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Putting humans in the loop: Social computing for Water Resources Management

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**A B S T R A C T**

The advent of online services, social networks, crowdsourcing, and serious Web games has promoted the emergence of a novel computation paradigm, where complex tasks are solved by exploiting the capacity of human beings and computer platforms in an integrated way. Water Resources Management systems can take advantage of human and social computation in several ways: collecting and validating data, complementing the analytic knowledge embodied in models with tacit knowledge from individuals and communities, using human sensors to monitor the variation of conditions at a fine grain and in real time, activating human networks to perform search tasks or actuate management actions. This exploratory paper overviews different forms of human and social computation and analyzes how they can be exploited to enhance the effectiveness of ICT-based Water Resources Management.

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1. Introduction

In recent times, the Web has evolved from a publishing platform, where the interaction of users was prevalently limited to the access of content created by others, to a collaborative and social tool, where users are active members of one or more communities, and meet online for sharing information and opinions, cooperating in the execution of tasks, playing games, or simply spending time together.

This phenomenon has prompted the emergence of a new computation paradigm, called Human Computation (von Ahn, 2009), applied in business, entertainment and science, where the interaction among users is harnessed to help in the cooperative solution of tasks. According to Quinn and Bederson (2011), a system belongs to the area of Human Computation when human collaboration is facilitated by the computer system and not by the initiative of the participants. The common baseline of the approaches that exploit humans in computing is the intelligent partition of functionality between machines and human beings: networked machines are used for task splitting, coordination, communication, and result collection; humans participate with their intuition and decision-making power (Parameswaran et al., 2010).

A classical example is content processing for multimedia search applications. In this domain, the goal is automatically classifying non-textual assets, audio, images, video, to enable information retrieval and similarity search, for example, finding songs similar to a tune whistled by the user or images with content resembling a given picture. Recognizing the meaning of aural and visual content is one of the skills where humans outperform machines, matured in hundreds of thousands of years of evolution. It is now commonly recognized that multimedia content analysis can benefit from large-scale classification performed by humans; applications like Google Labeler and the system proposed by Hu et al. (2009) submit images from a large collection to human users for receiving feedback about their content and position, which can be integrated with machine-based feature extraction algorithms.

Human Computation can also benefit the management of environmental resources, which are by definition shared and distributed and demand new approaches to their management, based on an increased consciousness of mankind’s collective responsibilities. Traditionally, the management of natural resources has been performed with a centralized approach, based on static policies (usually coded as laws and regulations), thus neglecting the intrinsically dynamic nature of both the systems and the management processes ruling their evolution. Human Computation can open up opportunities for a continuous involvement of stakeholders, in all phases: from the definition of the objectives and of the performance indicators, to the development of formal models.
to characterize the system behaviour, down to the selection of the best and most appropriate management decisions.

In this paper, based on our previous experiences, we focus on the case of water management, in order to describe the areas of intervention where Human Computation is likely to have a significant positive impact in the next few years. The paper is thus organized as follows. First, in Section 2, we summarize the main classes of Human Computation, describe the dimensions that characterize a Human Computation approach, and use this conceptual framework to categorize a number of Human Computation applications reported in the literature. Section 3 introduces water management issues and problems and describes how to identify the relevant communities of resource users and involve them in the planning and management loop; issues related to the elicitation and harmonization of collective knowledge are briefly discussed. Section 4 concludes the survey with a critical appraisal of the issues that must be addressed to apply Human Computation techniques effectively, in general and specifically to natural resource management.

2. Classes of Human Computation

Human Computation can assume a variety of forms, according to the scale at which humans are engaged, the tasks they are called to solve, and the incentive mechanisms that are designed to foster participation (Quinn and Bederson, 2011). A number of principal approaches can be catalogued:

Crowdsourcing: this approach focuses on the distributed assignment of work to an open community of executors (Howe, 2006). A typical crowdsourcing application has a Web interface that can be used by two kinds of people: work providers can enter in the system the specification of a piece of work they need (e.g., collecting addresses of businesses, classifying products by category, geo-referencing location names, etc); work performers can enrol, declare their skills, and take up and perform a piece of work. The application manages the work life cycle: performer assignment, time and price negotiation, result submission and verification, and payment. In some cases, the application is also able to split complex tasks into micro-tasks that can be assigned independently (Huang et al., 2010), e.g., breaking a complex form into sub-forms that can be filled by different workers. In addition to the web interface, some platforms offer Application Programming Interfaces (APIs), whereby third parties can integrate the distributed work management functionality into their custom applications. Examples of crowdsourcing solutions are Amazon Mechanical Turk and Microtask.com. Application areas are the most varied: speech transcription, translation, form filling, content tagging, and user evaluation studies are a few examples.

