7736	0,7668	0,6694	0,9771	0,9765	0,9552
2022Q3	0,1376	0,1426	0,2220	0,4893	0,4688	0,4441	0,8412	0,8460	0,7253
2022Q4	0,0851	0,1016	0,1964	0,7238	0,6818	0,5581	0,9170	0,9169	0,8789
2023Q1	0,0271	0,0366	0,0793	0,8789	0,8575	0,7490	0,9910	0,9890	0,9804
2023Q2	0,0626	0,0567	0,0867	0,7755	0,7721	0,7299	0,9846	0,9850	0,9741
2023Q3	0,1456	0,1323	0,2300	0,4728	0,4578	0,4699	0,8424	0,8610	0,7687
2023Q4	0,0780	0,0782	0,1775	0,7571	0,7334	0,5759	0,9219	0,9262	0,9025

Metric	Mean Absolute Error (MAE)			Structural Similarity Index (SSIM)			Accuracy (0.2 threshold)		
Year and quarter	2D Conv-based	3D Conv-based	TimeSformer	2D Conv-based	3D Conv-based	TimeSformer	2D Conv-based	3D Conv-based	TimeSformer
East-Siberian Sea									
2020Q1	0,0203	0,0371	0,0745	0,9146	0,8724	0,9057	0,9954	0,9951	0,9932
2020Q2	0,0564	0,0615	0,0927	0,7988	0,7749	0,7876	0,9870	0,9862	0,9849
2020Q3	0,1073	0,0994	0,4338	0,4889	0,4913	0,3090	0,8491	0,8416	0,5322
2020Q4	0,1763	0,1585	0,2320	0,6187	0,6055	0,6097	0,7930	0,8014	0,7789
2021Q1	0,0215	0,0309	0,0694	0,9098	0,8800	0,9020	0,9954	0,9953	0,9932
2021Q2	0,0524	0,0559	0,0904	0,7980	0,7865	0,7970	0,9822	0,9820	0,9798
2021Q3	0,1398	0,1023	0,3798	0,4421	0,4932	0,3360	0,8368	0,8772	0,6270
2021Q4	0,1058	0,1122	0,1452	0,7022	0,7029	0,7541	0,9308	0,9315	0,9152
2022Q1	0,0221	0,0282	0,0774	0,9147	0,8890	0,9063	0,9954	0,9953	0,9927
2022Q2	0,0605	0,0543	0,0744	0,8160	0,8042	0,8285	0,9893	0,9883	0,9872
2022Q3	0,1564	0,1398	0,3085	0,4524	0,4651	0,3844	0,8445	0,8556	0,7148
2022Q4	0,0955	0,0962	0,1490	0,7068	0,6943	0,7240	0,9133	0,9310	0,9029
2023Q1	0,0205	0,0253	0,0762	0,9167	0,8952	0,9071	0,9954	0,9953	0,9932
2023Q2	0,0694	0,0529	0,0774	0,7791	0,7923	0,8195	0,9923	0,9920	0,9905
2023Q3	0,1722	0,1430	0,3694	0,3918	0,4310	0,3388	0,7880	0,8274	0,6539
2023Q4	0,1182	0,0981	0,1666	0,7113	0,7014	0,7000	0,8857	0,8971	0,8834
Chukchi Sea									
2020Q1	0,0250	0,0463	0,1325	0,9095	0,8692	0,6736	0,9982	0,9894	0,9688
2020Q2	0,0791	0,0727	0,0910	0,7459	0,7756	0,7361	0,9626	0,9723	0,9573
2020Q3	0,1096	0,1029	0,2026	0,4853	0,5082	0,4040	0,8945	0,8947	0,7756
2020Q4	0,0839	0,0874	0,1394	0,6525	0,6524	0,5435	0,9173	0,9217	0,8625
2021Q1	0,0230	0,0368	0,1428	0,9195	0,8852	0,5981	0,9982	0,9897	0,9668
2021Q2	0,0731	0,0611	0,0940	0,7662	0,7892	0,6928	0,9752	0,9792	0,9670
2021Q3	0,1930	0,1546	0,1470	0,3894	0,4180	0,4088	0,8097	0,8327	0,8774
2021Q4	0,1337	0,1600	0,1789	0,6340	0,6024	0,4944	0,9050	0,9008	0,9098
2022Q1	0,0185	0,0324	0,1486	0,9359	0,9040	0,6951	0,9982	0,9898	0,9694
2022Q2	0,0503	0,0478	0,0869	0,7880	0,8181	0,7259	0,9854	0,9857	0,9660
2022Q3	0,1135	0,1023	0,1926	0,4749	0,5050	0,4382	0,9063	0,8931	0,7806
2022Q4	0,1126	0,0976	0,1618	0,6320	0,6459	0,5194	0,8883	0,8974	0,8704
2023Q1	0,0197	0,0361	0,1871	0,9231	0,8827	0,5857	0,9982	0,9896	0,9667
2023Q2	0,0617	0,0556	0,0882	0,7798	0,8162	0,7109	0,9812	0,9838	0,9707
2023Q3	0,1434	0,1363	0,2519	0,4389	0,4620	0,3972	0,8629	0,8535	0,7607
2023Q4	0,0995	0,0990	0,2111	0,6583	0,6726	0,4523	0,8988	0,8901	0,8172

