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Original scientific paper
UDC

A Romanian daily high-resolution gridded dataset of snow depth (2005-2015)

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This study presents the spatial interpolation procedure from snow depth measurements at weather stations implying the following stages: (1) Spatial interpolation at 1 km × 1 km resolution of the mean multiannual values (2005-2015) corresponding to each month, computed from the data extracted from the climatological database; (2) Computation of the daily deviations against the multiannual monthly mean for every day and year over 2005-2015 and their spatial interpolation; (3) Spatio-temporal datasets were obtained through merging the two surfaces obtained in stages 1 and 2. The anomalies were considered to be the ratio between the daily snow depth values and the climatology. The spatial variability of the data used in the first stage was accounted for through the use of a series of predictors derived from the digital elevation model (DEM). To plot the maps with the climatological normals (multiannual means), the Regression-Kriging (RK) spatial interpolation method was used. In order to choose the optimum method applied in spatializing deviations, four interpolation methods were tested using a cross-validation procedure: Multiquadratic, Ordinary Kriging (separated and pooled variograms) and 3d Kriging.

Keywords: snowpack; spatial interpolation; Kriging; multiquadratic; cross-validation; Romania.

1. Introduction

The realization of high-quality climatic data is essential for realistically assessing the impacts of climate variability and change of a region (Dumitrescu and Birsan, 2015; Dumitrescu et al., 2016). Gridded data are useful for evaluating the performance of regional climate models, and they serve as input data for spatially distributed agrometeorological and hydrological models (Tveito et al. 2006; Birsan, 2013).

Long-term climatic variability over Romania are well documented in various recent papers, pointing to an increase in drought and aridity (Cheval et al., 2014a,b, 2017; Dascălu et al., 2016) and in annual warm-related temperature extremes (*e.g.*, Birsan et al., 2014; Dobrinescu et al., 2015; Marin et al., 2014; Rimbu et al., 2015). Changes since 1961 show increasing temperatures in all seasons except autumn (Dumitrescu et al., 2015), an increasing rain shower frequency (Busuioc et al., 2016; Manea et al., 2016), decreasing trends in snow depth (Birsan and Dumitrescu, 2014) and in wind speed (Birsan et al., 2013).

Snow cover has major effects on surface albedo and energy balance, and represents a major storage of water. The snowpack strongly influences the overlying air, the underlying ground and the atmosphere downstream. Snow cover duration influences the growing season of the vegetation at high altitudes. Snow cover is a climatic parameter occurring exclusively in the cold season in Romania, being strongly conditioned by air temperature and precipitation type, strongly affecting the surface albedo, the energy balance, the water resources and the hydrological regime (*e.g.*, Birsan, 2015).

This paper presents the methodology for constructing a gridded dataset of daily snow depth over Romania measured during the cold season (December–March), from 2005 to 2015.

The spatial interpolation procedure implies completing the two stages below:

(1) Spatial interpolation at 1 km × 1 km spatial resolution of the mean multiannual values (2005–2015) corresponding to each cold season month, computed from data extracted from the climatological database;

(2) Computation of daily deviations against the multiannual monthly mean for each day and year from the same period, and combining the maps representing the deviations with the climatic maps.

The spatio-temporal datasets were obtained through merging the two surfaces obtained in stages 1 and 2. The anomalies were considered to be the ratios between the daily values and the monthly climatology.

2. Data and methods

2.1. Data

The main data used in this work consist of daily snow depth values recorded at 155 meteorological stations during the cold season between December 2005 to March 2015. The stations are located at elevations ranging from 1 to 2506 m.a.s.l., and have a good spatial coverage across the country, as well as a good altitudinal distribution (Fig. 2). All weather stations (Tab. 1) have full data records over the study period and were quality controlled. The dataset contains no reconstructed records – like extensions or missing values filled by means of computational algorithms.

(a)

(b)

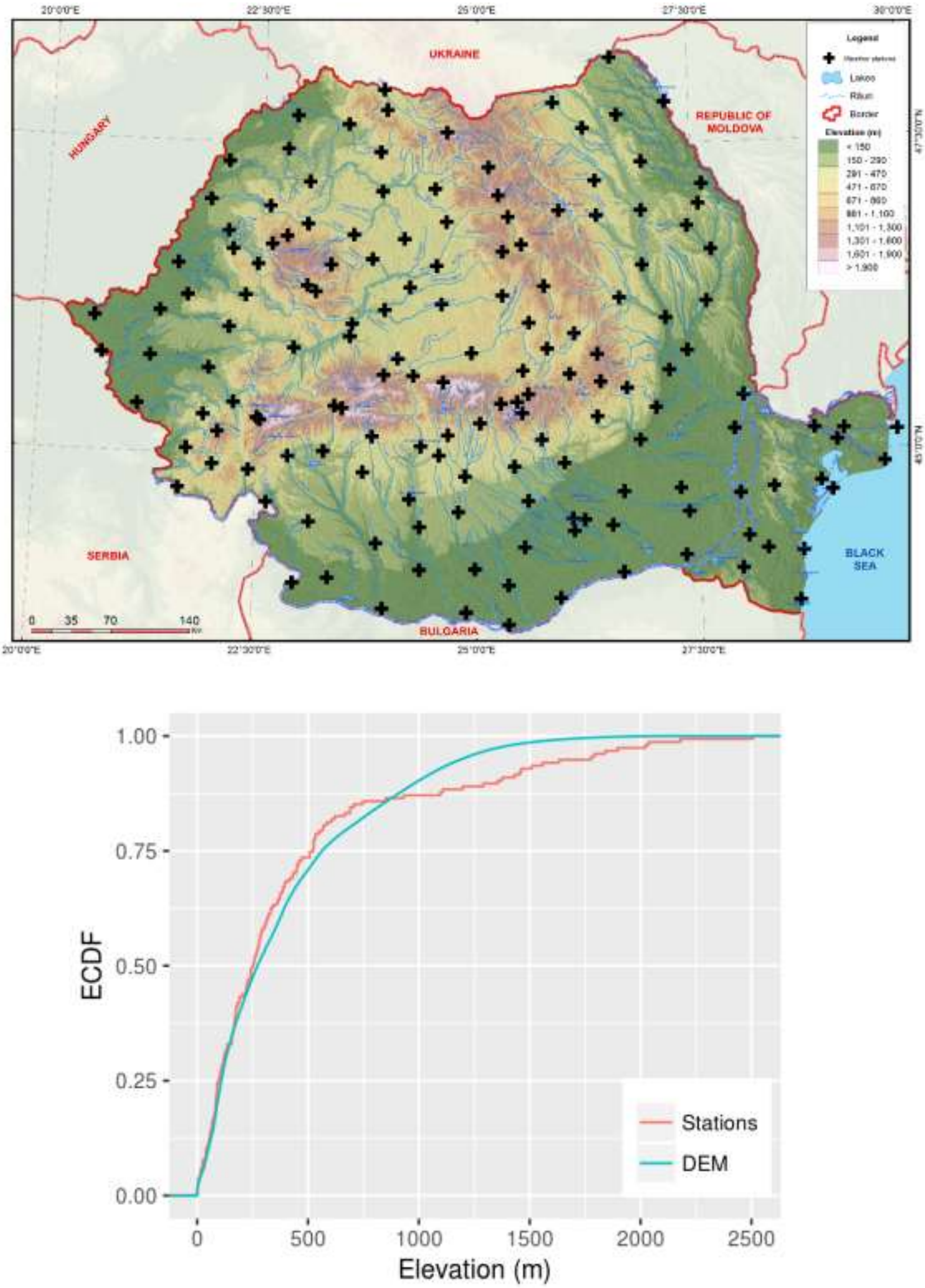

Figure 1. (*a*) The meteorological stations used in the present study. (*b*) The cummulative frequency functions of the altitude of the meteorological network (red) and the altitude of the counture 1 km Digital Elevation Model (DEM).

Table 1. List of the meteorological stations involved in the trend analysis, with their geographic coordinates, altitude, and multi-annual mean monthly snow depth (2005–2015).