Games with a Purpose (GWAPS): this line of work focuses on exploiting the billions of hours that people spend online playing with computer games to solve complex problems that involve human intelligence (von Ahn, 2006; Law and von Ahn, 2009). The emphasis is on embedding a problem solving task into an enjoyable user experience, which can be conducted by individual users or by groups. Several game design paradigms have been studied (Law and von Ahn, 2009) and the mechanics of users' involvement has begun to be modelled formally (Chan et al., 2009). GWAPS, and more generally useful applications where the user solves perceptive or cognitive problems without knowing, address such tasks as adding descriptive tags and recognising objects in images, checking the output of Optical Character Recognition (OCR) for correctness, helping protein folding and multiple sequence alignment algorithms in molecular biology and comparative genomic research (Cooper et al., 2010).

Social Mobilisation: this approach addresses problems with time constraints, where the efficiency of task spreading and of solution finding is essential. The DARPA Network Challenge (Pickard et al., 2010) is an example of the problem and of the techniques employed to face it. The challenge required teams to determine the coordinates of ten red weather balloons placed at unknown locations in the United States. The winning team employed a novel recursive incentive mechanism that permitted them to locate all balloons in under nine hours. Applications are also found in safety critical sectors (Shah et al., 2011), like civil protection (Hamilton et al., 2011) and disease control (Stothard et al., 2011).

Human sensors: this area of work leverages the pervasive diffusion of mobile terminals among the users, and, especially, the fact that more and more of these devices are equipped with sensors (Abdelzaher et al., 2007; Campbell et al., 2008). The focus is on the real-time collection of data, in order to realize time-critical decision support systems and emergency management. Early application areas include pollution monitoring (Dutta et al., 2009; Aulov and Halem, 2011), traffic and road condition control (Manasseh et al., 2009; Bansal and Srivastava, 2011), and earthquake monitoring (Sakaki et al., 2010). Interestingly, human behavioural patterns in the usage of mobile phones have been exploited to detect level of activity, so to examine the effects of the spreading of seasonal diseases (Madan et al., 2010).

The applications of Human Computation can be classified under a number of characteristic design dimensions. Fig. 1 shows several examples of such applications and correlates them with the general approach adopted to build them and with the most relevant dimensions in their design.

The design dimensions for classifying Human Computation applications are defined as follows:

Humans involved: a technique may require only one individual at a time (e.g., the reCaptcha system for OCR support (von Ahn et al., 2008)), a small group or a closed community of users (like the players of a GWAP) or an open community (like in work crowdsourcing (Howe, 2006), people mobilisation (Pickard et al., 2010), and distributed sensing applications (Dutta et al., 2009)).

Human faculty involved: a technique could leverage human ability at different levels: perception and/or emotion, like in content appraisal and user interface usability assessment, where human feedback is collected with techniques like physiological signal analysis and eye movement tracking to estimate the impact of content or of interface design (Koelstra et al., 2010); judgement, when the discriminating power of users is exploited, like in user studies, where people are requested to express comparative judgements on alternative solutions (Heer and Bostock, 2010); social behaviour is central to those approaches where collective task execution and inter-personal communication are prominent, like people mobilisation (Pickard et al., 2010) and social business process management, where communities of external stakeholders are involved in enterprise business processes (Brambilla et al., 2011).

Activity Type: the unit of work allocated to humans can be of different types; a game engages individuals or small groups in a challenge, where the resolution of the problem is a collateral result (Chan et al., 2009); instead, a task is an explicit unit of work, with well defined input/output and explicitly submitted to a recipient; it can be atomic (microtask (Huang et al., 2010)) or composite (process (Brambilla et al., 2011)); an intermediate situation occurs in implicit task execution, where a user may perform a useful task without necessarily knowing (like, e.g., in reCaptcha-enabled login forms (von Ahn et al., 2008)).