4 Detailed table with quality metrics - comparison of models with SEAS5

Metric	Mean Absolute Error (MAE)				Structural Similarity Index (SSIM)			
Year and quater	SEAS5	2D Conv-based	3D Conv-based	TimeSformer	SEAS5	2D Conv-based	3D Conv-based	TimeSformer
Kara Sea								
2020Q1	0,0839	0,0619	0,0645	0,0775	0,7437	0,7564	0,7524	0,7167
2020Q2	0,1107	0,0910	0,0891	0,1074	0,6522	0,6753	0,6757	0,6617
2020Q3	0,1163	0,0552	0,0518	0,1866	0,5037	0,6677	0,6216	0,2843
2021Q1	0,0814	0,0809	0,0837	0,0706	0,7491	0,7052	0,7059	0,7311
2021Q2	0,0898	0,1240	0,1119	0,0909	0,6908	0,6102	0,6192	0,6768
2021Q3	0,1101	0,0790	0,0706	0,1704	0,5345	0,6461	0,5915	0,3043
2022Q1	0,0840	0,0727	0,0715	0,0740	0,7400	0,7368	0,7386	0,7377
2022Q2	0,0911	0,0728	0,0791	0,0898	0,6773	0,6874	0,6647	0,7042
2022Q3	0,0956	0,0580	0,0773	0,1517	0,5510	0,6645	0,5910	0,3385
2023Q1	0,0774	0,0710	0,0657	0,0701	0,7418	0,7255	0,7321	0,7364
2023Q2	0,0955	0,0799	0,0850	0,0881	0,6992	0,6984	0,6812	0,7198
2023Q3	0,0881	0,0673	0,0653	0,1362	0,5621	0,6298	0,5895	0,3688
Averaged	0,0936	**0,0761**	0,0763	0,1094	0,6538	**0,6836**	0,6636	0,5817
Barents Sea								
2020Q1	0,0789	0,0691	0,0585	0,0988	0,6764	0,6596	0,6875	0,5886
2020Q2	0,0870	0,0941	0,0685	0,1131	0,6212	0,6098	0,6636	0,5278
2020Q3	0,0728	0,0492	0,0499	0,1849	0,5597	0,6607	0,6257	0,3845
2021Q1	0,0832	0,0889	0,0970	0,1299	0,6715	0,6581	0,6333	0,5377
2021Q2	0,0642	0,0876	0,0816	0,1082	0,6700	0,6241	0,6237	0,5114
2021Q3	0,0624	0,0363	0,0347	0,1596	0,5676	0,7210	0,6671	0,3905
2022Q1	0,0792	0,0684	0,0645	0,1092	0,6928	0,7394	0,7372	0,5744
2022Q2	0,0768	0,0630	0,0610	0,1115	0,6544	0,7010	0,6946	0,5299
2022Q3	0,0708	0,0363	0,0358	0,1539	0,5689	0,7094	0,6839	0,3922
2023Q1	0,0727	0,0652	0,0714	0,1286	0,6722	0,7099	0,6866	0,5211
2023Q2	0,0737	0,0642	0,0645	0,1171	0,6622	0,7038	0,7030	0,5180
2023Q3	0,0576	0,0349	0,0398	0,1374	0,5966	0,7146	0,6622	0,4025
Averaged	0,0733	0,0631	**0,0606**	0,1294	0,6345	**0,6843**	0,6724	0,4899
Laptev Sea								
2020Q1	0,0455	0,0313	0,0456	0,0928	0,8572	0,8622	0,8359	0,7068
2020Q2	0,0828	0,0594	0,0644	0,1097	0,7529	0,7674	0,7472	0,6698
2020Q3	0,2076	0,0861	0,0924	0,2713	0,4718	0,5669	0,5537	0,3840
2021Q1	0,0439	0,0296	0,0409	0,1017	0,8517	0,8647	0,8356	0,6846
