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MAPS CAN SUPPORT QUANTITATIVE EVALUATION OF EARTH'S SURFACE FEATURES WITH THEIR EVOLUTION IN TIME BETTER THAN GLOBAL NUMERICAL PARAMETERS

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Abstract

Global numerical parameters are recently preferred in scientific fields to evaluate Earth's surface features, namely in climate evolution. However, they may not fully represent the complexity of the issue they intend to qualify. The paper illustrates the fact that the intended aim can be better reached by adding the assistance provided by the evaluation of maps, especially in the case of Earth's parameters, a method already common in Spatial Big Data evaluation. Additionally, the fact that the map graphical representation is intrinsically mediating a parameter that is always associated with each data of experimental origin, datum uncertainty, so representing a kind of alternative way to model a database. Especially when maps illustrate a great variety of local situations, the visual (i.e., geometrical) examination offered by maps often allows superior information, so a more reliable and full evaluation of evolution typically in time. Cases are reported to exemplify these statements.

Keywords: global numerical parameter; data uncertainty; Earth maps; parameter spatial distribution; qualitative evaluation; quantitative evaluation.

1. Introduction

In recent years, the almost exclusive use of global numerical parameters is preferred to characterise trend changes in time in scientific fields like meteorology and climate science (see [1] as a reference of basic importance). The preference arises from the new possibilities allowed by the systematic use of informatics means to extract the relevant information from wider and wider databases having induced the new term 'Big Data'.[1]

On the contrary, the present trend of informing about global changes and related parameters is the one preferred by all the International Organisations involves in climate change, namely. [1] It consists in summarizing the changes via *global numerical* parameters, typically assumed to represent the evolution of the *mean* numerical value of big datasets correctly. However, in their synthesis, global numerical parameters may miss scientist's understanding of the existing complexity of the full set of values obtained from the measured data that they intend to qualify.

On the other hand, the traditional field of using maps for extended sets of data, namely the *spatial* one, was not surpassed in its unique capability to clearly convey, with its (visual) representation, details on the significance of the studied phenomena and of their variations in time, especially when the aim is to forecast future trends. In some fields, like that of analyses of the Earth's surface, maps have long since been used (e.g., [3–4]) and recently the Food and Agriculture Organization of the United Nations has also confirmed its preference for their use. [5] Accordingly, a revamp of the generalised advantages of visualisation in science occurred, as found in the literature, especially in philosophy of science. [6–8] On the other hand, within the recent developments of informatics one might also observe a possible increase of visualised–data misunderstanding [9–11].

Especially when the maps illustrate a great variety of situations, a comprehensive geometrical examination is recognised to report superior information – also *quantitative* since maps are graduated. This allows an overall and more reliable evaluation and its evolution, typically in time, a possibility that does not introduce any kind of conflict between mathematical and geometrical human examination but simply useful complementarities, already appreciated in the literature [12–13].

The paper will not follow the standard sequence of sections, due to the complexity of the matter.

In Section 2 it first provides a comprehensive introduction to the state–of–the art of data collation in databases and manipulation. Then, in Section 3 illustrates data visualisation by means of maps, but not from a cartographic–science viewpoint, instead from the viewpoint of *measurement–science*, according to the Journal readers main interest: this is a multidisciplinary frame allowing deep analyses of data of various origins according to the discipline of *metrology*, author's main competence. How the original numerical data can be used to plot a map is a cartography–science task. Providing evidence of the main new features introduced by Earth's mapping of climate parameters, and of the ways to take advantage of the different types of representation in the maps, will be the only author's aim.

However, the term 'visualisation' indicates a great variety of types of data graphical representation, from simple graphs, to 3D complex mapping, to its use in simulation. Therefore, the paper will restrict the subject matter *exclusively* to the examination of the mapping of Earth's surface – full or partial but never local, and *never* enter into the task of map realisation from the original dataset.

It only intends to bring evidence of map superior content of information: in addition to simple visualisation,

[1] As a consequence, also a brand-new discipline stepped in, called 'dataism', [2] even assumed in its extreme form to replace the traditional scientific procedures of metrology to analyse the quality of datasets.

this paper shows how maps allow to also retrieve underlying numerical data by means of a computer – based method recently introduced by the author [15]. It allows the interested scientist to extend her analysis beyond the global parameters without the need to retrieve the original dataset, so paralleling the qualitative analysis obtained by visualisation with the addition of quantitative analyses.

Some problems, related to the presently dominant way to get the desired local and overall information in climate science, are also shortly discussed according to the relevant literature but without the intention of making a review paper of those subject matters. The Global Mean Surface Temperature (GMST, look e.g. at the term 'GST' for its meaning in [16]) will be used as the single example because of its special importance and normally consideration by the Intergovernmental Panel on Climate Change (IPCC) [1] and others Committees, as one of the most popular parameter.

The basic features of a quantitative analysis of GMST with the method reported in this paper are fully reported in [17], so they will not be repeated here in full, but in Section 3 a *flowchart* summarises the procedure. For other popular global parameters: the show/ice surface annual coverage was already analysed by the author in [15]; the mean ocean level variation with time, is not suitable for map analysis.

Finally, *qualitative* examples of visualisation are reported in Section 4.1, while detailed *quantitative* examples and the related procedure are shortly introduced in Section 4.2, then, due to their extension, fully discussed in Appendix A.

2. State of the art of collation and manipulation of databases in climate science

As introduced, e.g. in [16], any estimate of the *spatial distribution* of climate data is affected by the *uncertainty*. The level of data *uncertainty* is, and remains, the basic 'quality factor' that scientifically must *always* be associated to every piece of knowledge. It can critically affect the overall evaluation concerning their meaning and use, even making it sometimes inconsistent or deficient depending also on the type of chosen data representation.

The evaluation of the effects of data uncertainty can be insufficient, or even deceiving, when limited to concern global numerical parameters, namely when they are intended to cover the whole Earth's surface: specifically, "a [data] fit does not obtain the *combined* [i.e., total] *uncertainty* of any summary parameter, but only *part of the random uncertainty components"* [17] .