Control: task definition, assignment and progress can be controlled centrally, as is the case in work automation platforms like Amazon Mechanical Turk and in Social Business Process Management, where people involvement is under the control of the workflow engine (Brambilla et al., 2011); alternatively task
activation may be managed in a distributed way, as in the DARPA Network Challenge strategy (Pickard et al., 2010), where a recursive incentive mechanism was used, which encouraged people to recruit effective workers so to improve their expected success rate and reward. The selection of the most efficient strategy to solve a task can also be facilitated by Human Computation, as shown in the case of harvesting renewable resources (Brede and Vries, 2010).

Motivation mechanism: users may engage in executing tasks for different reasons; purely for fun, like in GWAPs; for ethical reasons, like in volunteer work; or for an economical reward. Recent studies have examined the correlation between incentives, task definition policies and the resulting quality of task execution (Huang et al., 2010).

Time: Human Computation applications may have critical time requirements that make the execution of tasks and the propagation of actions or decisions along social links important. This is the case, for example, of civil protection scenarios like the one simulated in the DARPA Network Challenge (Pickard et al., 2010). The design of time-critical Human Computation applications can be addressed at the task and at the communication level. In the former case, the amount of time allotted for the execution of the task is set explicitly, so that potential performers can better self-evaluate their adequacy as problem solvers and not claim a task that they will not be able to perform at the requested speed (this solution is adopted by most crowdsourcing applications). In the latter case, a suitable incentive mechanism is defined that favours the rapid spread of information among potential performers. As an example of this latter approach, the winners of the DARPA Network Challenge adopted a reward mechanism by which the user gained a prize not only if he spotted one balloon personally, but also if a person recruited by him spotted one or in turn recruited a third person that directly or transitively contributed to the balloon identification. Such an incentive fostered the rapid creation of geographically distributed teams, because each user had a quantifiable advantage at selecting from his acquaintances the most active and geographically well-positioned members to add to the team.

3. Water Resources Management and Human Computation

Water Resources Systems (WRSs) provide a potentially interesting application for the Human Computation paradigm, particularly in the area of integrated planning and management.

A WRS is a complex system coupling natural and human factors, where the water cycle and the human activities interact and co-evolve (Liu et al., 2007). The natural water system consists of the hydrological processes of precipitation, evaporation, evapotranspiration, surface runoff, percolation and groundwater flow within an appropriately defined spatial entity (e.g., a watersheds bounded river basin). The human activity system is composed of the people living in that spatial entity (social system), the institutional and normative framework governing the use of the water resource (institutional system), and the infrastructures developed to store, convey and distribute water for economic or social purposes (infrastructure system), such as domestic water supply, irrigation, hydroelectric power, navigation, fisheries, recreation, and for the reduction of damages from flooding, water pollution, and droughts. Decision-making is central to water management: infrastructures are designed, developed, and subsequently controlled by solving planning and management problems that require planning long term decisions and making short term actions coherent with such decisions. The solution of any planning and/or management problem on a WRS encompasses a more or less formalised decision-making procedure that goes through the following sequential steps (Soncini-Sessa et al., 2003; Castelletti and Soncini-Sessa, 2006): i) the problem is defined, the decision-maker(s) and the stakeholders identified, and the overall purpose of the planning exercise is clearly stated; ii) data are collected and used to set-up descriptive...
and decision models; and iii) models are employed to inform decision-maker(s) on alternative trade-offs and to guide the process towards a final negotiated compromise solution.

A WRS revolves around a community of relevant, directly or indirectly involved individuals, which can be regarded as a physical social network in which concrete human actors constitute the nodes and their conscious or unconscious connections constitute links. Depending on the nature of the problem, actors can alternatively play the role of stakeholders or non-stakeholders, with one or more nodes acting as decision-makers. Human Computation techniques offer the potential of expanding the participation to the planning and management decision-making well beyond the limits of the individuals physically involved in the process, thanks to the capacity of engagement and communication power of online social networks.

More specifically, Human Computation can be integrated in water resources planning and management at three different levels: i) setting up a social network, for a better comprehension of the underlying social system; ii) putting humans in the loop, in order to exploit human potential as sensors, task solvers and decision makers; iii) eliciting collective knowledge (Gruber, 2007) on the WRS by exploiting situated and distributed knowledge and expertise, i.e., the so-called social capital (Cohen and Prusak, 2001).

Reaping the benefits of Human Computation in water planning and management also requires the development of new Information and Communication Technology (ICT) tools (the majority of which have yet to be envisaged), to effectively embed humans into the decision-making process.