2021Q2	0,0899	0,0618	0,0658	0,1145	0,7428	0,7696	0,7561	0,6675
2021Q3	0,2286	0,0976	0,0925	0,2432	0,4474	0,5790	0,5670	0,4101
2022Q1	0,0481	0,0269	0,0368	0,0899	0,8572	0,8709	0,8539	0,7150
2022Q2	0,0737	0,0614	0,0638	0,1127	0,7712	0,7736	0,7668	0,6694
2022Q3	0,1307	0,1376	0,1426	0,2220	0,5330	0,4893	0,4688	0,4441
2023Q1	0,0459	0,0271	0,0366	0,0793	0,8549	0,8789	0,8575	0,7490
2023Q2	0,0768	0,0626	0,0567	0,0867	0,7650	0,7755	0,7721	0,7299
2023Q3	0,1418	0,1456	0,1323	0,2300	0,5309	0,4728	0,4578	0,4699
Averaged	0,1013	**0,0689**	0,0725	0,1462	0,7030	**0,7226**	0,7060	0,6083
East-Siberian Sea								
2020Q1	0,0396	0,0203	0,0371	0,0745	0,8805	0,9146	0,8724	0,9057
2020Q2	0,0690	0,0564	0,0615	0,0927	0,7884	0,7988	0,7749	0,7876
2020Q3	0,2424	0,1073	0,0994	0,4338	0,4407	0,4889	0,4913	0,3090
2021Q1	0,0361	0,0215	0,0309	0,0694	0,8827	0,9098	0,8800	0,9020
2021Q2	0,0715	0,0524	0,0559	0,0904	0,7933	0,7980	0,7865	0,7970
2021Q3	0,2199	0,1398	0,1023	0,3798	0,4428	0,4421	0,4932	0,3360
2022Q1	0,0407	0,0221	0,0282	0,0774	0,8823	0,9147	0,8890	0,9063
2022Q2	0,0642	0,0605	0,0543	0,0744	0,8104	0,8160	0,8042	0,8285
2022Q3	0,1252	0,1564	0,1398	0,3085	0,5711	0,4524	0,4651	0,3844
2023Q1	0,0374	0,0205	0,0253	0,0762	0,8840	0,9167	0,8952	0,9071
2023Q2	0,0665	0,0694	0,0529	0,0774	0,7864	0,7791	0,7923	0,8195
2023Q3	0,1648	0,1722	0,1430	0,3694	0,5188	0,3918	0,4310	0,3388
Averaged	0,0981	0,0749	**0,0692**	0,1770	0,7234	**0,7186**	0,7146	0,6852
Chukchi Sea								
2020Q1	0,0376	0,0250	0,0463	0,1325	0,8847	0,9095	0,8692	0,6736
2020Q2	0,0533	0,0791	0,0727	0,0910	0,8328	0,7459	0,7756	0,7361
2020Q3	0,1152	0,1096	0,1029	0,2026	0,6118	0,4853	0,5082	0,4040
2021Q1	0,0347	0,0230	0,0368	0,1428	0,8925	0,9195	0,8852	0,5981
2021Q2	0,0530	0,0731	0,0611	0,0940	0,8409	0,7662	0,7892	0,6928
2021Q3	0,0780	0,1930	0,1546	0,1470	0,6334	0,3894	0,4180	0,4088
2022Q1	0,0348	0,0185	0,0324	0,1486	0,8950	0,9359	0,9040	0,6951
2022Q2	0,0575	0,0503	0,0478	0,0869	0,8142	0,7880	0,8181	0,7259
2022Q3	0,1222	0,1135	0,1023	0,1926	0,6069	0,4749	0,5050	0,4382
2023Q1	0,0346	0,0197	0,0361	0,1871	0,8885	0,9231	0,8827	0,5857
2023Q2	0,0482	0,0617	0,0556	0,0882	0,8370	0,7798	0,8162	0,7109
2023Q3	0,1411	0,1434	0,1363	0,2519	0,6268	0,4389	0,4620	0,3972
Averaged	**0,0675**	0,0758	0,0737	0,1471	**0,7804**	0,7130	0,7194	0,5889