The World Meteorological Organisation (WMO) [18] is the International Body deputed to measure hundredths of meteorological parameters, so also forming the most reputed databases of all World Organisations dedicated to climate science studies, since WMO also supplies the *accuracy* of each datum (see later Foot Note 4). For evaluating the Global Mean Surface Temperature (GMST), up to millions of WMO weather Stations, of different models using different methods, all using contact thermometers, are sparse on most of the ground surface (see Fig. 1 for the set of Stations in part of Europe); for the liquid surfaces, namely for the oceans, most results are today obtained instead from satellite observations, using total radiation thermometers. Nevertheless, the mean distance between stations *on ground* may still be too large, as shown in Fig. 1, for creating a sufficiently dense overall network of numerical information forming the climate Big Data repository:[2] a subsequent measured data *interpolation* is required via mathematical/geometrical means. Therefore, a set of *computed additional* values is added to the set of original *experimental* values to form the analysed overall data network. To each of these points, both original and computed, an *uncertainty* is necessarily associated–the computed ones must be integrated by components arising from the estimated interpolation uncertainty. In addition, the original *experimental* data are then subjected to several critical procedures for completeness of the distribution, such as 'cleaning', etc., called homogenisation, *each step contributing to the total uncertainty*.

The public databases are the final version after the above procedure. Overall, they are very large and normally *not reporting the associated uncertainty*. The set is then numerically treated to get, e.g., the *mean value*: for temperature the GMST is such value for temperature (see [19] for a discussion in the case of its extrapolation in time).

Instead, a complete scientific treatment should consist in determining first also the factors influencing the obtained numerical information and their effect, namely the *systematic* ones affecting the best stability of the chosen measurement *procedure*, when building the so–called *Uncertainty Budget* (UB), a basic mandatory tool of measurement science for the estimation of data *accuracy*.[3]

However, an analysis deeper than 'reproducibility', i.e. *precision*, is often *not* possible, namely for maps, since the evidence of the systematic components arises from the *process* of planning the measurements, *not* from the results of the measurements, the data. That is a general difficulty, if not often impossibility when the original provider of the results does not provide her own analysis including also systematic effects evaluation and then this analysis becomes available to the cartographic scientist – even though it might have a limited effect on the map construction.

In addition, in documents like IPCC Guide [20], the approach is rather more similar to the kind of uncertainty/quality evaluation typical of the economic frames, e.g. by using risk factor and similar parameters,

[2] For example, weather prediction models for 100 km operational forecasts are said to need be based on a 9 km grid spacing.

[3] The treatment, performed according to the full methodology of measurement science, whose most critical goal is to assign *accuracy* to the dataset, is intended to provide the *complete* detailed description of the procedure used for its estimation—including the *systematic effects*. [22]

and by using words instead of quantitative parameters– such limitations have already been noticed and commented, e.g. in [21].

Basically, a simple non-weighted *fit* of the *manipulated* database is generally performed for representing data accuracy – and incorrectly considered as such instead of only precision. This fact has been verified *by the author*, by making its own fit of some large databases publicly available from World Organisations, and then comparing his results with the corresponding published results. His obtained standard deviation (s.d., *s*) of the fits, i.e. the evaluation of data *precision*, constantly was of the same order of magnitude, or even higher, than *published* 'uncertainty' – in one case, even indicated with a 2*s* confidence limit– reported as the accuracy of the results.

From that type of analysis, in fact, only a component of uncertainty is provided: an evaluation of the *consistency/quality of the fitting trend* basically guiding toward the 'best fit' – defined as the one providing the minimum s.d. It is obtained by only *tracking the values* of the data, *not also* their associated uncertainties (possibly except when providing the weighted mean). There are also other statistical tools for a more substantial evaluation, but they are out the scope of this paper. In all instances, the *systematic components of uncertainty basically remain unexplored*: precision and accuracy are made to coincide. [4]

3. Plotting data onto a map: from a numerical to a geometrical representation of the same data

Like in previous author's publications on similar matters, author's intention is not to go into details of cartography science, which is not among his scientific competences, but to illustrate the metrological advantages of using published maps that are implicit in their kind of visualisation: "In such a representation, the measured values of the parameter(s) of interest are superposed on the geographical basic information (the map). The most efficient way, given the subsequent analysis, is generally not to use a continuous shift of the map colours to represent values, but to have the colours *discretised* in (small) spatial steps" [17]. The result is that a colour/gray map is formed of regions of different uniform tones. [5]

Tones form a scale of those parameters consisting of discrete contiguous steps representing a (small) range: e.g., for the GMST a step range of 0.5 °C for the full range from Δt = –0.5 °C to Δt = +0.5 °C (i.e., 20 steps/colours) is commonly used. [6]

Note also that, for the *geometrical* representation, the *same set* of numerical data of the database used to compute the global parameter is obviously used, by effectively *superposing* these values of the parameter(s) in question onto their geographical coordinates of Earth's surface representation. [7]

In summary, after having reported all values within the range of a single step, the Earth's coordinates of all data determine the boundary of each colour/gray region on the map, not necessarily unique or made of continuous portions. However, the extension of each specific colour/gray area is bounded by the most marginal coordinates of the measured data and must ensure that no gaps remain between continuous regions about different steps–i.e. that the set of these regions covers the *full* map surface.

In such conditions, the uncertainty affecting values located marginally of a given colour area of the map could determine an uncertainty in the correct position of the boundary of each coloured region. In the vast majority of cases, such indeterminacy corresponds to irrelevant changes in the total extension of the surface attributed to two adjacent steps. In all instances, this fact can be considered less critical than the effect of the uncertainty affecting numerical computations based on the numerical database. A possible more critical issue may arise when the chosen step/range size is *too narrow* with respect to the level of uncertainty assigned to most data, since it might increase too much the boundary in the determination or the correct positioning on the map– however most often not so critical in meteorology. This might occur, e.g., in the above example, should GMST steps of 0.25 °C be used instead of 0.5 °C. [3] Concluding, *a map normally takes implicitly and indirectly into account also the uncertainty associated with each value measured inside that single area*.