3.1. Setting-up the enlarged social network

The communities of interest around the management of a natural resource can be established by a top-down survey of the institutional stakeholders and then enlarged to a broader audience of grass-root stakeholders by exploiting data available from online social networks. When the communities are mapped into a digital representation, social network analysis techniques (Easley and Kleinberg, 2010) can be applied to mine knowledge useful for improving the planning and management tasks. The process of network formation and analysis can be conceptually divided in the sub-steps described next.

(1) Network identification. The network population and connection topology can be initialised using traditional stakeholder identification techniques (Grimble and Wellard, 1997), based on a top-down survey process relying on the information provided by key institutions, as well as using conventional Community Building methodologies (Prell et al., 2009). Online social network exploration can be exploited to extend the social system to the grass-root level, thus ensuring that the viewpoint of non-organised, socially and politically disadvantaged individuals and groups is considered. To this end, mobilisation campaigns can be conducted on mainstream social platforms to promote the explicit self-enrolment of grass-root stakeholders; alternatively, online social network crawling techniques can be applied (Catanese et al., 2011; Ye et al., 2010) to identify potential interest-bearing subjects, e.g., with the help of focused crawling based on geographic attributes of users, on explicit group membership, on declaration of interests, etc. A prominent effect of the use of online social networks is the introduction of asynchronicity into the stakeholders identification process: instead of the traditional synchronous approach based on initiatives like group meetings and round tables performed at fixed times in the planning and management lifecycle, an asynchronous, open, and continuous engagement process is enabled, which better fits the recursive nature of the decision-making process.

(2) Interest characterization. Stakeholder interests are investigated and, possibly, each stakeholder node is further qualified by the evaluation criterion adopted to judge whether a planning and/or management alternative meets his/her interests (Soncini-Sessa et al., 2007a). Automatic profiling of user interests can leverage existing techniques coming from recommender systems and from the joint analysis of user-generated content and social network links and interactions (Mislove et al., 2010; Xie et al., 2010).

(3) Stakeholder clustering and representative selection. The network topology can be analysed with Social Network Analysis techniques (Easley and Kleinberg, 2010) with the twofold purpose of recognising patterns and contexts of interaction between stakeholders and identifying clusters of stakeholders/nodes with shared interests, who can spontaneously form lobbies and groups of interest (called sectors) (Wen and Lin, 2010; Harper et al., 2007; Alsaleh et al., 2011). Within each sector, the potential influence over the process of the individual stakeholders can be studied with role analysis techniques (Benvenuto et al., 2009; Prell et al., 2008), which consider not only the formal position within an organisation but also social links. Nodes that i) have distinct positions in the network thus providing a minimal and non-redundant set of communication paths within the community; ii) belong to different stakeholder categories; iii) are relatively well-connected to others and tend to broker across different sub-networks can be selected as the potentially most appropriate representatives of their sectors.

A complementary technique for discovering hidden knowledge about people and support clustering and representative selection is based on the use of games with a purpose (Zhang et al., 2011) alternatively employed to support mutual understanding and stakeholder negotiation: role games (Barreteau, 2003), traditionally employed to support mutual understanding and
3.2. Putting humans in the loop

When the network of stakeholders underlying the system is set-up, its members can be involved in the planning and management directly, as executors of a variety of different activities.