5 Accuracy - comparison of models with IceNet ice edge

Area	Target month	IceNet	2D Conv-based	3D Conv-based	TimeSformer
Kara Sea	2020-01	0,9285	0,9687	0,9623	0,9515
	2020-02	0,9429	0,9678	0,9668	0,9613
	2020-03	0,9368	0,9679	0,9694	0,9615
	2020-04	0,9289	0,9633	0,9560	0,9671
	2020-05	0,9397	0,9315	0,9347	0,9130
	2020-06	0,8326	0,8764	0,8716	0,8223
Averaged forecast horizon		0,9182	**0,9459**	0,9435	0,9295
Barents Sea	2020-01	0,9265	0,9593	0,9599	0,9183
	2020-02	0,9348	0,9466	0,9544	0,9219
	2020-03	0,9197	0,9327	0,9560	0,9445
	2020-04	0,8958	0,9286	0,9499	0,9362
	2020-05	0,9175	0,9138	0,9429	0,9172
	2020-06	0,8444	0,8564	0,9014	0,8594
Averaged forecast horizon		0,9065	0,9229	**0,9441**	0,9162
Laptev Sea	2020-01	0,9739	0,9910	0,9831	0,9787
	2020-02	0,9739	0,9910	0,9931	0,9803
	2020-03	0,9739	0,9910	0,9936	0,9801
	2020-04	0,9739	0,9910	0,9906	0,9759
	2020-05	0,9739	0,9879	0,9590	0,9707
	2020-06	0,9376	0,9438	0,9626	0,9109
Averaged forecast horizon		0,9679	**0,9826**	0,9803	0,9661
East-Siberian Sea	2020-01	0,9838	0,9954	0,9951	0,9934
	2020-02	0,9838	0,9954	0,9953	0,9933
	2020-03	0,9838	0,9954	0,9951	0,9930
	2020-04	0,9838	0,9954	0,9951	0,9932
	2020-05	0,9838	0,9943	0,9938	0,9923
	2020-06	0,9642	0,9691	0,9676	0,9671
Averaged forecast horizon		0,9806	**0,9908**	0,9903	0,9887
Chukchi Sea	2020-01	0,9871	0,9982	0,9865	0,9669
	2020-02	0,9871	0,9982	0,9905	0,9708
	2020-03	0,9871	0,9982	0,9905	0,9692
	2020-04	0,9871	0,9960	0,9907	0,9721
	2020-05	0,9871	0,9394	0,9875	0,9578
	2020-06	0,9140	0,9441	0,9444	0,9382
Averaged forecast horizon		0,9749	0,9790	**0,9817**	0,9625

6 Additional experiments with SwinLSTM

Additional experiments were conducted to predict 12 values forward in 30-day increments (Monthly forecast), which is the same predicted range - one year. For this problem formulation, the model showed more realistic results.

Comparison of the prediction results of SwinLSTM trained on predictions with weekly and monthly intervals are shown in the Figure 3.