Station ID	Station Name	Longitude (°)	Latitude (°)	Altitude (m a.s.l.)	Mean snow depth (cm)			
					Dec	Jan	Feb	Mar
408800	ADAMCLISI	27.96708685	44.0885409	156	1	3.2	4	0.1
606705	ADJUD	27.17193378	46.10497436	101	3.5	4.1	6.9	0.9
604335	ALBA IULIA	23.56497369	46.06421292	252	1.4	2	3.5	0.4
359521	ALEXANDRIA	25.35433507	43.97823168	85	1.7	5.9	5.1	0.5
608121	ARAD	21.35521862	46.13385055	117	1.1	0.8	3.3	0.5
635658	BACAU	26.91406725	46.53214746	183	5.5	8.4	11.1	3.9
428307	BACLES	23.11460051	44.47651622	313	1.4	4.7	5	1.9
740330	BAIA MARE	23.49323787	47.66112768	224	3.1	4.5	8.2	2.1
452230	BAILE HERCULANE	22.41799279	44.88136802	190	1.3	3.5	7.4	1
401321	BAILESTI	23.33273765	44.02960523	59	1.8	4.6	7.6	1
634322	BAISOARA	23.31182227	46.53576855	1357	12.5	18.5	28.5	22.3
536437	BALEA LAC	24.61629602	45.60422396	2037	78.9	131.7	183.4	226.7
523108	BANLOC	21.13797416	45.38305095	83	2	1.6	4.1	0.4
605537	BARAOLT	25.59739847	46.08104168	508	3.6	5.5	6.1	0.8
614740	BARLAD	27.64597711	46.23328751	168	2.9	3.3	4.1	1
700733	BARNOVA (RADAR)	27.58416224	47.01261684	395	8.2	12.9	16.5	8
654438	BATOS	24.64696015	46.88644023	450	2.5	4	5.3	1.5
347357	BECHET	23.94568627	43.79005613	39	1.6	4.5	7.1	0.7
533642	BISOCA	26.7118645	45.54916417	851	7.2	8.8	19.1	8.5
708430	BISTRITA	24.51555219	47.14937051	374	2.7	4.1	6.3	1.8
611355	BLAJ	23.93675021	46.17873184	342	0.8	1	3.7	0.6
538416	BOITA	24.27310565	45.65326161	523	1.5	4.4	6.5	1.7
659236	BOROD	22.59183633	46.99395328	333	1.1	1.5	3.5	0.9
741640	BOTOSANI	26.64713891	47.73587871	160	4.5	5.8	8	1.1
455200	BOZOVICI	22.00773783	44.91865121	256	1.5	3	6.1	0.5
512755	BRAILA	27.92119899	45.20685343	17	2.1	4.3	5.5	0.4
542532	BRASOV	25.52772077	45.69613319	535	3.2	5.5	5.1	0.9
639518	BUCIN	25.29808384	46.64927031	1290	30	47.3	71.5	75.2
430613	BUCURESTI AFUMATI	26.21429086	44.50038552	90	1.8	4.9	5.9	1
430608	BUCURESTI BANEASA	26.07968642	44.51072385	90	2	5.1	6.6	1

Station ID	Station Name	Longitude (°)	Latitude (°)	Altitude (m a.s.l.)	Mean snow depth (cm)			
					Dec	Jan	Feb	Mar
425606	BUCURESTI FILARET	26.09532212	44.41235543	82	2	6.5	9.2	1.4
509649	BUZAU	26.85323649	45.13293184	89	1.3	2.4	4.3	0.3
359257	CALAFAT	22.94756876	43.98524562	61	1.9	4.7	7.8	1.4
412721	CALARASI	27.33978003	44.20601637	22	1.9	4.1	5.7	0.3
706515	CALIMANI (RETITIS)	25.24776979	47.09817701	2022	28.7	39.5	62.7	85.1
622303	CAMPENI (BISTRA)	23.04195345	46.36410439	621	3.4	4	6.5	2.2
517545	CAMPINA	25.73494434	45.1439892	461	2.6	5	9	1.8
517507	CAMPULUNG MUSCEL	25.03812971	45.27505407	690	2.5	3.9	7.8	3.2
406421	CARACAL	24.35881328	44.10044411	105	1.7	6.4	7.9	0.9
525215	CARANSEBES	22.22784657	45.41743522	241	2	1.5	4.2	0.7
656555	CEAHLAU TOACA	25.95151254	46.97775945	1897	25.1	43.5	62.1	73.1
421803	CERNAVODA	28.04517747	44.34590422	90	1.2	2.9	4.9	0
632130	CHISINEU CRIS	21.54326795	46.51884784	96	0.8	0.8	3.3	0.5
647334	CLUJ-NAPOCA	23.57289952	46.77805966	417	1.7	2.8	4.7	1
413838	CONSTANTA	28.64702037	44.2140732	13	0.4	1.6	0.7	0
444820	CORUGEA	28.34352163	44.73458896	221	0.2	0.8	1	0
722657	COTNARI	26.92720859	47.35854811	289	6.1	6	9.4	1.6
414352	CRAIOVA	23.86850048	44.31046723	192	2.1	6.6	9.5	1.1
518231	CUNTU	22.50304974	45.30081051	1456	23.4	44.3	76.7	78.7
509441	CURTEA DE ARGES	24.6712742	45.17909091	449	2.1	3.3	7	1.1
812637	DARABANI	26.57508418	48.19512074	259	6.4	8.5	12.6	2.7
500432	DEDULESTI-MORARESTI	24.57167643	45.01661345	550	3.7	7	11.5	2.4
709352	DEJ	23.90045935	47.12827194	240	2.6	4	6.5	1.7
553254	DEVA	22.90037882	45.86523795	230	0.9	0.9	1.9	0.5
444417	DRAGASANI	24.23870812	44.66575461	275	2.3	5.2	7.8	1
438238	DROBETA TURNU SEVERIN	22.62761176	44.62679852	77	1.5	3.7	5.2	0.6
614436	DUMBRAVENI	24.59317787	46.2281542	323	2.3	3.5	5.1	1
639210	DUMBRAVITA DE CODRU	22.17280803	46.64493673	586	3.2	3.4	9	3.8
551459	FAGARAS	24.93680407	45.83653909	435	2.2	3.5	4.2	0.5

Station ID	Station Name	Longitude (°)	Latitude (°)	Altitude (m a.s.l.)	Mean snow depth (cm)			
					Dec	Jan	Feb	Mar
541712	FOCSANI	27.20130534	45.68777697	47	3.1	5.1	10.5	2.1
528518	FUNDATA	25.27307088	45.43175707	1376	12.2	22.5	32.5	26.1
428632	FUNDULEA	26.52505125	44.45322764	67	2.4	6.1	8.9	1
530801	GALATI	28.03380058	45.47316338	71	2.9	4	5.6	0.5
352557	GIURGIU	25.93422078	43.87547042	24	1.9	5.8	5.7	0.4
511912	GORGOVA	29.15827387	45.17710656	3	0.2	1	1.3	0
445718	GRIVITA	27.29608598	44.74105792	51	0.8	2.9	8.6	0.5
441900	GURA PORTITEI	29.00045229	44.69008267	4	0.1	0.8	0.8	0
617220	GURAHONT	22.33489688	46.27950832	177	1.6	1	2.3	0.4
441757	HARSOVA	27.96501275	44.69195657	41	0.5	1.3	2.7	0.1
646207	HOLOD	22.11387211	46.78889456	163	1.5	0.8	3.6	0.5
651305	HUEDIN	23.03414742	46.85760813	566	2.6	3.1	6.3	1.6
710736	IASI	27.62986822	47.17118906	103	3.8	6	6.7	1.9
737439	IEZER	24.65062962	47.60283971	1792	13.4	21.5	26.9	41.5
541601	INTORSURA BUZAULUI	26.0583039	45.66854534	707	6.1	10.5	11.5	3
547042	JIMBOLIA	20.70395027	45.78120011	79	0.7	0.7	3.5	0.6
642540	JOSENI	25.51414214	46.70599974	747	7.3	8.5	11.9	4.7
446853	JURILOVCA	28.87788675	44.76631771	36	0.1	0.7	2.5	0
551621	LACAUTI	26.37708527	45.82418134	1778	34.2	63.4	108.3	122.8
541154	LUGOJ	21.93486205	45.68687373	168	2	1.1	4.7	0.6
505904	MAHMUDIA	29.07487145	45.0874159	175	0.3	1.6	2.9	0.1
349835	MANGALIA	28.58889581	43.81639105	1	0.5	2.1	0.5	0.1
415816	MEDGIDIA	28.2528599	44.24346248	67	1	2	2.3	0
622544	MIERCUREA CIUC	25.77417211	46.37157943	667	6.8	9	14.2	5.7
444127	MOLDOVA VECHE	21.63480975	44.72279567	82	1.1	1.5	4.3	0.3
650727	NEGRESTI (VASLUI)	27.44369453	46.83832816	134	3.5	6.2	6.3	1.8
747356	OCNA SUGATAG	23.94208347	47.77732798	508	3	4.5	6.9	3.3
618518	ODORHEIUL SECUIESC	25.29332105	46.29704279	532	1.8	3.5	5.1	1.2
404638	OLTENITA	26.63861373	44.07498393	14	2.1	6.5	6	0.5
703156	ORADEA	21.89754503	47.03601962	136	0.8	0.7	3.4	0.6
502141	ORAVITA	21.7120422	45.03905829	309	1.7	2.4	8.1	1.5