3.2.1. Human sensing

Data collection is a critical task since data quality affects, through models and model-based evaluations, the reliability and robustness of the final compromise alternative. The pervasive diffusion of mobile terminals equipped with sensors has fostered the diffusion of human-based, mobile sensor networks, which exploit users’ mobility to collect data at low-cost and on a large scale (Abdelzaher et al., 2007). Human sensed observations are primarily used to gather physical data, e.g., air quality data in urban spaces (Dutta et al., 2009), surveillance of invasive species (Cacho et al., 2011) and noise pollution (Maisonneuve et al., 2009). Recently, experiences have been reported in human sensing of water quality. The World Water Monitoring Day initiative, 1 coordinated by the Water Environment Federation (WEF) and the International Water Association (IWA), uses online dissemination means to recruit students in water quality monitoring worldwide; data are collected manually with water measurement kits and results are reported in an online GIS. The organizers plan to expand participation to one million people by 2012. The work described in Kim et al. (2011) makes a more intensive use of ICT and mobile technology: a mobile and fixed Internet application has been designed (called CreekWatch2) whereby people can post data about watersheds rapidly and without other instrument than a standard mobile phone, like the amount of water, the rate of flow, the presence of trash and pictures of the waterway. The application design has focused both on the user interfaces, on the incentive mechanisms for engaging citizens, and on the utility of data for the scientific community that consumes them. Social media have also been experimented for harvesting more heterogeneous and complex data, such as reporting on urban flooding events using geo-referenced tweet functionalities (Liu et al., 2011). Here the authors leveraged a popular microblogging service, Twitter.com, to customise a smart-phone application for citizen event reporting. The system uses an existing professional controlled vocabulary (e.g., ‘basement flooding’, ‘powerline down’), which is particularly useful in emergency conditions to deliver timely response. Similar experiments of streaming human visual experience into data have been conducted in Thailand to map flooded areas and the associated damage. 1 Another relevant aspect is to integrate human and artificial sensors, in order to make information available for further processing. A notable effort in this direction has been realised by Hill et al. (2011) with the NCSA virtual sensor system. This software tool provides a facilitated process to build wrappers around sensors, independently of their human or artificial nature, exposing functions which can be integrated in web-based applications.

3.2.2. Human judgement for task solving

In traditional WRS planning and management, problem solving requires technical knowledge and is delegated to a small number of domain experts. Human Computation methods can help assign problem solving tasks to a broader set of performers, recruited both from the physical social network of stakeholders, non-stakeholders and decision-makers and from large-scale online communities (Cooper et al., 2010; Hand, 2010). Socially gathered human expertise can be exploited to support the identification of the system components (e.g., the catchment areas), of their interactions (exploratory modelling), and of the main causal networks within each domain. To this end, cooperative work tools, such as Wikis (Cunningham and Leuf, 2001), questions and answers forums, and large-scale argumentation support applications (Landoli et al., 2009) can be used. Another use of human judgement for task solving is the exploitation of tacit knowledge and traditional wisdom about the behaviour of the natural system as a complement to descriptive models, e.g., to predict the effects of a specific action on the value of an indicator. Expert-based models can replace mathematical models in a convenient way whenever the knowledge about a social, environmental or economic process is not sufficiently formalised or data required for reliable model identification are not available, quite a common situation when human decisions impact the hydro-ecological systems (Mouton et al., 2009). In traditional co-evolutionary system modelling (Rammel et al., 2007), expert knowledge is captured through the quantification of the empirical expert judgement, using such techniques as Bayesian belief Networks (Varis and Kuikka, 1997; Castelletti and Soncini-Sessa, 2007a,b). The integration of expert empirical evaluations and computer-based mathematical models can then be addressed with imprecise-probability models like Credal Networks (Antonucci and Zaffalon, 2008), which have been applied to fuse human judgement and sensor data for the assessment of debris flow hazard (Salvetti et al., 2008).

3.2.3. Co-deciding

When stakeholders are given a co-deciding role (Hare et al., 2003) or when multiple decision-makers are involved, as in transnational contexts, the comparison and ranking of different alternative options and the subsequent negotiations among the parties can take considerable advantage of Human Computation. Most conventional approaches for group decision-making, like the Nominal Group Technique (Delbecq et al., 1975), the Delphi method (Turoff, 1970), and voting procedures, as well as advanced techniques, like Pareto race negotiation (Korhonen and Laakso, 1986), are intrinsically interactive, bottom-up, and structurally amenable to be computed assisted (Thiessen and Loucks, 1992). For example, Pérez et al. (2010) describe a mobile decision support system supporting dynamic group decision-making, which shows the feasibility of implementing a global-scale asynchronous consensus process with experts located in different places.

3.3. Eliciting collective (global) knowledge

Even with the more sophisticated and prescriptive approaches to supporting decision-making, the technical supervision by an analyst is always required to assist, step-by-step, the implementation of the process. In traditional computer assisted decision-making, support systems can only react to the analyst’s stimuli. In other words, mathematical and expert-based models are only able to answer questions of the form “What’s the effect of action A (e.g., building a new dam) on output B (e.g., loss of arable land in the downstream irrigation district)?”. 1

1 www.worldwatermonitoringday.org.
2 www.creekwatch.org

4 The example is related to Aswan High Dam construction: the red-brick construction industry, which consisted of hundreds of factories that used Nile sediment deposits along the river, has been negatively affected by the presence of the dam. Deprived of sediment, they started using the older alluvium of otherwise arable land taking out of production up to 120,000 ha every year.
This kind of question requires some ability by the analyst to anticipate a causal relationship between $A$ and $B$, and so the possible existence of some effects on $B$. Thus analyst prediction ability and expertise have a considerable potential effect on the final decision (the topic has been extensively analysed in financial studies, see, e.g., Lang et al. (2003) and references therein).