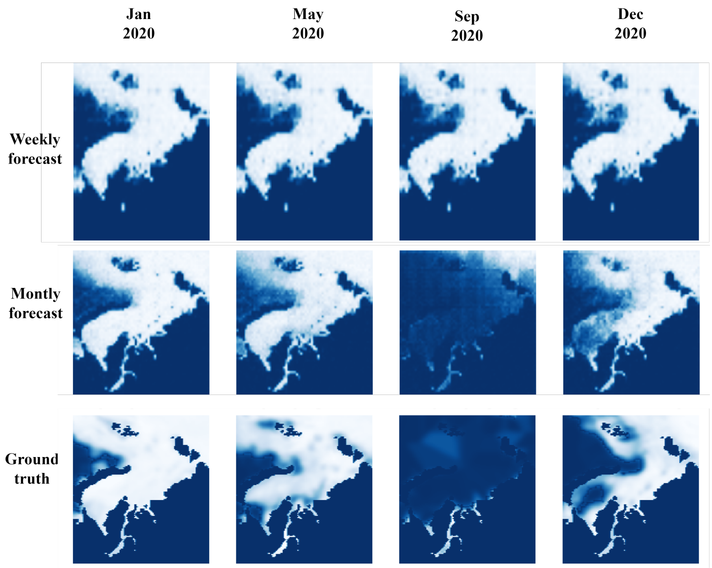

Figure 3: SwinLSTM prediction for 52 (weekly forecast) and 12 (monthly forecast) steps ahead

7 Media data convergence

Convergence graphs confirm that the number of epochs for training is sufficient. It is also worth noting the difference in the model optimization process. The convolutional network improves the image "from general to particular" while simultaneously optimizing the average error by the matrix. The transformer initially sets a smaller weight for the part of the image with the least variability and improves it only after the contours match perfectly.