Station ID	Station Name	Longitude (°)	Latitude (°)	Altitude (m a.s.l.)	Mean snow depth (cm)			
					Dec	Jan	Feb	Mar
501252	PADES (APA NEAGRA)	22.86105375	44.99713632	260	3.5	6.7	11.2	3.1
539357	PALTINIS	23.93399847	45.6574256	1462	18.8	33.5	48.6	45.7
523328	PARANG	23.46462206	45.38768614	1559	18.1	32.8	52.9	52
519622	PATARLAGELE	26.37102399	45.32492469	293	1.8	2.6	5.8	0.7
536625	PENTELEU	26.4113611	45.60293306	1633	23.7	36.6	60.4	53.8
525323	PETROSANI	23.37825439	45.40661039	607	3.5	4.7	8.2	2
656621	PIATRA NEAMT	26.39108318	46.9339225	360	5.1	6.5	10	2.5
452452	PITESTI	24.86750921	44.84923476	332	1.9	4	6.5	1.1
457600	PLOIESTI	25.98892923	44.95603747	172	2	3.5	6.4	0.9
719507	POIANA STAMPEI	25.1360444	47.32492031	931	7.5	11.1	15.7	11
511349	POLOVRAGI	23.81014792	45.16576349	525	2.4	6	10	2.7
530535	PREDEAL	25.58503687	45.50656525	1096	15.3	31.7	44.5	31
751555	RADAUTI	25.89205125	47.83809571	387	5.1	7	10.4	2.9
523703	RAMNICU SARAT	27.0400409	45.39090463	155	2.3	3.7	8.3	1.1
506422	RAMNICU VALCEA	24.36434679	45.08912725	242	0.9	2.4	4.2	0.5
518155	RESITA	21.88855542	45.31470699	279	1.7	1.5	5.5	1.1
655650	ROMAN	26.9133941	46.96933778	218	4.5	5.5	8.1	2.1
619308	ROSIA MONTANA	23.1406312	46.31789822	1198	8.7	12.1	23.7	19.3
407500	ROSIORII DE VEDE	24.98023756	44.10752732	111	1.1	4.6	3.9	0.3
722205	SACUIENI	22.09613632	47.34446092	124	1.1	1.3	3.7	0.5
604037	SANNICOLAU MARE	20.60316254	46.07163314	85	1	0.9	2.8	0.5
645410	SARMASU	24.16139046	46.74783378	397	3	4.5	6.8	1.3
748253	SATU MARE	22.88878229	47.72176829	128	1.3	1.6	4.1	0.5
557334	SEBES (ALBA)	23.54305247	45.96444435	267	0.9	1.5	2	0.2
507158	SEMENIC	22.05736497	45.18173383	1432	25.7	45.8	74.9	80.7
454936	SFANTU GHEORGHE (DELTA)	29.60056995	44.8978816	1	0.1	0.6	1.2	0
552548	SFANTU GHEORGHE (MUNTE)	25.80365983	45.87183011	525	3.7	5.9	6.4	0.8
548409	SIBIU	24.09297678	45.78960481	453	2	3.7	4.2	0.6

Station ID	Station Name	Longitude (°)	Latitude (°)	Altitude (m a.s.l.)	Mean snow depth (cm)			
					Dec	Jan	Feb	Mar
758355	SIGHETUL MARMATIEI	23.9059651	47.93956747	283	1.8	5.7	7.8	2.7
523530	SINAIA 1500	25.51571273	45.35525599	1510	23.3	38.2	59.7	59.2
616140	SIRIA	21.66438116	46.26518273	473	1.6	1.6	5.8	1.3
426421	SLATINA	24.35604254	44.4424926	172	1.7	4.9	7.9	1
433724	SLOBOZIA	27.38504422	44.55302996	53	1.4	2.6	4.1	0.2
641237	STANA DE VALE	22.62498402	46.69012519	1108	23.4	40.3	61.2	58.6
749713	STEFANESTI STANCA	27.22130911	47.83246931	110	3.4	3.8	5.8	0.8
632229	STEI (PETRU GROZA)	22.46809247	46.52831717	278	1.6	1.8	3.5	0.7
436447	STOLNICI	24.7913224	44.56302854	225	1.5	3.9	6.6	1
739615	SUCEAVA	26.24214328	47.6331339	366	5.8	7.4	11.9	2.8
509940	SULINA	29.76044896	45.14869404	3	0	0	0	0
728247	SUPURU DE JOS	22.78520612	47.45537856	166	1	1	2.7	0.5
515231	TARCU	22.53428015	45.2813352	2180	28.9	56.5	91	107.9
456526	TARGOVISTE	25.42719989	44.92983528	285	1.9	3.8	6	1.2
502317	TARGU JIU	23.260882	45.04095796	204	1.3	3.3	7.8	1
726352	TARGU LAPUS	23.87382703	47.43990113	375	3.9	7.5	12.5	6
453344	TARGU LOGRESTI	23.71023619	44.87841799	271	2.2	4.6	8.2	1.3
632432	TARGU MURES	24.53535631	46.53357831	317	3.1	3.7	5.3	0.7
714623	TARGU NEAMT	26.38076511	47.21237637	385	5.4	6.6	9.7	2.5
617637	TARGU OCNA	26.64258627	46.27295943	245	4	3.6	5.5	0.8
600608	TARGU SECUIESC	26.11661582	45.99316541	571	4.5	6.5	7.8	1.4
622414	TARNAVENI (BOBOHALMA)	24.22754861	46.36036358	525	3.2	4.1	6.1	2.5
551716	TECUCI	27.41053329	45.84181804	57	1.8	2.7	4.2	0.7
546115	TIMISOARA	21.25965761	45.77139806	86	1.4	1	3.5	0.3
439534	TITU	25.58070721	44.65315439	174	1.9	4.5	7.1	1.2
655522	TOPLITA	25.36148301	46.92665148	690	7.5	10.1	13.5	6
511849	TULCEA	28.82564167	45.19074534	5	0.9	2.3	2.4	0.1
635347	TURDA	23.79283447	46.58333693	431	2.7	3.1	5.2	1.5
346452	TURNU MAGURELE	24.87996008	43.76047002	25	1.5	7.2	8	0.5

Station ID	Station Name	Longitude (°)	Latitude (°)	Altitude (m a.s.l.)	Mean snow depth (cm)			
					Dec	Jan	Feb	Mar
443639	URZICENI	26.6587029	44.7220144	65	1.7	2.7	4.6	0.2
602213	VARADIA DE MURES	22.15253875	46.01953169	156	1.4	0.7	3.3	0.7
527527	VARFUL OMU	25.45822182	45.44607647	2506	49.1	69.5	89.6	111.1
639744	VASLUI	27.71598538	46.64634703	121	4.3	6.5	6.5	2.4
417530	VIDELE	25.53849985	44.28316981	118	1.8	4.5	4.9	0.5
646247	VLADEASA 1800	22.79578515	46.75955615	1840	9.4	15.5	19.7	19.9
711305	ZALAU	23.04835118	47.19517188	303	1.4	2.2	4.4	0.9
340521	ZIMNICEA	25.35509607	43.66183202	39	1.8	7.5	7.5	0.5

Also, the auxiliary data listed further, derived from the Digital Elevation Model (DEM) were used for interpolating the multiannual values: altitude, mean altitude in a 20-km radius, latitude, distance to the Black Sea and distance to the Adriatic Sea.