In other words, a map is a consistent visual representation of the overall variability of the parameter value across the map dataset (but see later FootNote 9 about the need to use the correct *type of map*), not significantly affected by the uncertainty, i.e. about the *exact* position on the map, of each *single* dot–information. [7]

Thus, a picture of the distribution in space of the dataset is obtained via the visualisation of the *measured* values at the correct Earth's coordinates, independently from its *density*. This feature might be considered a form of *averaging* over passing the uncertainty of the numerical values, sufficient in meteorology for the semi–quantitative analyses generally made. In fact, as it

[4] Until recently, WMO assigned to each worldwide meteorological Station an *accuracy* of ± 1 °C [23-27]. Then, since a few years, WMO decided to classify the Stations under 4 classes: #1-2 accuracy ± 0.2 °C [28]; #3 accuracy ± 0.6 °C; #4 accuracy ± 1 °C. [29] Classes 1-2 are still a minority of the certifications so far provided

[5] Actually most often, in the paper-printed/file representation, a colour step is actually consisting of a *narrow range* of contiguous colours: see later about its handling.

[6] Note that the GMST is expressed as the temperature change Δt of the specific year from the temperature of a (previous) *reference* year: $\Delta t = T_{\text{actual}} - T_{\text{ref-yr}}$, for each determination.

[7] Basically a World map is merely a 2-dimensional representation of Earth features with respect to their geographical coordinates.

clearly comes, e.g., from Fig. 2, when *iso–regions* of the measured values for the chosen parameters are added to the map, e.g. uniform regions in 0.5 °C steps, the criticality of the uncertainty associated with the value measured by each Station is largely over passed, also considering that those regions are certainly also smoothed in mapping. [8]

In this way, a geometrical visualisation is generally quite more informative than a table of numbers or its mere interpolation, and the needed approximation produced by such a *discretisation* is generally sufficiently accurate to compensate for the lack of a numerical indication on a map of the uncertainty of the original data.

One might either argue that a map cannot compete in *resolution* with a dataset, with possibly the exception of very extended maps. That is anyway only partially true: low resolution could generally be enough for the purpose of a printed map–but, in principle, a map distance resolution can be, if needed, as precise as 30–100 m when embedding data from satellite observations. On the other hand, when, for example, the interest is to track overall *surface temperature* variations to compute the GMST, one is certainly not interested in identifying small details on the map.

Finally, there exists an *additional bonus*, *not to be confused with the above properties*, and normally not considered in the literature, represented by the *reverse possibility* of retrieving, with sufficient precision by using due techniques, the underlying numerical values from any published map. Instead, this may become as a double–check of *the consistency level of the original numerical values*–as found in [15, 30], and as later illustrated in Sections 4.2 and in the Appendix A. See in [15] how *a UB can be estimated* when using maps. Also see in the above references a discussion about *the evaluation of the precision* of the reversely computed numerical data.

4. Using maps for a deeper evaluation of phenomena in climate science, through examples

The reported examples, all concerning the surface temperature distribution bringing to the GMST, are exclusively intended to discuss how a map conveys more information than the simple analytical treatment of the numerical database. For this purpose, a larger set of these maps is reported in Fig. 3: all taken from the literature concern the variation in time of the SAMT, and show a variety of results. Concerning instead the parameter 'seasonal ice coverage', e.g. see Ref. 15.

All these maps are full–World and of Robinson–like types (see later when that type of map must be used and when not), where the colours indicate the distribution of different levels of *temperature variation values with respect to a previous reference* year–not in all the same reference is used, nor all refer to the same end year of the period shown: this may contribute to the observed *variety of parameter–value distributions* shown in different maps, but it could instead more likely arise from differences existing in the collected datasets.

In cases like that of temperature distribution, the *correct map* type must be used,[9] the one with iso–surfaces, i.e. the Peters' or the recent Equal Earth one, [31–32] rarely used in the scientific literature where the Mercator or Robinson ones are used instead, of the distance – proportional type.

4.1 *Qualitative* map analyses: an example

In first instance, maps can be metrologically analysed to simply detect *qualitative* features–something only revealed by the use of maps–such as *an insufficiently univocal* estimate of the temperature–change *patterns* related to their changes in time in different maps or different surface portions.

In the case of the GMST parameter, the first basic feature is its difference between land and water surfaces, obviously implicitly embedded in the database and in the GMST computation, amounting to $\Delta t \approx$ 0.5 °C of lower increase in time for oceans, according to published estimates (e.g. Ref. 20).

That feature, alone, makes a big difference between partial 'G(M)ST's (GST will be used in the following for such 'local' meanings) of what are called the two 'land and water hemispheres' [27], i.e. the occurring extreme grouping of lands such that the 'water hemisphere' surface is instead made of water for its 89%–while the 'land hemisphere' is made of water for only the 53% (a similar difference exists also for the North and South hemispheres, somewhat, but not basically, different). See later the Appendix (d) for a quantitative evaluation from a map.

As to the *land* – the portions of Earth's surface where all humans live–the distribution of the (local) GST values is extremely varied. In Figs. 2a and 3a the only regions consistently hotter are in Europe, with an extension to Siberia on the East if the considered period

[8] In addition, one should also realise that the provided WMO uncertainty value concerns the *punctual* local temperature value assigned (i.e. also corrected for systematic errors) to the thermometer *inside* the Station, so conventionally representing the mean temperature of the volume of air within the Station at a 2 m elevation from ground. It is then assumed to be valid for an *indefinitely* large volume of atmospheric air in the surroundings—a reason limiting accuracy.