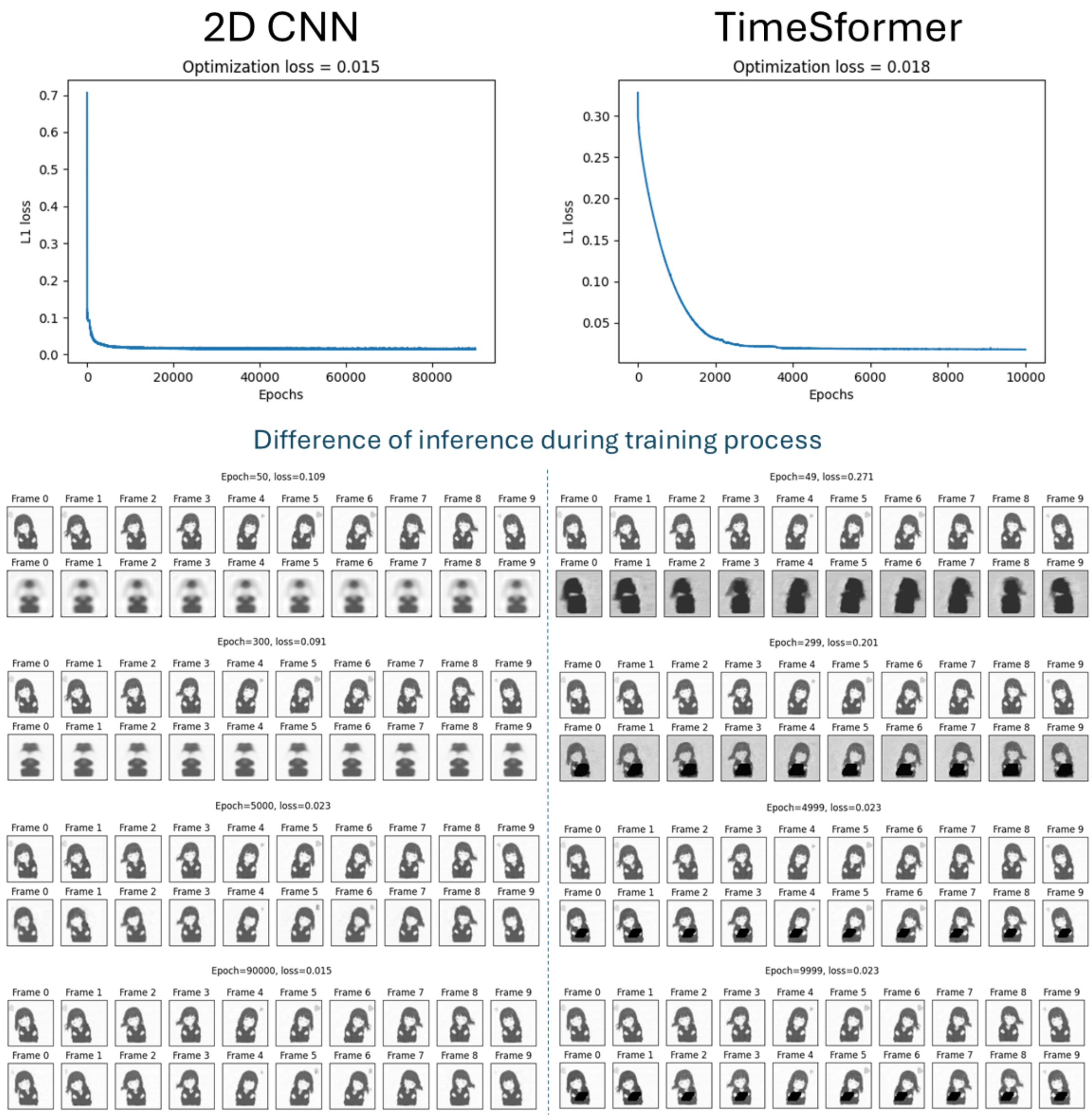

Figure 4: Convergence curves and inference examples of train process for 2D CNN and TimeSformer for media data

8 Setup configuration

8.1 Baseline CNN

In the process of configuring the CNN based on 2D convolutions we tested:

- different numbers of convolutional and transposed layers (2 - 5),
- activation functions between layers (ReLU, GELU, Sigmoid),
- the presence or absence of a final activation layer,
- the kernel size (3, 3), (4, 4), (5, 5).

In final configuration we stopped on 5 convolutional and 5 transposed layers with ReLU activation function between them, ReLU final activation function and (5, 5) kernel size.

8.2 Baseline CNN 3D

In the process of configuring the CNN based on 3D convolutions we tested:

- different numbers of convolutional and transposed layers (2 - 5),
- activation functions between layers (ReLU, GELU),
- the presence or absence of a final activation layer (ReLU, Sigmoid),
- the kernel sizes $K_1 = 3, 4, 8, 12, 52$ (different periods of ice melting) and $(K_2, K_3) = (3, 3), (5, 5), (7, 7), (13, 13)$
- various schedulers (cyclic and linear) to avoid learning instability or getting stuck on a plateau
- the presence or absence of separate convolutional blocks after the decoder for additional non-linearity
- different number of epochs and various learning rates

The final architecture looks like 2 convolution layers in the encoder part and 2 transposed convolution layers in the decoder part. The activation function is ReLU. The kernel size is (52, 3, 3). The training was with the AdamW optimizer and without any schedulers.

8.3 TimeSformer

For the TimeSformer model, experiments were conducted to select model parameters for the training conditions considered. Within these experiments, the following parameters of Transformer were compared: depth was chosen from the values 6,8,12, number of heads between 8 and 12, embedding size was chosen in the range from 64 to 256, patch size was taken as 2, and also the values between 0, 0.1, 0.25 for dropout rate in attention blocks were compared. And also the configuration for convolutional decoder was compared. Different number of convolution layers (from 1 to 4) was tested in the decoder, and for each layer different number of channels from 32 to 512 was selected.

As a result of parameter selection, the following final parameters were chosen: timesfromer depth is 12, number of heads is 12, embedding size is 156, patch size was taken equal to 2, dropout rate in blocks attention was taken equal to 0.1, 3 layers of convolutional decoder, with 384 channels for each layer, batchnorm, ReLU activation function.

Also for TimeSformer model we compared the use of constant leerning rate equal to 0.0001 and cosine learning rate scheduler with warm-up. warm-up was performed from 0.000001 to 0.0005 and lasted for 5 epochs, and then within 90 epochs lerning rate was decreased to 0.00001. As a result of this comparison it was decided to use Cosine learning rate scheduler together with AdamW optimizer.

8.4 SwinLSTM

For the SwinLSTM model, the default configuration of the SwinLSTM-D variant of the model was used. The main parameters of the model were taken by default, namely: patch size is 2, embedding dimension is 128, window size was taken as 2. The depths for the Downsample and Upsample parts were taken as [2,6] and [6,2].