Human Computation could provide tools to complement the analyst skills and so democratise also this aspect of decision-making. Indeed, the above question could be formulated in two steps by first investigating on the existence of potential effects of $A$, “Is $A$ impacting on any sector/indicator/variable?”, and then, once $B$ has been individuated, exploring the magnitude of this effect in a quantitative way by invoking task solving functionalities (machine-based or human). Finding the proper answer to these meta-questions involves recognising similarities in different problems and connections across different domains, while integrating insights from several sources.

Research on the formalisation of knowledge on causal relationships in systems has started to develop with the advent of semantic networks (Sowa, 1991). Also early work by Forbus (Forbus, 1981) showed how an explicit representation of the causal relationship in a physical process can help automated reasoning about it. This research also inspired the declarative, logic-based, approach to modelling, as described in Robertson et al. (1991) in the context of modelling ecological processes. The main benefit of these approaches to knowledge representation was the ability to separate the concern of the implementation of a model describing a process from its logical and abstract specification. This added transparency and enhanced the ability to share concepts and knowledge among researchers. The limit of this approach was the inability to share the knowledge across a large number of scientists, due to lack of a common infrastructure for sharing such artifacts.

A collective knowledge system (Gruber, 2007), composed of situated and distributed expertise, could be suitably exploited for solving these high level tasks by using a semantically-explicit representation of the causal structure of a system. Such a representation can be formalised using ontologies, which are now a standard means for knowledge sharing across the internet, thanks to such representations as OWL (Ontology Web Language) and RDF (Resource Description Framework). Software tools for ontology development are widely available too, such as Protégé5 and NeOn6 (Resource Description Framework). Software tools for ontology development are widely available too, such as Protégé and NeOn and specific research is ongoing on collaborative ontology development (Braun et al., 2007). The use of ontologies has already proven effective in large projects, where scientists from different disciplines have to harmonize their views on the data exchanged across model interfaces (Janssen et al., 2009, 2011). The work by Nesić et al. (2011), within the TaToo project, aims at the development of collaborative tools for creating and enriching semantically unified views of environmental information. Users provide annotations to environment-related resources published on the internet such as models, datasets, observations, measurements, and so on. This will improve the relevance of search results, and create collective knowledge explicitly formalized and machine processable, opening the way to effective human computing in the area of environmental, and particularly water, research.

Thanks to ontologies, alternative views on causal relationships, attributable to different domains and crafted by different experts, can be expressed in a common formalism, therefore helping the analysts in finding alternative explanations for the same phenomenon. At the same time, systems such as TaToo allow experts and stakeholders to evaluate explanations and potential solutions, by ‘tagging’ resources as users now tag photos, books and other items. Such ‘tagging’ does not bring any scientific support to a given explanation per se, but allows the system analyst to identify the different viewpoints and discover the experts and the stakeholders who voiced their opinion on a specific issue. This process enables both expert finding and the mining of causal inferences. The interaction with this global intelligence will often induce recursions in the sequential decision-making process, including the re-qualification of the social networks where former non-stakeholder nodes might become stakeholder nodes. Therefore, each interaction with the collective knowledge base may trigger a new round of the Social Network Analysis.

3.4. Human Computation vs the traditional approach

Although the Human Computation approaches presented so far have not been yet experimented in a real world water management problem, in Table 1 we analyse the potential advantages it could bring to a real decision-making process compared to the landline tools traditionally used in this kind of processes. As a reference we use the Participatory and Integrated Planning procedure described in Castelletti and Soncini-Sessa (2006) and adopted to guide the decision-making process in the long standing conflict between Italy and Switzerland on the management of the transboundary Lake Maggiore (Soncini-Sessa et al., 2007b). The procedure is reported in Fig. 2. We consider only those phases (grey boxes in the figure) for which it does make sense to use Human Computation tools. The procedure and its application to the Lake Maggiore problem are extensively described in the above mentioned references.