[9] Most of the literature maps use the Mercator/Robinson-type of Earth's representation, as it can be appreciated from the large size of the Polar regions: that means that the maps are *not* representing proportionally the different portions of the Earth surface—differences are listed in Table 1 of [30]. That is a strong limitation in correctly comparing in the real proportions the surface (cont) showing different temperature variations. Note: the NOAA maps used here in Appendix A as the examples of computation show in gray tone the two Polar regions, so excluding them from the assignment of temperature-change colour tones.

of time is anticipated of 10 years with respect to Fig. 2b. Total hotter surface is found to effectively increase only when starting the comparison much earlier, to 1951 as done in Fig. 3b(ii). However, when comparing identical periods (2020 situation with respect to 1981–2000) the differences in Fig. 2a and Fig. 3b(iii) are still remarkable.

On the *oceans*, the blue regions indicating a lowered GST are also remarkable and quite varying in time. On land such a lowering on land is much less extended and frequent, especially in the northern hemisphere.

Apparently, most of the GMST increase happened before 1980, as shown in Fig. 3b, apart from the Arctic region–while the Antarctic hot region disappeared–but the extension of such areas is altered when choosing different map types, as commented in Foot Note 9. Siberia looks like the land region with the most variability in time.

It is *not* the aim of this paper to discuss the reasons for the evident differences between maps shown in similar periods, but only basically to provide evidence, from them, of the fact that the evaluation of the *distribution of surface temperature* can basically be *insufficiently consistent* when expressed by the value of a single global numerical parameter. [10]

On the other hand, the importance of the data *uncertainty* of each single measured point constituting the database is *strongly limited* in the maps and can even normally be disregarded–a useful issue when the uncertainty evaluation might be controversial.

4.2 Examples of computations based on maps: *quantitative* retrieval of the original numerical information for specific evaluation of parts of the maps

Additionally, the *numerical information* (*not* the original data from a database used to build the map) underlying a map can *be retrieved back quantitatively* from each map [15], obviously affected by an *uncertainty corresponding* (at least) *to the width of the colour* step due to the *discretisation* of their geographical coordinates.

This possibility may be important and useful for *any scientist interested to retrieve of her own* (numerical) information from the surface portions reported with the *same* colour and able to compare her own findings with the ones in the literature. That possibility necessarily requires, as in the case illustrated in [17], the use of an iso–surface projection, the Peters'–resulting more correct than Robinson's ones (see Footnote 9): based on it, e.g., the *uncertainty* of the GSMT retrieval estimated within ≈ ± 5% was obtained in [30]. From different map *types*, instead, differences in the GMST value of up to ≈20% were found to occur. [11]

The remaining contents of this Section are moved to Appendix A in order to make evident the fact that a specific technicality is needed not strictly related to the normal visual analyses of maps. The author found it useful in several circumstances, requiring a procedure that can be found in details in his previous publications on this subject matter [15, 17, 19, 30], here summarised in the flowchart of Table 1a below and with results reproduced for this paper in Table 2 (see Appendix A).

5. CONCLUSIONS

The retrieval of the numerical value of some global numerical parameters could now be obtained by starting from a type of visualisation consisting of maps of the distribution of the relevant parameter(s) over the full/partial spatial extension of an Earth map. The possibility of this retrieval is a new opportunity for the scientists interested to understand or double–check the quality of the published analysis results. The uncertainty of such evaluation may even be comparable to the one attributed to the parameters by means of a direct numerical analysis of the databases. This use would limit the risk of a poor estimation of the uncertainty of the databases, with the consequence of standing controversy.

Actually, maps additionally allow a more *extensive* and *complete* analysis of the collected information, qualitative and quantitative, thanks to the visualisation of the *distribution* of the information over their whole extension: e.g., that advantage especially concerns the evidence of the *extent of non–uniformity on the surface of the values of interest*, so making possible the evaluation of the geographical/'political' reasons for that [30]. Such richness of information is lost when summarised in a single numerical parameter. Maps are less 'apodictic' than global parameters and allow scientists to form their own diversity of thoughts, which is the basis of science [31].

Similar exercises as the one illustrated above, made on other maps, would also show a variety of situations that otherwise may remain implicit or undetected in a numerical treatment: in the case of meteorology and climate science, they should be explored in the context of their spatial distributions.

Concerning the extent of information on the Earth's surface, a geometrical representation looks superseding the pure mathematical one, and revealing a possible risk for the *scientific meaning* of a global purely *numerical parameter*, so becoming *significantly weak or even rather irrelevant*. That is particularly important when it is necessary to avoid such a situation in the case the analyses are directed to make forecasts. [19].

[10] As another example of the need of referring a situation occurring in specified places of a map, the authors in [21] had to indicate a feature of the Northern hemisphere only. See similar situations also in APPENDIX (d).

[11] In that respect, however, an *uncertainty* of 20% of the current GMST value taken as the reference in recent literature, Δt = 1.2 °C, would mean an interval of possible values from Δt = (+0.9 to +1.3) °C: this is still within the actual uncertainty of the GMST value according to the correct metrological analysis based on the WMO indications. [18, 28]

APPENDIX A

Examples of computation procedures concerning retrieval of *quantitative* numerical information in maps

The procedure for the computations is summarised in Table 1 of Section 4.2, where the full procedure *flowchart* is reported, related to Figs. 2–4 (for full instructions see [15]).

Table 1 – Tabular flowchart showing the procedure to obtain the retrieval of the numerical information (*not* the original data) underlying a map.