The purpose of the DEM-derived predictors was to take into account both the altitudinal and latitudinal distribution of snow depth. The direct influence of the major water bodies as the main source of moisture was taken into account by including as predictors the distances to the Black Sea and to the Adriatic Sea, respectively (Dumitrescu et. al., 2016). The monthly regression models were also improved by adding two more predictors, namely the grids of mean multiannual monthly precipitation and mean multiannual monthly temperature, computed for the same period (2005-2015).

2.2. Methods

To interpolate the maps with the climatological normals (multiannual means), the Regression-Kriging (RK) spatial interpolation method was used. To choose the optimum method for gridding the deviations, four interpolation methods were tested through the cross validation procedure: Multiquadratic (MQ), Ordinary Kriging with separate (sepOK) and pooled semivariograms (pvOK) and 3D Kriging (K3d).

RK is a multivariate method that include one or more variables with a spatially continuous distribution (digital elevation model, satellite images, etc.) in the computations. It results from summing the surface determined through the least squares method (applied to multiple regression) and the surface obtained through spatially interpolating the regression residuals, using the Kriging method. With this method, the first step consists in statistically validating the deterministic model, in the sense of verifying the intensity of the relationships between predictors and the dependent variable. The best regression model could be determined applying stepwise regression. In the case of RK method, the matrix of the multiple regression grid points represents the large-scale variability of the analysed parameter modelled by the explanatory variables. The interpolated residuals represent the local peculiarities of the target variable, modelled with the help of the semivariogram (Hengl et al., 2007):

$$\acute{Z}(s_0) = \sum_{k=1}^{p} \acute{\beta}_k \cdot q_k(s_0) + \sum_{i=1}^{N} \lambda_i \cdot e(s_i) \quad (1)$$

where $\acute{\beta}_k$ are the coefficients of the regression model, q_k is the value of the predictor in the point localised through the s_0 coordinates for which a new value is estimated and λ_i are the weighting coefficients of the residuals of $e(s_i)$ regression with s_i coordinates. Regression coefficients can be obtained either through the simple method of the least squares or through applying the generalised regression model.

MQ belongs to the class of exact interpolation methods called Radial Base Functions (RBF), which resembles very much to the Kriging family class only differing through that it does not benefit from the contribution of the data spatial structure analysis through the semivariogram. Johnston et al. 2001 defines the general form of this category of interpolators as follow:

$$\acute{Z}(s_0) = \sum_{i=1}^{N} \omega_i \, \phi(\|s_i - s_0\|) \omega_{n+1} \quad (2)$$

where $\phi(r)$ is the radial base function, $r = \|s_i - s_0\|$ is the radial distance between the point for which a new s_0 value is computed and the points with s_i measured values and ω symbolises the weights to be estimated.

The value of the weight of each point used in interpolation results after solving a system of equations using the matrix computation of the type:

$$\begin{pmatrix} \phi & 1' \\ 1 & 0 \end{pmatrix} \begin{pmatrix} w \\ \omega_{n+1} \end{pmatrix} = \begin{pmatrix} z \\ 0 \end{pmatrix} \quad (3)$$

with ϕ being the matrix of the distance between the points with known values to which a radial base function is applied; z denotes the vector with the distances between the location chosen for estimation and the points with measurements, to which the same radial base function is applied; w are the estimated weights and ω_{n+1} are the residuals.

MQ radial function is given by the relationship

$$\phi(r) = (r^2 + \sigma^2)^{-1/2} \quad (4)$$

The smoothing parameter σ can be chosen through computing the minimum sum of squared errors resulted from the application of the cross validation procedure or directly by the user.

OK computes the weights on the basis of the functions that also take for computation the spatial configuration of data (Isaaks and Srivastava, 1989). The first step in the interpolation through the OK method is the analysis of the spatial interdependence of the dataset, performed through constructing the semivariogram of the sampled points (Pebesma, 2004):

$$\hat{\lambda}(\overline{h}_j) = \frac{1}{2N_j}\sum_{i=1}^{N_j}[Z(s_i) - Z(s_i + h)]^2$$

where N_j is a set of pairs of locations separated by the distance h and $\overline{h}$ = the average of the distances between the N_j distinct pairs.

The assessment in a new location is based on regression against local neighborhood data of the surrounding data points, weighted according to the spatial covariance values (Johnston et al., 2001):

$$\acute{Z}(s_0) = \textstyle\sum_{i=1}^{N} \lambda_i \, Z(s_i), \;\; \sum_{i=1}^{N} \lambda_i = 1 \tag{5}$$

OK weighting functions take for computation both distance and the geographical arrangement of data. The value of the weights of each point used in interpolation results from solving a system of equations through a matrix calculus of the type:

$$\begin{pmatrix} C & 1' \\ 1 & 0 \end{pmatrix}\begin{pmatrix} \lambda \\ m \end{pmatrix} = \begin{pmatrix} c \\ 1 \end{pmatrix} \tag{6}$$

matrix C representing the covariance's between the points with known values, vector c being made up of the covariances between the points with known values and the point with unknown value, λ = vector of the Kriging weighting coefficients and m = Lagrange multiplier utilized in minimizing errors through the relationship:

$$\sigma^2 = \textstyle\sum_{i=1}^{N} \lambda_i \, c + m \tag{7}$$

In this work two versions of OK method were investigated: (1) with daily estimation of the variograms (separated fitted daily semivariograms – sepOK), and (2) with pooled semivariograms (one single variogram is constructed relying on all data, treating each day as a copy of the same spatial dependence structure – pvOK) (Gräler et al., 2013).

3dK is a three-dimensional extension of the two-dimensional Kriging method, which considers time to be the third orthogonal dimension. The predictions from the space-time cube are based only on one semivariogram model for the period of analysis, while the classical Kriging interpolation models require one semivariogram per time unit (Pebesma, 2013). Because good results of this method are achieved when an isotropic covariance model is used, the time dimension must be rescaled in order to align to the spatial directions (Hiemstra et al., 2009).

2.3. Validation

To choose the optimum method for interpolating the deviations, the leave-one-out cross validation was applied. This implies the elimination one by one of the values from the set of observed values and determining the value of the point excluded on the basis of the other observed data. The difference between the P estimated data and the O measured ones represents the ε experimental value:

$$\varepsilon_i = P(s_i) - O(s_i)$$

Quantification of differences between estimations and observed data was performed with the help of the error measurement indicators:

– mean error (*ME*) represents the means of the differences between estimated and measured values respectively:

$$ME = \frac{1}{N}\sum_{i=1}^{N}(Ps_i - Os_i)$$

– mean absolute error (*MAE*) represents the means of the absolute differences between estimated and measured values respectively:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|Ps_i - Os_i|$$

– root mean square error (*RMSE*) is sensitive to the presence of large errors, the squaring process attributing the residuals disproportionate weights:

$$RMSE = \frac{1}{N}\sum_{i=1}^{N}[(Ps_i - Os_i)^2]^{\frac{1}{2}}$$

The box-plot and Taylor-type diagram were also used in the quantitative analysis of results yielded by the four interpolation methods applied in interpolating the ratios (Taylor, 2001).

3. Results

3.1. Climatological maps

In order to achieve the gridded climatology, the mean multiannual monthly snow depth data (1 December 2005 – 31 March 2015) was used. Maps representing the climatological normals were obtained with the RK method.

Due to the existence of the collinearity effect, the predictors were subjected to the filtering process through the principal component analysis. Filtering the predictors through the principal component analysis (PCA) is performed through transforming the initial variables into a new set of variables, uncorrelated and of a smaller size. The new data set thus obtained contains most part of the original dataset variability (Fig. 2).