4. Open issues in Human Computation design

The application of Human Computation to water resources planning and management can produce solutions that are more participative, more reactive to external stimuli from stakeholders, and more effective at informing decision-makers and subsequently communicating decisions to the general public.

However, the design of Human Computation systems must take into consideration a number of issues that arise when humans are included in the loop (Ipeirotis and Paritosh, 2011).

Human factors in computing and decision-making: the human cognitive processes interplay with affective states and may exhibit systematic and predictable bias, which, if overlooked, may threaten the validity of human-assigned tasks. Human factors in decision-making have been studied separately in neuroscience, behavioural economics and cognitive psychology; recently, the interdisciplinary field of neuroeconomics has addressed the integration of multiple techniques to examine decision-making by considering cognitive and neural constraints, used in psychology and neuroscience, in the construction of mathematical decision models, typical of economics (Sanfey, 2007). Anchoring and sequential effects (the dependency of responses on prior information) have been studied (e.g., the ‘anchoring bias’ studied by Tversky and Kahneman (1974) and well known in the environmental decision-making literature) and mitigation measures have been proposed that could be applied to crowdsourcing and online judgement elicitation (Mozer et al., 2010).

Quality of human output and malicious behaviour: a major issue in Human Computation design is measuring and improving the quality of human contributions, which requires estimating the financial cost of human labour and the quality of human output and malicious behaviour. In fact, human workers may exhibit various forms of maliciousness, such as productivity deficits caused by inappropriate motivations, which may arise from complexity of tasks and lack of feedback; or defects caused by...
the quality measure to the probability that a response is correct (Kuncheva et al., 2003). Refined approaches rely on the estimation of user’s quality and combine the responses taking such estimation into account. As an extreme case, performers may intentionally cheat, producing incorrect results, which requires suitable techniques for detecting spammers (Ipeirotis et al., 2010), or they may simply be negligent, an attitude that can be detected by pre-task screening (Downs et al., 2010).

Markets are natural and uncoordinated. However, today's markets are increasingly hybrid, where human and machine coordination is required. Human Computation techniques and traditional approaches can be contrasted and compared in some of the phases (grey boxes in Fig. 2) of the PIP decision-making procedure.

### Table 1

Human Computation techniques vs traditional approaches in some of the phases (grey boxes in Fig. 2) of the PIP decision-making procedure.

<table>
<thead>
<tr>
<th>Phase</th>
<th>Tasks</th>
<th>Traditional Tools</th>
<th>HC Tools</th>
<th>Advantages</th>
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<tr>
<td>0. Reconnaissance</td>
<td>A. System understanding</td>
<td>Survey, interview to experts and institutional stakeholders.</td>
<td>Cooperative work tools, such as Wikis, questions and answers forums, and large-scale argumentation support applications.</td>
<td>Improved reliable knowledge about the system functioning.</td>
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<td></td>
<td>B. Stakeholders identification</td>
<td>Surveys, top-down engagement by institutional stakeholders.</td>
<td>Mobilisation campaigns on social platforms, social net crawling and community building methodologies.</td>
<td>Deeper and larger involvement, down to the grass-root stakeholders; self-enrolment is facilitated through an asynchronous, open, and continuous engagement process.</td>
</tr>
<tr>
<td></td>
<td>C. Stakeholder clustering into sectors and identification of representative stakeholders</td>
<td>Meeting and direct interaction with involved stakeholders, representative election (voting).</td>
<td>Automatic profiling, social network analysis, games with a purpose and tagging.</td>
<td>An enhanced reliable characterisation of stakeholders and social connections.</td>
</tr>
<tr>
<td></td>
<td>D. Data collection and validation</td>
<td>Traditional data collection campaign with traditional sensors.</td>
<td>Human sensors and crowdsourcing.</td>
<td>An enhanced dense, robust, and possibly socially credible datacube.</td>
</tr>
<tr>
<td>1. Defining Actions</td>
<td></td>
<td>Brain storming during workshops, interview to experts and stakeholder representatives, and questionnaires.</td>
<td>Semantic network and ontologies.</td>
<td>A creative and wide process is stimulated, involving also collective knowledge on the web; a wider range of potentially interesting actions can emerge.</td>
</tr>
<tr>
<td>2. Defining Criteria and Indicators</td>
<td></td>
<td>Knowledge elicitation during workshops and interviews with experts and stakeholder representatives.</td>
<td>Ontologies and games with a purposes.</td>
<td>Hierarchies of criteria and the associated indicators can be identified and validated across a larger audience of stakeholders and experts. Improved ability of disambiguation of semantics associated with cross-domain concepts represented in the criteria.</td>
</tr>
<tr>
<td>3. Identifying Model</td>
<td>A. Identification of system components and their interactions</td>
<td>Workshop and meeting with stakeholders representatives.</td>
<td>Cooperative work tools, such as Wikis, questions and answers forums, and large-scale argumentation support applications.</td>
<td>An improved identification of the system topology, particularly for the more peripheral and indirectly connected components.</td>
</tr>
<tr>
<td></td>
<td>B. Identification of the causal network within each component</td>
<td>When possible, collaborative modelling based on one-to-one meetings with sector experts. More generally conducted by the analyst.</td>
<td>As above but at the level of the experts only.</td>
<td>Improved inference capability, particularly for the less unstructured and theoretically grounded aspects, like those involving human–nature interaction.</td>
</tr>
<tr>
<td></td>
<td>C. Identification of the model for each component</td>
<td>Mainly conducted by the analyst.</td>
<td>As above.</td>
<td>Improved model fidelity and augmented characterisation capability of the coupled social and natural processes through the direct involvement of stakeholders and both situated or distributed experts in the model building activities at all stages.</td>
</tr>
<tr>
<td>6. Evaluation</td>
<td>Value function identification</td>
<td>Interviews with stakeholder representatives.</td>
<td>Cooperative work tools, such as Wikis, questions and answers forums.</td>
<td>An effective and reliable identification of the value functions.</td>
</tr>
<tr>
<td>7. Negotiations</td>
<td></td>
<td>One or more plenary meetings with stakeholder representatives and decision-makers.</td>
<td>Games with a purposes in conjunction with social network information propagation capacity.</td>
<td>Negotiations can be extended to larger base of stakeholders thus enabling a truly co-deciding involvement. Moreover, an improved, effective management of the negotiation process that can be conducted remotely and asynchronously, thus avoiding psychological and physical fatigue (negotiation fatigue syndrome) that often prevent an happy ending for the process.</td>
</tr>
</tbody>
</table>