1.1		Copy on an Excel (or equivalent) a full Earth map of Peters proportional–surface type [31] The map should have a dimension of 300'000 pixels or more. The background *must* be white or colourless, apart the colour–scale strip (see 1.2). **Record the total pixel number of the map** (i.e. no borders or other outside the Earth surface)
1.2		Ensure that the map also show (below it, NOT on it) a strip of boxes with the colour coding for the full parameter range (e.g., 20 boxes each for 0.5 °C from negative to positive values). NOTE: The box should *not* be taken from any other file
1.3		Make a check of the colour–tone homogeneity on the recorded file, as follows:
	1.31	Set the colour selection tool for "non contiguous" and "tolerance" = 0
	1.32	Click on one of the colour boxes (i.e., *not* on the map)
	1.33	Adjust the *tolerance*, by increasing it by steps, until the selected tone box looks (almost) completely selected
	1.34	Increase a bit the tolerance until some pixels in a *contiguous* box becomes also selected
	1.35	You will possibly find a (small) range of tolerances in the two cases: if not, use it; if yes, select the mean tolerance for the subsequent steps
	1.36	All box counts should provide the same pixel count, within a few. That is a component of the total uncertainty of the procedure. **Record the pixel count of each and the tolerance**
	1.37	For the computation of the 50% of the pixel distribution use the values in 1.36 as explained in the text concerning Table 3. VERIFICARE
	1.38	If you are making the comparison of **two** maps, make the same of above for the second. The map must be uploaded with an identical dimension in pixels, adjusting it size as necessary, within 1–2%. For its colour scale proceed as in 1.2 and 1.31–1.36
1.4		Now start with the first map and use the colour tolerance selected in 1.36
	1.41	Select both the map *and* its colour strip, and click on a central–value colour on the trip
	1.42	Different areas on the map will also be selected in addition to the full colour box
	1.43	Open the window showing the pixel count for the selection: record the pixel count and subtract the count saved in 1.36. **That is the value in pixel of the area on the map**
	1.44	Do it for all the boxes of the colours trip
	1.45	**Sum up all the registered values**: the sum should correspond to the total map surface value in pixel … but rarely exactly
	1.46	You may *repeat* the steps of tolerance adjustment above and modify a bit it until get the exact total value. However this is OK only for very small adjustments (change of ±1–3)
	1.47	Double check that no pixels are selected outside the map surface: you can check it by **selecting all colours** and check the difference with respect to the value in step 1.1 (and double check its correctness), with a circular adjustment procedure of all previous steps. A precision between 2% and 5% is in general satisfactory
1.5		For the adjustment you consider satisfactory, **record all the pixel counts for all the colours, and estimate precision**
	1.51	**Reduce to 0** (zero) all final counts lower than precision, as they are not significant
1.6		Start with the next map
Partial surface		If you are interested on only a partial surface, upload only that portion of the map, then act as above on it
Ground/ water (sea)		In general, you should find ground and sea naturally separated by their parameter (colour) differences. Otherwise, you may try to make ticker or with a new colour the boundaries of all ground portions, in order to be able to select only ground or only water.
Polar regions		To exclude polar regions, if not already greyed as they are in certain maps, you can select their boundaries and change their colour to gray
Comparing maps		You may (visually) compare a map with another map (e.g. of population density), by keeping the superposed upper one of exactly the same dimensions and by making it sufficiently transparent. This may make easier to retrieve also the data from the latter.

For the retrieval, the graphical programme Photoshop has been used by the author, but others can provide an equivalent suitable tool.[12]

Since, in this case, two maps have to be compared, they are first copied on separate files with the *same dimensions* (i.e. number of pixels) to avoid unnecessary conversion factors. Each map is provided with a colour scale. As already alerted in [15], one should not assume that in a scale in 20 steps, from deep blue to yellow and deep red colours, each step is made of a *single pure tone* of the colour scale of 256 total tones: that is the typical change caused on the original map by its downloading from a public version–typically from a file reported in a publication–onto the computer for the analysis. Therefore, a first necessary alert is that the user must be aware of the fact that any coloured area representing 'one tone' (in the case of the example a temperature range of 0.5 °C) contains pixels over a *small range of tones*: a 'tolerance' must then be provided to the tool selecting the desired tone range. In the present example, a tolerance of 35 colour tones was found necessary and sufficient–otherwise not the whole sample area is selected or, in the reverse case, more than one sample areas are selected. In this case, the selected sample in the reported scale corresponded to ≈600 pixels for *each* sample tone in the 20–tone scale reported below the map, providing an *additional* total of 12000 pixels in the *count of the map size*, which has to be eliminated from that count; ≈600 pixels must be eliminated when making the count of each colour selection in the map (the tone–scale must remain *visible* and selectable, to visually ensure that the selection of the desired tone on the map is correct).

On the other hand, the file must contain only the map and the colour scale on a uniform background, typically white (or colour absent). The size of the map must ensure a sufficiently high number of pixels for the maps to be examined to allow sufficient precision of the recovery.

Some specific issues are now illustrated.

<u>(a) Total size of the map</u>. The first step consists of obtaining the total number of pixels of the entire map, i.e. of the map by excluding the uniform background: in the present case (Fig. 2) it was ≈ 350'000. In order to compare several maps, it is better to scale up them to about the same dimension: in the following, the two maps (a) and (b) differed in the surface by 2%, almost irrelevant–but the final values of the parameters were anyway corrected for that small difference in total surface.

One can notice that in the maps in Fig. 2 the two polar regions are greyed (the gray being distinct from the tone scale: probably no data in those regions). That is good because the map is of the Robinson type, i.e. a non–iso–surface type. When a Peters' projection is not available, like in this case, in first approximation one must *halve the surfaces* (*number of pixels*) in the regions above 60° of latitude of both hemispheres [15] if they have to be taken into account, to make a sufficient correction.

In the present case, these gray areas were left out of the computations, thanks to their specific colour, except for some final elaborations and considerations (see later). They represent a different amount of surface in the map: the North Pole region is 6% of the North hemisphere, while the Antarctic Pole region is 21% of the South hemisphere (for map (a), 6% and 19% for map (b)). They represent in total 14% of map (a) (actually the 7% after correction), or 12% of map (a) (actually the 6%): this issue is commented on later and represents already a relevant difference in the determination of the GMST.

Thus the colour analysis has been performed on about 95% of the surface (for a more exact difference in the surface distribution from the two types of maps, see [23]), the one where most humans are living.

<u>(b) Colour distribution analysis</u>. Now one can analyse the coloured portions of the maps, and get a distribution of the surfaces (measured with the unit pixel, provided by Photoshop under the 'Histogram' tool).