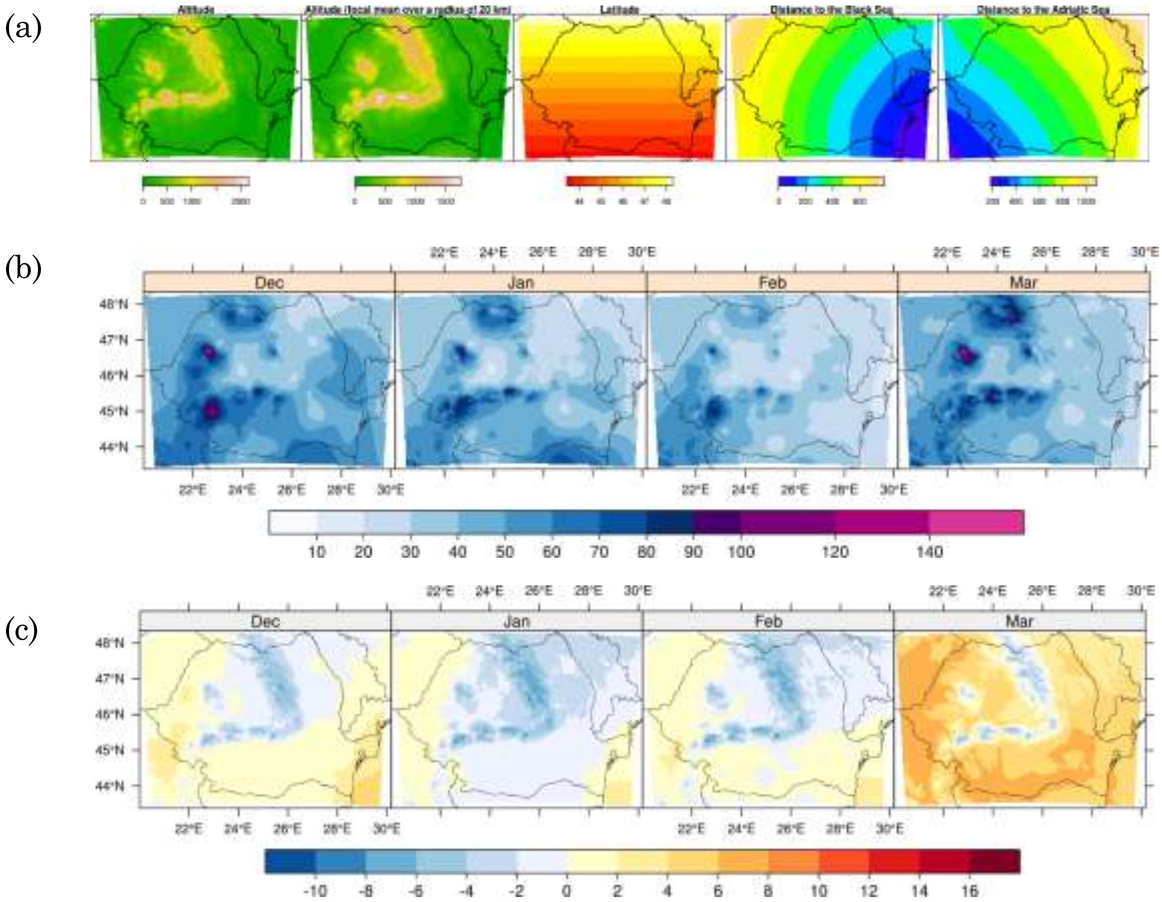

Figure 2. Maps of the predictors used in the study: (*a*) predictors derived from DEM; (*b*) mean monthly multiannual precipitation in mm; (*c*) mean monthly multiannual temperature in °C.

Figure 3 depicts the explained variance of the seven principal components for each month. It can be seen that the first three components explain the main characteristics regarding the spatial variability, representing the strongest configurations in explaining 90% or more of the variance present in the predictor fields, hence only those were taken for computation of the climatological maps.

Prior to applying the RK method the statistical relationships between snow depth and the auxiliary variables (PCA predictors) for each month were identified. Through applying the backward type stepwise regression there can be selected for each case (month) taken apart the statistically significant predictors (Tab. 2). Analyzing the frequency distributions it was noted that the snow depth had a positive skewed distribution. Therefore, they were transformed to a close normal distribution by applying the natural logarithm function. The log1p() function from R language was used, which can also be applied when the data series contain values of zero. The estimations were back-transformed to real values with a help of expm1() function (https://stat.ethz.ch/R-manual/R-devel/library/base/html/Log.html).

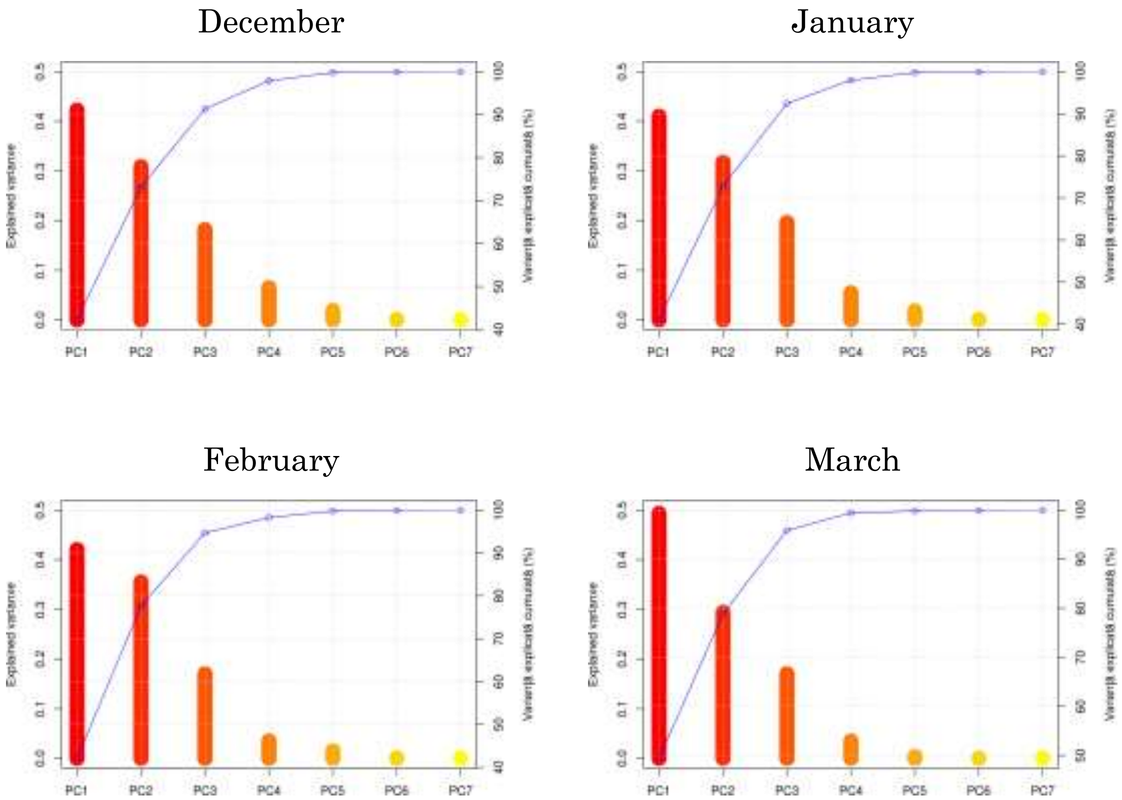

Figure 3. Variance explained by the principal components (PCA) computed from the set of predictors obtained from the numerical altimetric model.

Table 2. Snowpack depth: predictors selected through using the stepwise regression and R^2 determination coefficients.

Month	Predictors	R^2
log1p(Jan)	PC1 + I(PC1^2) + PC3 + PC5	0.860
log1p(Feb)	PC1 + I(PC1^2) + PC3 + PC4 + PC5	0.862
log1p(Mar)	PC1 + PC2 + PC3 + PC5	0.908
log1p(Apr)	PC1 + I(PC1^2) + PC4 + PC5	0.922
log1p(Oct)	PC1 + I(PC1^2)	0.868
log1p(Nov)	PC1 + I(PC1^2) + PC2 + PC3 + PC5	0.914
log1p(Dec)	PC1 + PC2 + PC3 + PC4 + PC5	0.854

The predictive power of the regression models varies from month to month, with smallest R-squared value in January, and the largest value in March. For all months more than 70% of the spatial variability of snowpack depth being explained by the predictors. For some months the nonlinear influence of some predictors was quantified in the regression model by using a 2nd degree polynomial regression model.

In order to verify the interpolation results, a cross-validation was performed for the climatological maps for each month. The results are presented in Fig. 4, together with the *MAE*, *RMSE* and *CORR* between the original and the cross-validation values.