Fig. 2. The procedure for Participatory and Integrated Planning (Castelletti and Soncini-Sessa, 2006). The grey boxes are the phases analysed in Table 1.

reciprocal trust between buyers and sellers, and can be hampered by opportunistic or fraudulent behaviours. Trust and reputation systems used in e-commerce and recommender systems (Jøsang et al., 2007) apply to Human Computation too, but need to be adapted to the specificity of Human Computation environments.

Ethical and legal aspects. Human Computation applications question the ethical and legal framework at the base of the human condition (Zittrain, 2008). Many applications of Human Computation (e.g., expert finding and task-to-worker matching) require processing user’s data, e.g., profiles and friendship links extracted from social networks. These requirements may collide with the user’s expectation about data protection and privacy. Furthermore, the disconnection of workers from employers implied by crowdsourcing is also changing the workplace relationships, with such potential consequences as worker’s alienation, incapacity of judgement about the moral valence of tasks, and overmonitoring by the commissioner.

5. Conclusions and outlook

In this paper we have discussed some of the ways in which Water Resources Management can take advantage of the emerging trends in Human Computation, which are redefining the way in which humans and machine cooperate to perform complex tasks.

The fundamental idea is that planning and management ICT systems acquire more flexibility, if they can be built out of modular models that can be orchestrated to achieve a precise, yet increasing agility, prediction. Human Computation can also contribute to the management process, by encouraging participative negotiations, thanks to consensus building tools and people mobilisation for timely data collection and effect verification campaigns.

Crowdsourcing platforms, with their capacity of distributing work to a large pool of performers, provide another valuable opportunity, for delegating batches of work, like data analysis activities. Finally, gaming with a purpose techniques could be an innovative option for training stakeholders in the negotiation process and for informing citizens about the way alternative decisions affect the behaviour of the system and impact the community.

Our future work will concentrate mostly on the implementation, deployment and validation of some of the ideas proposed in this paper. We plan to use them both in Ecuador and in the lake region of Como, Italy, so to experiment Human Computation solutions in very different social contexts, from rural areas to highly industrialised urban scenarios. This will give us the opportunity to test different tasks formulation and incentive mechanisms for fine tuning the participative tools to the expectations, cultural background, and local skills of the communities where the water management system is embedded.

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