To select a colour for the totally selected map, one has to click on the sample in the colour–scale, corresponding to the indicated temperature range: all the corresponding pixels (within the chosen tolerance, here of 35 pixels) will be selected and the total reported. Table 2 reports these values for both maps. Then one has to subtract 200 pixels from the reported value, for each interval selected of 0.5 °C [13] (for specific reasons one could also select more than one sample/interval [14]), getting the correct proportion. Selected values less than 600 pixels should then be zeroed for that interval (e.g., as it happens for extreme values of $\Delta t \geq \pm 3$ °C).

In Table 1 also the fractions in percent of the total surface are reported.

The so–obtained sum of the surfaces can be somewhat different from 100% because the pixel selection feature is not 100% exact, but the difference between 2% and 5% can be considered acceptable. Otherwise one can try adjusting the tolerance value (as done, e.g., in [23]), for the best approximation.

<u>(c) An example of computation of the retrieved data</u>. The GMST is defined as the mean surface temperature variation for the whole surface. Therefore, it corresponds to 50% of the pixel selection. It can be obtained in different ways: by computation from Table 1 or directly from each map (so also getting an indication of the precision of the obtained values).

[12] It is easy to anticipate that professional AI may play a useful future role in patterns recognition on maps.

[13] Colour intervals equivalent to a temperature range of 0.5 °C are sufficient for the analysis, though sometimes maps report colour intervals of 0.25 °C.

[14] A two contiguous steps analysis is useful if data uncertainty is higher than the size of colour steps, in order to check for possible differences in the surface-attribution evaluation.

In the present case, one additional issue of interest is to understand if the two maps bring *significantly different situations*, as they report it for periods of time subsequent by 10 years.

From pixel counts in Fig. 2 one gets GMST values indicating even a lowering for the period (1991–2020) with respect to the period (1981–2010), from Δt = +0.50 °C to Δt = +0.34 °C.

The fact that this evaluation does not include the two Polar regions cannot be considered to significantly affect the computations, for two reasons: first their real surface is much smaller (6–7 %) than it looks in the Robinson type of maps, and these regions are inhabited, a feature that can basically induce an effect only on the mean ocean level–namely on the South only, since on the North the marine–sea ice melt does not produce any effect on the sea level, and Greenland is responsible for only a minimal contribution to the total Earth ice amount.

The GMST can also be computed differently: by plotting the data in the 'Proportions' columns, as reported in Fig. 4a,b. From them, GMST values are Δt = +0.56 °C and Δt =+0.38 °C are obtained, basically confirming the previous values. The pixel count varies in dependence of the tolerance assigned to the search of its best value, i.e., in the Figure the chosen "best tolerance" is used.

In order to find it (according to steps 1.33–1.36 in Table 1) you should use the following procedure:

(i) Start from a low tolerance, e.g., 8 pixels, and make a table of the pixels counted for each and all the colour steps used in the map on analysis, and compute their total;

(ii) Repeat the operation for increasing tolerance values in steps, e.g., of 8 pixels: you will get different values and different totals. Initially the total number increases, but, above a certain tolerance value you will find, a decrease–then again a rapid increase;

(iii) That point in general corresponds to near the 50% of the total pixels of the map;

(iv) If you are within a few percent close to 50% you can stop and record the tolerance.

In Fig. 5 the result is reported for such a search for Fig. 3a: the optimal tolerance was 16 pixels for the second trial, being 14 and 32 the adjacent trials. The corresponding selected pixels were 54'707, 92'640 and 79'285, corresponding to 0.47, 0.69, 0.48 for a *map of the Robinson type*. However, as already pointed out, the correct map type is the *Peters* one, having a different pixel distribution per latitude (as indicated in Table 2 [17]) therefore the number of counted pixels for latitudes >60° can simply be divided by 2, as already suggested. The corresponding counts for a Peters mapbecome 0.42, **0.55**, 0.39, thus tolerance 16 is sufficiently close to the goal.

<u>(d) More information from maps: polar North–South hemispheres difference</u>.[15] The greyed surface regions in the two hemispheres are quite different in size: while the North one is basically limited to the North Polar Sea and neigh borough lands (a total of 12300/12800 pixels *for the two maps*, of which sea is the 91%/92%), the South Polar region exceeds 42000/37000 pixels, not only because the Antarctic land covers 16000 pixels, but also because the South Polar sea surface is considered extending for 25000/21000 pixels, about the 60%/56% of the total. The overall effect is that the map representation is not equivalent for the two hemispheres, with the whole North colour map exceeding the South part by about 11°–14° in terms of latitude in the two maps.

On the other hand, one can certainly appreciate the fact that the land distribution in the two hemispheres is *substantially different*, with most of the human activities (if assumed to influence the climate) being concentrated in the northern hemisphere.

It is also possible to make a *comparison of the two hemispheres* about the proportion of the temperature changes, Δt = (–5 – 0) °C and Δt = (0 – +5) °C. The difference is *substantial*: the North hemisphere is 40% higher in temperature increases and very poor in decreases, while the South hemisphere is 5 *times* richer in temperature *decreases*, basically concentrated on the oceans, which are predominant in the Southern hemisphere (where the IPCC estimate of the GMST increase for ocean water is of only $\Delta t \approx$ +0.5 °C).

Table 2 – Comparison of the position of the latitudes on a linear scale and on Peters' scale [a] [17]

Latitude (degree)	Peters Map	Width change	Latitude displacement (degree)
0 (equator)	–	–	–
5	8.4%	–	+3.4
10	17.7%	9.3%	+7.7
15	26.6%	8.9%	+11.6
20	34.9%	8.4%	+14.9
25	42.8%	7.9%	+17.8
30	50.1%	7.4%	+20.1
35	57.0%	6.8%	+22.0
40	63.3%	6.4%	+23.3
45	69.2%	5.9%	+24.2
50	74.5%	5.4%	+24.5
55	79.4%	4.9%	+24.4
60	83.7%	4.3%	+23.7
65	87.6%	3.9%	+22.6
70	90.9%	3.4%	+20.9
75	93.8%	2.9%	+18.8
80	96.1%	2.4%	+16.1
85	98.0%	1.9%	+13.0
90 (pole)	–	1.4%	–

[a] Peters projection is basically the projection of a circle arc onto the radius.