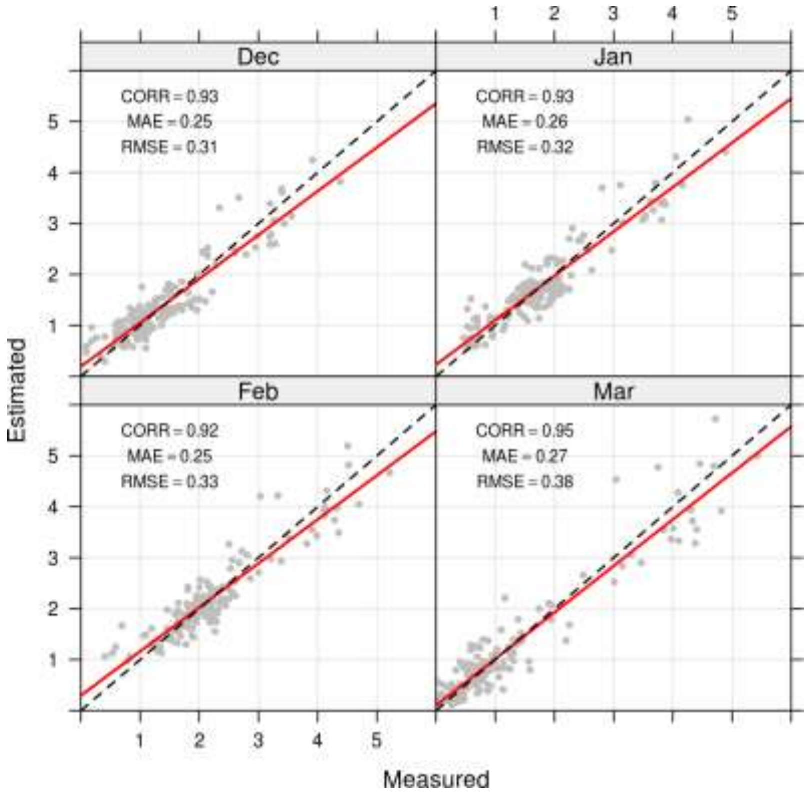

Figure 4. Plots of the original and the cross-validation values for the four months.

From analyzing the maps constructed with RK method (Fig. 5), it can be seen that the highest values are recorded in the closing month of the cold season, being generated by persisting below zero temperatures at high altitudes, which favours constant accretion of snow.

3.2. Daily gridded dataset

At this stage a number of interpolation methods were tested in order to find the optimum interpolation method for daily anomalies: Multiquadratic (MQ), Ordinary Kriging – separate (sepOK) and pooled variograms (pvOK) – and 3D Kriging (K3d). For the sepOK method the semivariograms were automatically estimated through the use of the automap R package (Hiemstra et al., 2009). For the pvOK and K3d methods the variograms were fitted by using the fit.variogram function from gstat R package (Pebesma, 2013).

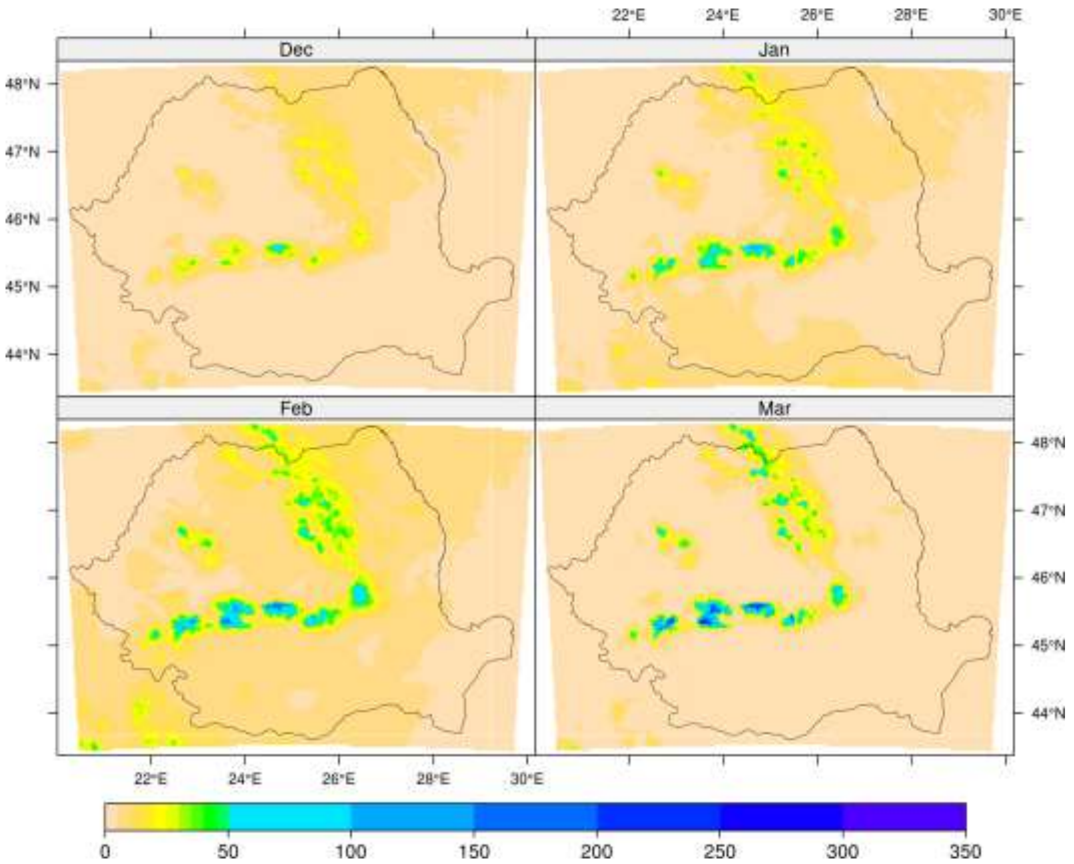

Figure 5. Mean monthly snow depth (cm), December – March, 2005–2015.

Since there are regions where the mean multiannual snowpack depth is equal to zero, at the stations located on lower altitudes, a 1 cm value was added to the multiannual means prior to computing the daily anomalies.

The cross validation procedure was applied to the anomalies computed over the period 1 December 2014 – 31 March 2015. According to Fig. 6, estimations performed with the four methods are very similar, a difference being apparent with the help of *RMSE* indicators, and *ME* that points out the superior estimations performed with K3d method.

The Taylor diagrams (Fig. 7) confirm that the best estimates are provided by K3d method, regardless the month analyzed. pvOK obtains comparable results, with nearly the same computed values for Pearson's correlation coefficient and slightly larger standard deviation values. sepOK has the poorest accuracy in terms of the three computed indicators. Note that all methods underestimate the variability of the observed data, the poorest performance being computed for the March month, when the snowpack depth value are greater than 0 only in the mountain regions.

Due to the good results in interpolating ratios and to the fewer steps required for producing the maps, K3d method was chosen to generate daily anomaly maps. The final daily snowpack depth maps were generated by multiplying the ratio maps with those representing the monthly climatology.

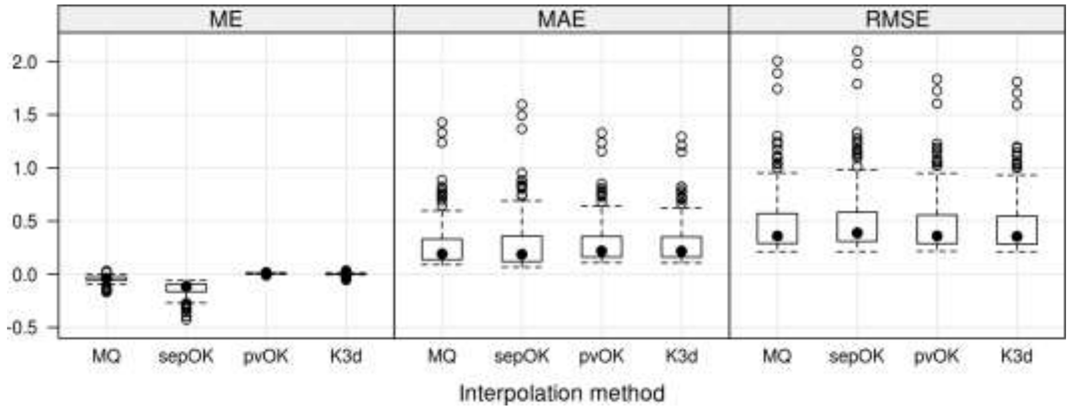

Figure 6. Mean Box-plot type diagram of daily anomalies (Dec 2014–Mar 2015), *ME* (*left*), *MAE* (*middle*) and *RMSE* (*right*) computed through using the original datasets against those estimated through the cross validation procedure using MQ, sepOK, pvOK and K3d interpolation methods.