[15] See also the already cited [15].

Table 3. Quantitative analysis by pixel count for the maps in Fig. 2.

(a) 2022 (**ref. 1981–2010**).

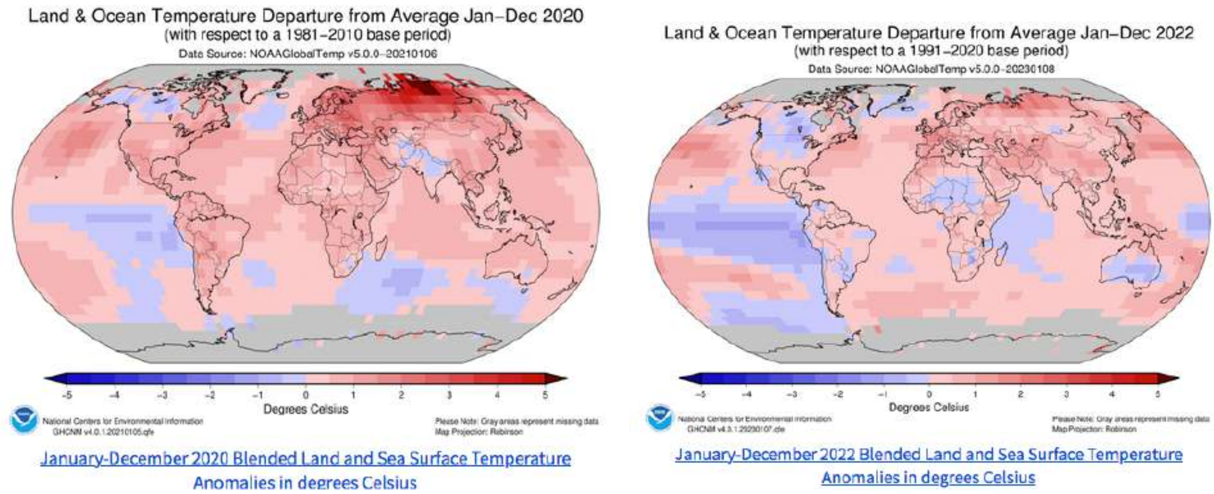
Δt (°C)	N° pixels total	Proportions Net (pixels)	Proportions %	Progressive coverage		*Comments*
–5.0 – –3.0	2300	0				
–3.0 – –2.5	604	0				
–2.5 – –2.0	585	0				≤ 600 px/tone
–2.0 – –1.5	593	0				
–1.5 – –1.0	589	0				
–1.0 – –0.5	6384	47600	12.4%			< 0 °C
–0.5 – **0**	42426			12.4%		
					0.50°C **(50%)**	**Mean (GMST2022)**
0 – 0.5	97000	96400	25.1%	37.6%		
0 – 1.0	*(202000)*		***(52.4%)***			
0.5 – **1.0**	141000	140400	36.6%	74.2%		
1.0 – **1.5**	27300	26700	**43.6%**	82.3%		
0.5 – 2.0	*(181000)*		*(46.9%)*			> 0 °C
1.5 – 2.0	8400	7800	2.0%	84.3%		
2.0 – 2.5	4400	6300				
2.5 – 3.0	3100	2500				
3.0 – 5.0	6200	3800	1.0%	85.3%		
Totals	**340880**	**331500**	**84%**	**85.3%**		*Without Poles*

(b) 2022 (**ref. 1991–2020**)

Δt (°C)	N° pixels total	Proportions (pixels)	Proportions %	Progressive coverage (*corrected*) [1]		*Comments*
–5.0 – –3.0	2100	0				
–3.0 – –2.5	530	0				≤ ≈600 px/tone
–2.5 – –2.0	550	0				
–2.0 – –1.5	500	0				
–1.5 – –1.0	3700	3100	0.8%	0.8%		
–1.0 – –0.5	21800	64600				< 0 °C
–0.5 – **0**	44000		18%	18.8%		
					0.34 °C **(50%)**	**Mean (GMST2022)**
0 – 0.5	133000	132400				
0 – 1.0	192500	191900	37%	55.7%		> 0 °C
0.5 – 1.0	105000	104400	53%			
1.0 – 1.5	19300	18700				
0.5 – 2.0			**39%**	94.6%		
1.5 – 2.0	4300	3100				
2.0 – 2.5	1100	0				
2.5 – 3.0	620	0				≤ ≈600 px/tone
3.0 – 5.0	2100	0				
Totals	**338600**	**326800**	**92%**	**94.6%**		*Without Poles*

[1] Corrected by ≈ 2% for the total surface difference to (a).

Figure 1. Map of the WMO stations in a portion of Europe: their data are most of the sources of data included in the international databases used by IPCC, NOAA, HadCRUT, NASA, etc. [18]



a) b)

Figure 2. Maps from different periods: (a) 2022 (1981–2010); (b) 2022 (1991–2020). (NOAA)

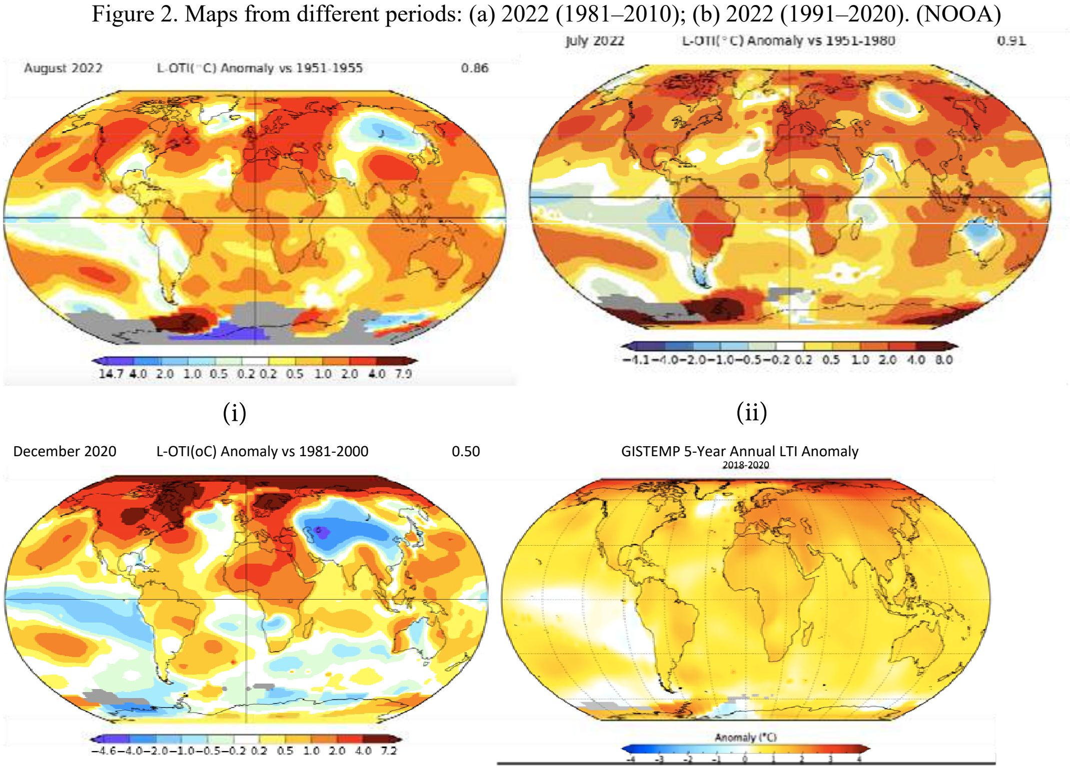


Figure 3a. Maps from another source: GISTTEMP L–OTI (NASA) [35]: (i) 2022 (ref. 1951–1955); (ii) 2022 (ref. 1951–1980); (iii) 2020 (ref. 1981–2000); (iv) 2018–2022.

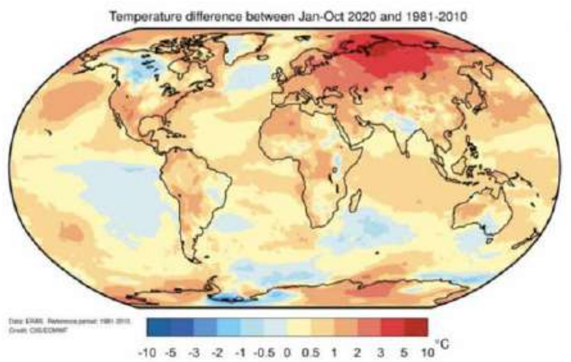
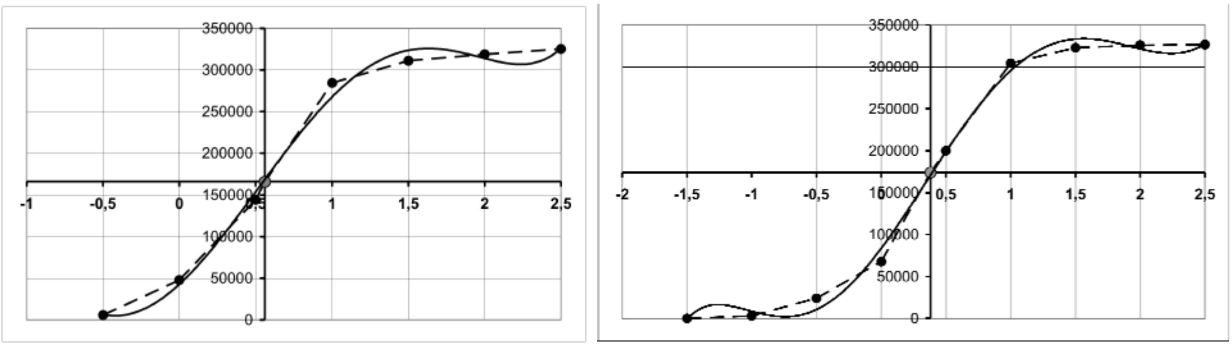


Figure 3b. Maps from another source: HadCRUT [27] (2020), the reference is the same period of NOAA 2(a): 1981–2010.



(a) (b)

Figure 4. From Fig. 2. The re–computed GMST value (larger gray dot) is reported *at the axes crossing* (of the graph Δ*T*/°C *vs* pixel count), here respectively +0.56 °C and +0.38 °C. The continuous curve is the interpolation of the measured pixel counts (here dots) of Table 3.

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Карти можуть краще підтримувати кількісну оцінку характеристик поверхні Землі з їх еволюцією в часі, ніж глобальні числові параметри

Франко Павезе

Анотація

Глобальні числові параметри останнім часом стали більш популярними в наукових галузях для оцінки характеристик поверхні Землі, зокрема в еволюції клімату. Однак вони можуть не повністю відображати складність питання, яке вони мають на меті кваліфікувати. У статті ілюструється той факт, що поставленої мети можна краще досягти, додавши допомогу, яку надає оцінка карт, особливо у випадку параметрів Землі, метод, який вже поширений в оцінці просторових великих даних. Крім того, той факт, що графічне представлення карти є внутрішньо посередником параметра, який завжди пов'язаний з кожними даними експериментального походження, невизначеності даних, таким чином представляючи собою своєрідний альтернативний спосіб моделювання бази даних. Особливо, коли карти ілюструють велику різноманітність локальних ситуацій, візуальне (тобто геометричне) дослідження, яке пропонують карти, часто дозволяє отримати кращу інформацію, тому більш надійну та повну оцінку еволюції, як правило, в часі. Наведено приклади випадків, що підтверджують ці твердження.

Ключові слова: глобальний числовий параметр; невизначеність даних; карти Землі; просторовий розподіл параметрів; якісна оцінка; кількісна оцінка.