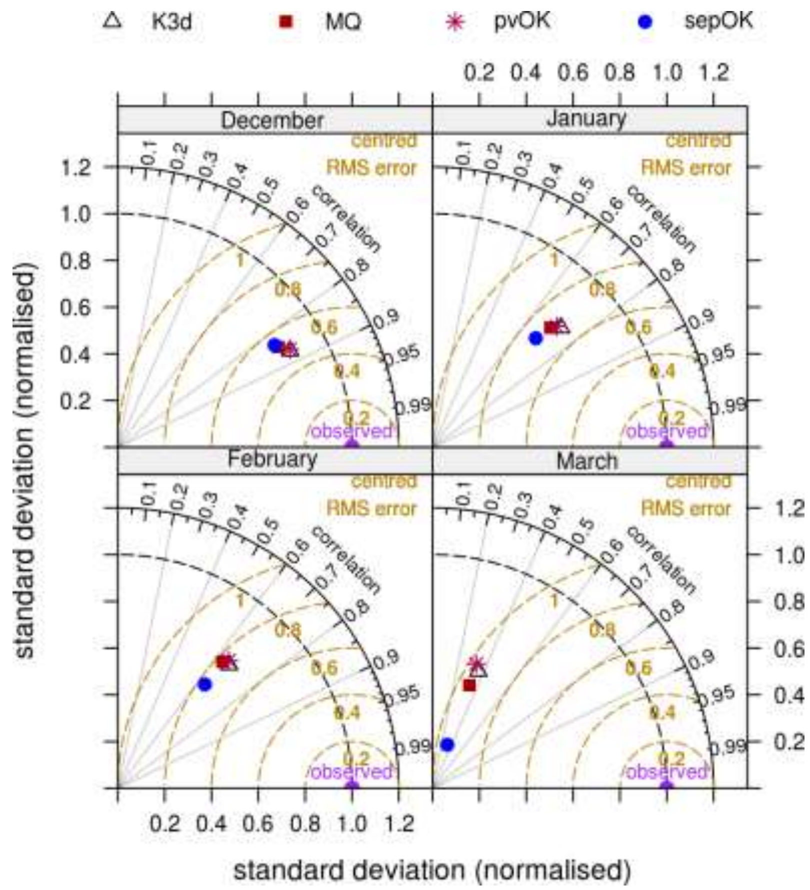

Figure 7. Taylor-type diagram of daily deviations obtained through the cross validation procedure for the four interpolation methods (MQ, sepOK , pvOK and K3d).

Using gridded daily data regarding the snowpack depth, constructed with the help of the K3d method, the monthly maximum snowpack depth was computed in every grid point (Fig. 8). The highest values of this parameter correspond to the high mountain areas (more than 200 cm starting from January), persisting till March due to the negative mean temperatures. A considerable snowpack (deeper than 50 cm) can also be found in the extra-Carpathian areas as a consequence of the blizzard episodes specific to January and February.

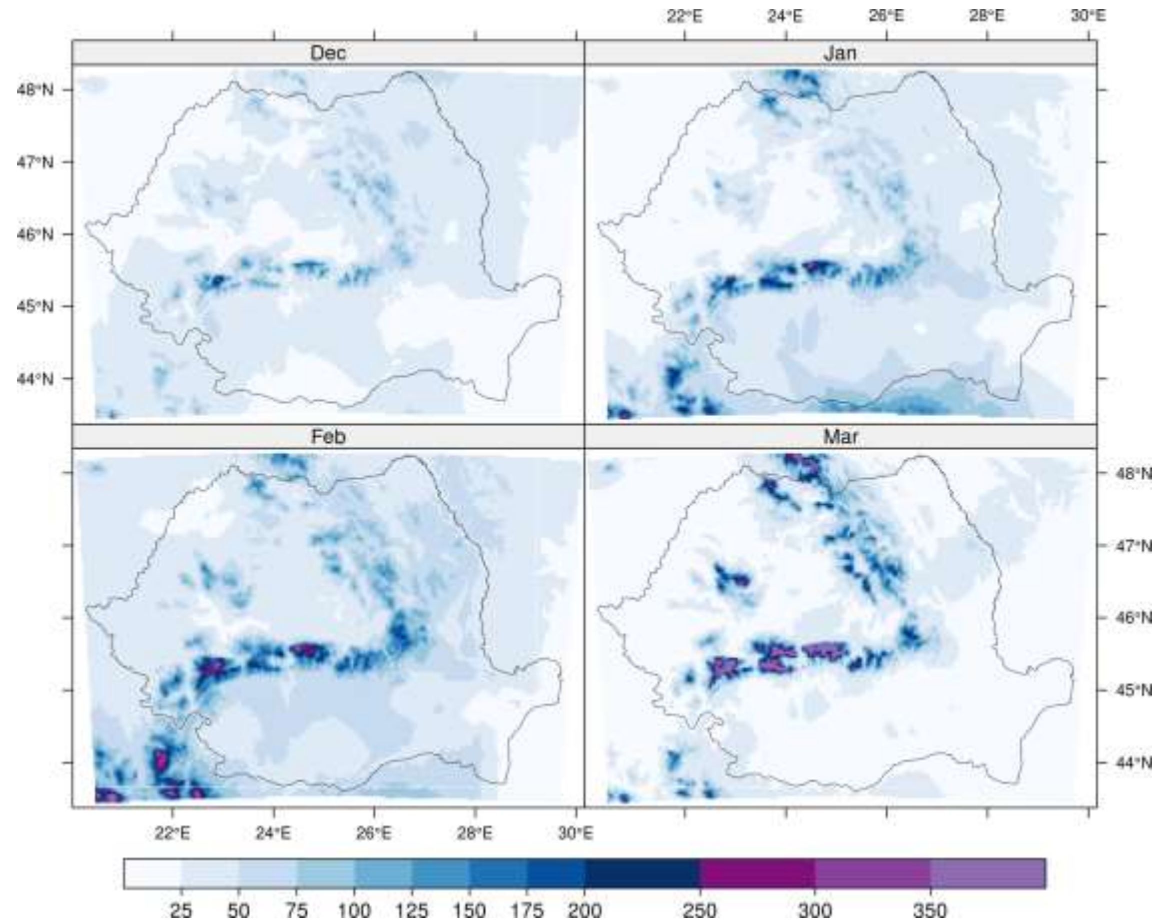

Figure 8. Maximum monthly snow depth (2005–2015).

4. Conclusions

Using an interpolation procedure that implies completion of a number of stages, there were obtained the gridded datasets for the snowpack depth values. Those were constructed at 1000 m × 1000 m spatial resolution, using meteorological records from 2005 to 2015, only for the months December, January, February and March.

In the first stage, the monthly climatology maps were constructed based on a multivariate geostatistical model based on the RK method. This can take for computation in the process of spatialization one or more variables with a continuous spatial distribution. The purpose of the DEM-derived predictors was to take into account both the altitudinal and latitudinal distribution of snow depth. The direct influence of the major water bodies as the main source of moisture was also accounted for by using as predictors the distances to the Black Sea and to the Adriatic Sea, respectively. The monthly regression models were also improved by adding two more predictors: the multiannual monthly mean of precipitation and temperature grids, computed for the same period (2005–2015). In order to choose the optimum combination of potential predictors, the stepwise regression was used, selecting in the interpolation process only those predictors which are statistically significant for each analyzed case (month).

The second stage implied spatial interpolation of the daily deviations against the monthly normals. In view to choose the optimum interpolation method, four spatialization methods were tested. Through using the cross validation procedure and computing some error indicators, conclusion was drawn that the best estimates are obtained through the 3d Kriging (which includes time as the third dimension), hence this method was applied in interpolating the anomalies. Through combining the maps with the daily anomalies with those rendering the monthly normals, daily snow depth maps were constructed.

Using the gridded daily data, other parameters may be computed: number of days with snowpack, the first and last day with snowpack, the maximum snowpack depth, etc.

Maps obtained within this stage supply an overall picture of the analyzed variables, however with a precision directly influenced by the scale at which those were performed, by the spatial estimation errors specific to the geostatistical methods and by the density of the measurement points (weather stations operated by the National Meteorological Administration). In certain areas, where peculiar climatic conditions are specific and where no meteorological measurements are performed, it is recommended to achieve detailed studies regarding the spatio-temporal variability of the parameters of interest stressing the spatio-temporal local development character of the meteorological phenomena.

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References

Birsan, M. V. (2013): Application of a distributed physically-based hydrological model on the upper river basin of Somesul Mare (Northern Romania), *Rom. Rep. Phys.*, **65**, 1469–1478.

Birsan, M. V. (2015): Trends in Monthly Natural Streamflow in Romania and Linkages to Atmospheric Circulation in the North Atlantic, *Water Resour. Manage.*, **29**, 3305–3313, DOI: 10.1007/s11269-015-0999-6.

Birsan, M. V. and Dumitrescu, A. (2014): Snow variability in Romania in connection to large-scale atmospheric circulation, *Int. J. Climatol.*, **34**, 134–144, DOI: 10.1002/joc.3671.

Birsan, M. V., Marin, L. and Dumitrescu, A. (2013): Seasonal changes in wind speed in Romania, *Rom. Rep. Phys.,* **65**, 1479–1484.

Birsan, M. V., Dumitrescu, A., Micu, D. M., and Cheval, S. (2014): Changes in annual temperature extremes in the Carpathians since AD 1961., *Nat. Hazards*, **74**, 1899–1910, DOI: 10.1007/s11069-014-1290-5.

Busuioc, A., Birsan, M. V., Carbunaru, D. Baciu, M. and Orzan, A. (2016): Changes in the large-scale thermodynamic instability and connection with rain shower frequency over Romania. Verification of the Clausius–Clapeyron scaling, *Int. J. Climatol.*, **36**, 2015–2034, DOI: 10.1002/joc.4477.

Cheval, S., Birsan, M. V. and Dumitrescu, A. (2014a): Climate variability in the Carpathian Mountains Region over 1961–2010, *Global Planet. Change*, **118**, 85–96, DOI: 10.1016/j.gloplacha.2014.04.005.

Cheval, S., Busuioc, A., Dumitrescu, A. and Birsan, M. V. (2014b): Spatiotemporal variability of meteorological drought in Romania using the standardized precipitation index (SPI), *Clim. Res.*, **60**, 235–248, DOI: 10.3354/cr01245.

Cheval, S., Birsan, M. V. and Dumitrescu, A. (2017): Variability of the aridity in the South-Eastern Europe over 1961–2050, *Catena*, **151**, 74-86, DOI: 10.1016/j.catena.2016.11.029.

Dascălu, S. I., Gothard, M., Bojariu, R., Birsan, M. V., Cică, R., Vintilă, R., Adler, M. J., Chendeș, V. and Mic, R. P. (2016): Drought-related variables over the Bârlad basin (Eastern Romania) under climate change scenarios, *Catena*, **141**, 92–99, DOI: 10.1016/j.catena.2016.02.018.

Dobrinescu, A., Busuioc, A., Birsan, M. V. and Dumitrescu, A. (2015): Changes in thermal discomfort indices in Romania and responsible large-scale mechanisms, *Clim. Res.*, **64**, 213–226, DOI: 10.3354/cr01312.

Dumitrescu, A. and Birsan, M.V. (2015): ROCADA: a gridded daily climatic dataset over Romania (1961–2013) for nine meteorological variables, *Nat. Hazards*, **78**, 1045–1063, DOI: 10.1007/s11069-015-1757-z.

Dumitrescu, A., Birsan, M. V. and Manea, A. (2016): Spatio-temporal interpolation of sub-daily (6-hour) precipitation over Romania for the period 1975–2010, *Int. J. Climatol.*, **36**(3), 1331–1343, DOI: 10.1002/joc.4427.

Dumitrescu, A., Bojariu, R., Birsan, M. V., Marin, L. and Manea, A. (2015): Recent climatic changes in Romania from observational data (1961-2013), *Theor. Appl. Climatol.*, **122**, 111–119, DOI: 10.1007/s00704-014-1290-0.

Gräler, B., Rehr, M., Gerharz, L. and Pebesma, E. (2013): *Spatio-temporal analysis and interpolation of PM10 measurements in Europe for 2009*. Technical Paper 2011/10, The European TopiCentre on Air Pollution and Climate Change Mitigation (ETC/ACM).

Hengl, T., Heuvelink, G. B. M. and Rossiter, D. G. (2007): About Regression-Kriging: From Equations to Case Studies, *Comput. Geosci.*, **33**, 1301–1315.

Hiemstra, J. M., Pebesma, E. J., Twenhöfel, C. L. W. and Heuvelink, G. B. M. (2009): Real-time automatic interpolation of ambient gamma dose rates from the Dutch Radioactivity Monitoring Network, *Comput. Geosci.*, **35**, 1711–1721, DOI:

10.1016/j.cageo.2008.10.011.

Isaaks, E. H. and Srivastava, R. M. (1989): *An introduction to applied geostatistics*. Oxford University Press, 561 pp.

Johnston, K., Ver Hoef, J. M., Krivoruchko, K. and Lucas, N. (2001): *Using ArcGIS geostatistical analyst*. ESRI Press, Redlands, 306 pp.

Manea, A., Birsan, M. V., Tudorache, G. and Cărbunaru, F. (2016): Changes in the type of precipitation and associated cloud types in Eastern Romania (1961–2008), *Atmos. Res.*, **169**, 357–365, DOI: 10.1016/j.atmosres.2015.10.020.

Marin, L., Birsan, M. V., Bojariu, R., Dumitrescu, A., Micu, D. M. and Manea, A. (2014): An overview of annual climatic changes in Romania: trends in air temperature, precipitation, sunshine hours, cloud cover, relative humidity and wind speed during the 1961–2013 period, *Carpath. J. Earth Env.*, **9**, 253–258.

Pebesma, E. (2013): *Spatio-temporal geostatistics using gstat*, available online at: http://cran.r-project.org/web/packages/gstat/vignettes/st.pdf

Pebesma, E. J. (2004): Multivariable geostatistics in S: The Gstat package, *Comput. Geosci.*, **30**, 683–691.

Rimbu, N., Stefan, S. and Necula, C. (2015): The variability of winter high temperature extremes in Romania and its relationship with large-scale atmospheric circulation, *Theor. Appl. Climatol.*, **121**, 121–130, DOI: 10.1007/s00704-014-1219-7.

Taylor, K. E. (2001): Summarizing multiple aspects of model performance in a single diagram, *J. Geophys. Res.*, **106**(D7), 7183–7192, DOI:10.1029/2000JD900719.

Tveito, O. E., Wegehenkel, M., van der Wel, F. and Dobesch, F. (2006): *The use of geographic information systems in climatology and meteorology*. COST Action 719 Final Report, Office for Official Publications of the European Communities, Luxembourg, 246 pp.

SAŽETAK

Gridovi fine prostorne rezolucije dnevnih visina snijega za Rumunjsku (2005.–2015.)

Alexandru Dumitrescu, Marius-Victor Birsan i Ion-Andrei Nita

Ova studija prikazuje proceduru prostorne interpolacije mjerenja dubine snijega na meteorološkim postajama koja podrazumijeva sljedeće faze: (1) prostorna interpolacija pri rezoluciji od 1 km x 1 km srednjih višegodišnjih vrijednosti (2005.–2015.), koja se provodi s podacima iz klimatološke baze; (2) izračunavanje dnevnih odstupanja od višegodišnjeg mjesečnog srednjaka za svaki dan i godinu tijekom razdoblja od 2005. do 2015. i njihova prostorna interpolacija; (3) prostorno-vremenski skup podataka dobiven je združivanjem procjena dobivenih u fazi 1 i 2. Odstupanja su definirana kao omjeri dnevnih vrijednosti dubine snijeg i klimatološkog srednjaka. Prostorna varijabilnost podataka korištenih u prvoj fazi objašnjena je korištenjem niza prediktora izvedenih iz digitalnog modela visina (DEM). Karte klimatoloških normala (višegodišnji srednjaci) izrađene su metodom prostorne interpolacije zvanom regresijski kriging (RK). Za odabir optimalne metode za prostornu interpolaciju odstupanja, testirane su četiri metode interpolacije i ocijenjene pomoću postupka poprečne validacije: multikvadratična, obični kriging (razdvojeni i skupni variogrami) i 3D kriging.

Ključne riječi: snježni pokrivač, prostorna interpolacija, kriging, multikvadratična, poprečna validacija, Rumunjska

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